Economies of the future

Robots and Artificial Intelligence, the new economic motor or downfall of the working class?

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Robots and Artificial Intelligence, the new economic motor or downfall of the working class?

by
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Preface

Dear reader,

This thesis marks the end of a 2-year journey at the Delft University of Technology. As for many students, and almost too cliché to put on paper in this section (but I will do it anyway), it has been struggle, an iterative process of learning, a process of confrontations with my self, and a process with great reward. I would like to express my sincere gratitude for everyone's support over the past 2 years and, especially, the last months. But first, a note.

This thesis started even before I started the Engineering and Policy Analysis master. Technology is developed at an accelerating pace and increasingly changing the world we live in. This provides opportunities and challenges. Depending on your position and perspective these developments may be favourable or threatening, opportune or inauspicious, and motivating or discouraging. This may seem somewhat overstated, but technology is becoming more and more human like and will change how we work and who has work. Prior to the master, I worked for a company that develops advanced robotics for automation of specialised and sensorimotor-depended manual labour. In general, the systems would replace employees in production and design. In nearly all cases, these employees would be trained to operate the systems or would be transferred to other products and tasks. The employees were often low educated and clearly needed to do their utmost best to understand how the system worked and how to (safely) operate it. In this sense, rarely did a company fire its staff due to replacement. Yet, one day this sparked an important question. What if this technology will (eventually) replace these people, what if this technology at the forefront will become widely adopted, and what if similar technologies emerge to perform a far wider range of labour? These were not necessarily moral or ethical dilemmas, but they sparked an interested in the broader context, the potential problems, and especially the opportunities. And here we are now, an attempt in contributing to the scientific understanding and societal knowledge on what may lie ahead.

As all whom have been involved in, and supportive of, this thesis process know, it has been inspiring but a long challenge. I would, especially, like to thank Erik Pruyt, Servaas Storm, and Jeroen van den Hoven for their continued support, understanding, and motivating words to deliver the quality I pursued. Erik, as my first supervisor, has been, as always, an inspiration and energy boost with his limitless enthusiasm and motivation. Servaas Storm, as my second supervisor, provided healthy criticism throughout the process and the occasional reality checks when necessary. And Jeroen van den Hoven for being the chair of my committee and introducing the broader societal and political backbone of this work.

I would like to thank the EPA students, with whom I jointly went through a 2-year learning curve of hurdles and challenges, for their moral support, inspiration, and comradery. Guru for his enthusiasms, dedication to always go one step further, and occasional pc lending service. Erin, Ellen, and Patrick for moral support and the occasional pressure relief.

Lastly, I would like to thank my family for their support, occasional dinner service, and advice. And in particular, Marit for being there with me during the whole process and providing the required pep talks.

I do hope, dear reader, that you will enjoy reading this thesis. I also hope it can contribute to our understanding of the challenges we face, motivate future research and policy intervention, and undo common misconceptions revolving round the threat of robotisation.

Koen Spaanderman
Oktober 2018

Executive Summary

Technological progress and innovation have significantly contributed to global economic growth, societal advancement, and higher living standards. However, there is growing concern over the future that lies ahead because of increasing robotisation and progress in artificial intelligence (AI), which are feared to cause significant loss of labour demand. The body of posterior economic scientific work addressing this topic mostly concludes on a positive note. Namely, recent technological advancements have resulted in a net increase in labour demand, but this demand is redistributed to different tasks and occupations. Yet, future oriented research, most notably by Frey and Osborne (2017), has sparked a debate on the future of work due to estimations that indicate that over 40% of jobs will become automatable in the next 20 years. Therefore, the societal question remains: Robots and Artificial Intelligence, the new economic motor or downfall of the working class?

In consideration of this context, the future effect of advanced information and robotic technology (IT and RT) on labour substitution, unemployment, and labour force adaptability has been studied using dynamic simulation following the Robust Decision Making (RDM) framework. The technological change and labour substitution framework literature (Task Based Technological Change (TBTC) and Routine Replacing Technological Change (RRTC)) was synthesized with a systems approach to conceptualise and operationalise a future-oriented model to simulate plausible future labour market outcomes in relation with future technological advancements. This model has been operationalised with System Dynamics (SD), simulated using Exploratory Modelling and Analysis (EMA), and analysed using the Patient Rule Induction Method (PRIM) algorithm to determine plausible future unemployment and potential for policy intervention in relation with technological change and associated uncertainties to answer,

> *To what extend is the labour force capable of adapting to labour substitution by advanced robotics and artificial intelligence, and can be incentivised to do so, to mitigate future unemployment?*

Future unemployment is highly unlikely to reach beyond current unemployment levels

Simulation across a variety of future scenarios[1] with increasing automatibility and labour substitution (compared to the current rate) illustrate that acceleration of unemployment is unlikely, except when the substitution rate 3- to 4-folds in the next 20 years (from the current maximum annual rate of 0.51% of labour hour demand, or approximately 10% in 20 years). Although technological automatibility (i.e. the ability of technology to automate and replace human labour input in tasks) may develop at this pace, the implementation of technology and the substitution of labour takes considerably longer due to financial, technological, competitive, legal, social, sectoral, and structural factors (Arntz, Gregory, and Zierahn (2016), Brynjolfsson, Rock, and Syverson (2017)). Moreover, the outcomes for the Netherlands suggest that only in adverse conditions where labour input in abstract tasks is substituted in addition to manual and routine tasks, that unemployment will significantly rise above current levels (i.e. a combination of 2- to 3-fold of manual and routine task input substitution at 1.41% annually and abstract task input substitution of 0.57% annually). In contrast, the literature highlights that it is highly improbable that abstract tasks - that employ the high skilled labour force - will be automatable due to the social, communicative, creative, intuition, and inductive reasoning aspects of these tasks (Arntz, Gregory, and Zierahn (2016), Frey and Osborne (2017), Nedelkoska and Quintini (2018)). As a result, the total substituted labour input of abstract tasks is expected to be around 1-1.5% over the next 20 years. Hence, this combination of manual, routine, and abstract task labour input substitution conflicts with the current scientific consensus. Therefore, based on the outcomes it is concluded that technological advancement is highly improbable to result in future unemployment growth in the Netherlands – even if the substitution rate grows considerably.

[1] Gregory, Salomons, and Zierahn (2016), Frey and Osborne (2017), Arntz, Gregory, and Zierahn (2016), Nedelkoska and Quintini (2018), and Deloitte (2016)

Labour force adaptability though labour reallocation and skill attainment are central to remain at current unemployment levels

This study shows that, although labour may become increasingly substitutable by technology, labour force adaptability via labour supply reallocation and skill attainment will be able to successfully counteract the loss of employability in most but the extreme cases. As a result, the unemployment rate remains low (2-6%) and near or below current unemployment levels relative to the ratio of substituted labour. The adaptability of the labour force under these conditions does require that approximately 1.0% of the low, middle, and high skilled labour force needs to be reskilled to work with future technology and approximately 2.3% of the low skilled and 7.9% of the middle skilled labour force needs to be upskilled in the next 20 years in the Netherlands. Furthermore, spill-over effects that arise because of productivity growth associated with technological change may further offset the substituted labour demand loss. Yet, it should be noted that this productivity growth has failed to materialise, resulting in an observed Solow paradox between the technological advancement we observe and simultaneous stagnation of productivity growth. Hence, ensuring accessibility of education, incentivisation of skill attainment, and adequately equipped education systems is key and a shared responsibility of governments and businesses.

Inequality will continue to grow across all future scenarios

In respect of both inequality and policy making, the outcomes highlight that growing unemployment as a result of technological advancement is highly unlikely, even when treating substitution as being equal to automatibility. In contrast, the outcomes concerning the wage share point to a continuous decline of the position of the labour force in respect of economic growth and growing inequality. The outcomes point to a continuation of the current trend of a reduction of the labour share of 0.3% annually or acceleration to 0.58% or higher. Hence, inequality should be at the centre of the policy debate given the societal implications associated with inequality. In respect of this study and its fundamental academic underpinnings, future attention should, therefore, shift to integrally studying inequality resulting from technological advancement. To conclude and in consideration of the title of this thesis, IT and RT will not be the downfall of the working class in terms of employment and will only become the economic motor if the Solow paradox ceases to exist. Yet, the question that needs to be raised for future research, is whether the working class will share in the economic outcomes that technology may bring.

List of Figures

List of Tables

Contents

1 Introduction

Technological progress and innovation have driven economic growth through productivity- and cost-advantages on a global scale across different periods (DeCanio, 2016; Frey & Osborne, 2015, 2017). The industrial revolutions are periods characterised by rapid technological change and consequential productivity growth that reshaped the economy, production, labour, and society. Since the second world war, various periods of macro-economic development have been driven by the introduction of technology-based production or labour innovations, of which the most recent are advanced robotics and Artificial Intelligence (AI) (DeCanio, 2016; Frey & Osborne, 2017; Arntz, Gregory, Zierahn, 2016). Although the developments have significantly contributed to global economic growth, societal advancement, and higher living standards, there is growing concern over the future ahead.

1.1 Societal relevance - The uncertainty revolving around future technological change

These concerns stem from the contrast between previous periods of labour substitution and the current technological development forefront. Prior technologies augmented labour activities or substituted labour input in unproductive, dangerous, and/or heavy tasks (Autor, 2015). Humans, as in the labour production factor, remained a vital input for adaptive, reactive, flexible, sensorimotor, cognitive, and social activities (Autor, 2015; Autor, Levy, Murnane, 2003; IFR, 2017). However, the current and future generations of robotics, information technology (IT), and combinations of the two is expected to shrink the human-exclusive domain. On the one hand, physical tasks become more automatable due to more advanced, cheaper, and scalable mechanical manipulators, sensors, and computational capabilities. On the other hand, artificial intelligence (as in the advanced form of IT including sub-types as e.g. machine learning) will become able to reproduce or outperform rational human(-like) decision making, analysis, and interaction with the environment. In this sense, technology is becoming a more direct competitor with humans to perform different tasks. However, technology has a distinct advantage in productivity and applicability.

Predicting the future capabilities and development pace of technology is inherently difficult (Frey & Osborne, 2017) and can be notoriously unreliable (Armstrong, Sotala, & Ó hÉigeartaigh, 2014). Yet, it catalyses the concern revolving around the uncertain consequences of technological progress for society, particularly through the labour-side of the economy (Autor, 2015; Autor, Dorn, & Hanson, 2015; Frey & Osborne, 2017; Goos, Manning, & Salomons, 2014; IFR, 2017). Namely, technological change is feared to cause significant labour substitution[2], which may have drastic adverse effects for society. These consequences manifest themselves as declining wages, higher unemployment, job polarisation, and higher economic inequality. Moreover, economic (market) mechanisms may reinforce this development, resulting in a wedge between those whom benefit from -and can adopt to- technological progress, and those whom are essentially replaced by technology (Autor, Dorn, & Hanson, 2015). Consequently, the indelible loss of the economic position of the middle/working class is feared to result in societal segregation and growing inequality. Yet, these societal fears bear a resemblance to historic periods of significant technological change and fear for unemployment (Frey & Osborne, 2015, 2017; Mokyr, Vickers, & Ziebarth, 2015)[3]. In hindsight, the fears turned out to be premature. Technology disrupted conventional labour markets and significantly changed how we work and what types of tasks and occupations we perform, but it has never resulted in mass unemployment due to labour supply reallocation and new tasks and occupations (in different sectors).

[2] Replacing human occupations or tasks by capital (e.g. machines, robots, or computers)
[3] For a more detailed evaluation of historic patterns is provided by Frey & Osborne (2017) and Mokyr, Vickers, & Ziebarth (2015)

1.2 Scientific relevance - Absence of consensus concerning the future

Historically, the process and impact of technology on labour has been central to the work of economists (DeCanio, 2016; Frey & Osborne, 2017). Most evident is John Maynard Keynes's prediction of widespread technological unemployment because of *'our discovery of means of economising the use of labour outrunning the pace at which we can find new uses for labour'* (Keynes, 1933, p. 3 from Frey & Osborne, 2017, p. 254). The current body of scientific work addressing this topic originates mostly from an econom(etr)ic domain using an economic-statistical or expert-based methodology. In case of the prior, explanatory models are developed to perform posterior analysis on the effects of technology and conclude on the current trend, or project those trends into the future (Arntz et al., 2016; Autor et al., 2015; Frey & Osborne, 2017; Goos et al., 2011; Graetz & Michaels, 2017; Gregory, Salomons, & Zierahn, 2016). These studies distinguish from one and other by analysing the developments with various specific datasets across spatial demarcations, time demarcations, scopes (e.g. technology), and the substitution framework. Therefore, scientific literature provides different predictions depending on the model, scope, and framework (Arntz, Gregory, Zierahn, 2016). However, the current results systematically demonstrate that earlier technological changes have resulted in more jobs (although different ones, at different levels) and economic growth rather than the portrayed doom scenario for the working class (Frey & Osborne, 2017; Gregory, Salomons & Zierahn, 2016; IFR, 2017).

In case of the latter methodology, experts are consulted to estimate the probability of, and timeframe within which, technology will be able to substitute specific human capabilities, activities, or tasks (Arntz, Gregory, Zierahn, 2016; Frey & Osborne, 2015, 2017; Nedelkoska & Quintini, 2018). These results are then extrapolated across a large set of occupations based on their characteristics and calibrated to the economic composition. The most influential work – and widespread, even in popular media – by Frey and Osborne (Frey & Osborne, 2017) predicts that 47% of jobs in the United States are at high risk to be automated in the next 2 decades or so. However, this estimate only considers the technological substitutability without regards for labour adaptation and economic spill-over effects (Arntz, Gregory, & Zierahn, 2016; Frey & Osborne, 2017; Nedelkoska & Quintini, 2018). In this respect, recent trends and future predictions contrast significantly. Moreover, literature on the future effect of technology such as robotics and Artificial Intelligence (AI) is scarce (Frey & Osborne, 2017), especially when excluding expert estimations.

With both methodologies (econom(etr)ic and expert based), the dynamic interconnectivity of economic, technological, and societal systems is rarely explored in an integral manner (Arntz, Gregory, Zierahn, 2016). Moreover, an equilibrium or static model is used without feedback mechanisms to reduce complexity and/or simplifications to limit the number of dependent variables since they complicate algebraic analysis (Goos, Manning, & Salomons, 2011). Yet, these feedback mechanisms may be vital to assess the impact of technology on the labour market (Arntz, Gregory, Zierahn, 2016). Another limitation stems from the inherent accuracy restraints of expert predictions, in case of technology (Armstrong, Sotala, & Ó hÉigeartaigh, 2014), and in general (Camerer & Johnson, 1991). This results in the conclusion that '*studies illustrate several important principles, such as the general overconfidence of experts, the superiority of models over expert judgement and the need for greater uncertainty in all types of predictions'* (Armstrong, Sotala, & Ó hÉigeartaigh, 2014, p. 317). This conclusion is rather problematic considering the limited work exploring the future impact of technology on the labour market. As Frey and Osborne (2017) formulate, '*To our knowledge, no study has yet quantified what recent technological progress is likely to mean for the future of employment'* (p. 255). Hence, exploration of this uncertainty including the feedback mechanisms and avoiding the limitations of expert judgements seems critical to provide robust strategies and useful prognosis of plausible future labour market developments and robust strategies.

Concerning such strategies, there is only a limited body of literature concerned with policies. The adaptability of the labour force is essential to avoid mass unemployment (as portrayed by future oriented research) (Autor & Salomons, 2017; Frey & Osborne, 2017; IFR, 2017). Adaptability implies that the labour force is able to reallocate labour supply to other occupation sources and/or is able to attain new and additional skills to improve employment potential. Problematically, *'Given the gravity of the technological transformation we are undergoing, there is astonishingly little research effort in understanding the subsequent response through skill adjustment.'* Yet, the authors continue based on the little research that *'re-qualification and upskilling play a key role in mitigating the difficult transitions awaiting workers whose skills have been rendered obsolete by technological progress.'* (Nedelkoska & Quintini, 2018, p. 36). Moreover,

> *'we are far from a satisfactory understanding of how automation in general, and AI and robotics impact the labor market and productivity.'* (Acemoglu & Restrepo, 2018, p. 1)

To conclude, in the current scientific, political, societal and economic debates, conflicting perspectives are emerging and contradictory claims about the impact of technology are made. The significant economic and societal impact of new technologies demands for a structured exploration of the complex system as a whole. This study will make a first attempt in bridging the current *a posteriori* and *a priori* methodologies and findings using System Dynamics (SD) modelling and exploration of the uncertainties with Exploratory Modelling and Analysis (EMA)[4] (Kwakkel & Pruyt, 2013). This method will incorporate the economic feedback mechanisms via a differential equation model (based on the *a posteriori* labour economic models) and incorporate the uncertainty associated with future technological impact (based on the *a priori* expert judgment based outcomes) via exploratory simulation. The model is developed, operationalised, and simulated following the Robust Decision Making (RDM) framework to identify policy levers and strategies to minimize unemployment and maximize economic potential of robots and AI.

On a side note, the following video[5] provides a comprehensive summary on the topic.

1.3 Outline

This research is organised as follows. First, this part continues with a definition of the research gap, theoretical framework, and methodology. Hereafter, this document is divided in three parts, namely

- **Part I Production, Demographics, Labour, Education, and Technology: a complex systems model**
  A model is constructed to simulate the plausible future co-development of technology and the labour market. To do so, the model is structured according to five interrelated sub-models, namely, economic production, demographics, labour market, education, and technology. In this part, the process of labour substitution is constructed based on substitution frameworks. Economic models developed to study the impact of technology from a posterior perspective are adopted to define the SD model for future oriented analysis. Associated systems are defined to study the adaptability of the labour force in reaction to labour substitution. More specifically, how the labour force (as part of the demographic model) reallocates supply (labour market model) and adapts to changing skill demand (education model). Lastly, the plausible future scenarios of technological progress and associated uncertainties are defined and the complete conceptual model constructed using SD software.

- **Part II Case study on the future impact of robotics and AI on the labour market in the Netherlands**
  The model developed in Part I is simulated for the Netherlands based on the current labour market composition for the next 20 years. The future scenarios (of technological development and uncertainties) are simulated to determine how the labour force natively (without intervention) will adapt to replaced labour inputs and loss of labour demand. This provides a range of plausible futures, i.e. how technology and labour could co-develop given the uncertainties faced. This base

[4] *'The main purpose of this combination of EMA and SD is to gain insight into what kinds of surprising dynamics can occur given a variety of uncertainties and a basic understanding of the system.'* (Kwakkel & Pruyt, 2013 p.419)
[5] If the link does not work, copy and paste: https://youtu.be/TUmyygCMMGA

case is expanded upon by exploring the critical sensitivities that can mitigate unemployment. A profile of policies is established given these outcomes.

- Part III Synthesis of findings
  The results generated for the Netherlands are reflected upon from a theoretical and empirical perspective. The implications of technological progress are placed in a broader international and societal/social context. To conclude, the research question is revisited, reflected upon, and the methodology and outcomes are discussed.

2 Research definition

The focus of this study is to explore the plausible effects of technology on future labour markets. More specifically how robot and information technology will compete with labour and change the skill requirements of the labour force. To achieve this, the research gap and research question are explicitly defined and the problem scoped. Hereafter, the applied method is set forth and document flow diagram is presented.

2.1 Research gap and research question

It is difficult to assess the future impact of robotics and information technology on the labour market due to uncertainties and high complexity. There is limited research to date that explores the substitution of technology from a *a priori* perspective outside of expert elicitation estimates. Meanwhile an extensive body of posterior analysis of technological progress is available. Conversely, there is widespread concern for future mass unemployment among society, academics, and politicians because of recent technological advancements. These advanced information and robotic technologies will become increasingly capable of replacing human labour and outperform our capabilities. In this respect, a paradox is observed. Namely, the concern involving, and projected implications of, labour substituting technology are wide spread but the scope for future oriented research is limited. Hence, the following gap has been observed;

> *There is a need for exploration of the implication of future technologies on the labour market and labour force given the current academic knowledge on substitution processes and in consideration of the larger system of influences and uncertainties.*

2.1.1 Research question

This leads to the following main research question;

> *To what extent is the labour force capable of adapting to labour substitution by advanced robotics and artificial intelligence, and can be incentivised to do so, to mitigate future unemployment?*

This question addresses three key aspects; the impact and advancement of technology, the adaptability of the labour force, and possibilities to limit unemployment due to substitution.

2.1.2 Research sub questions

The scientific relevance, identified research gap, and formulated research question are divided in manageable and comprehensible sub-questions. First, the mechanisms that determine the development and impact of technological advancement and the labour adaptability need to be defined. Thus, an understanding of the process of substitution needs to be attained and operationalised, resulting in the following question:

> *I - How can the current literature, frameworks, and models be operationalised for future oriented analysis of the co-development of technology and labour?*

After operationalisation, the next step is to determine what the current expectations are concerning future technological advancement and the labour market. This may require adaptation of the operationalisation to allow for model development and simulation in conformity with the associated data (sources, types, ranges, and uncertainties) and literature. The operationalisation needs to be verified and validated to determine:

> *II – What are the labour market implications of technological advancement in the next 20 years?*

The developed model and the range of scenarios and implications is then used to study the potential of policy intervention and the absence of policy interventions. These interventions are aimed at the adaptability of the labour force (established in sub question I). Therefore, the following research question is formulated:

> *III – Which policy levers are available to mitigate the projected future unemployment trends and maximise economic and living standard growth brought about by advanced robotics and artificial intelligence?*

The implications of labour substitution expand beyond the labour market and economic processes. Therefore, the results of the sub questions are reflected upon from a socio-economic perspective to place the outcomes in a societal context. Moreover, based on the outcomes, it is then necessary to reflect on the methodology, model, and results.

2.1.3 Research deliverables

Answering the aforementioned research question and sub questions, the following deliverables are provided:

- A review of the state of the art literature to develop a dynamic model for future oriented analysis
- An operationalisation of the theoretical model with System Dynamics (i.e. a SD model)
- A case study of model implementation and simulation to determine the plausible range of future implications and policy alternatives
- A reflection and discussion on the study, the representativeness, and a reflection from an ethical and societal perspective

2.2 Research process

In correspondence with the previous sub section, the research approach, theoretical framework, and methodology are defined and summarised in a flow diagram.

2.2.1 Approach

The presented research questions dictate the suitable research approach to a large extent. The final product will be an exploration of plausible future unemployment and available policies levers to mitigate unemployment given the introduction of technological innovation (Robotisation and AI) in the economy. Therefore, the analysis will focus on the evaluation of different institutional arrangements in the future. Hence, the *modelling approach* naturally follows the research question. However, within this approach, the construction of a model rooted in labour economics and technological substitution paradigms demands for the establishment of qualitative and quantitative causal relation between factors. In other words, to make a useful model (that is able to provide accurate information about the future states of the system), first the relation between elements needs to be substantiated (how does A influence B) and quantified (to what extent does a change in A result in change in B). Some of these relations can be extracted from prior scientific work (for example the relation between the introduction of robots and labour demand by Gregory, Salomons, and Zierahn (2016). However, many relations will need to be determined based on analysis of data and literature. Therefore, a *deductive approach* is required in preparation of the modelling approach.

Given the orientation towards societal benefits (i.e. unemployment and inequality), qualitative research will need to be embedded in the primarily quantitative approach. Therefore, the quantitative results will need to be placed into the societal context to give them meaning. Moreover, the deductive approach may rely on triangulation techniques (e.g. elicitation and conversion of qualitative estimates into quantitative ones) to provide input into the model. As a result, the qualitative approach may provide '*a more complete, holistic, and contextual portrayal of the unit(s) under study*' (Jick, 2010, p. 603). To summarise, the research approach relies on a mixed deductive and modelling approach using quantitative and qualitative research methods.

2.2.2 Method

This research follows the Robust Decision Making (RDM) framework and methodology to explore the possible future labour scenarios given technological substitution estimates versus demographic labour force dynamics, labour reallocation, re- and up-skilling, and spill-over effects. RDM consists of four steps to reach robust policy decisions given the uncertainties faced with (Kwakkel, Haasnoot, & Walker, 2016). The first three steps will be performed since the fourth step is aimed at trade-off analysis of real world policies (Kwakkel, Haasnoot, & Walker, 2016) which extends beyond the scope of this thesis.

> *"In brief, RDM first helps decision makers characterize the vulnerabilities of a series of candidate strategies and then helps these decision makers identify and choose among alternative means for ameliorating the vulnerabilities. Scenario discovery facilitates this first step, concisely summarizing a wide range of future states of the world in a way that helps decision makers more clearly understand the strengths and weaknesses of candidate strategies."* (Bryant & Lempert, 2010, p. 36)

First, the relevant system is conceptualised, uncertainties identified, and outcomes of interest specified (Kwakkel, Haasnoot, & Walker, 2016). The system conceptualisation and system model are based on the current technological change literature and labour substitution frameworks. These are explored to define the process of labour substitution. Following Frey and Osborne's (2017) and Arntz, Gregory, and Zierahn's (2016) method, a production model is constructed to study future labour substitution and technological change with a task based approach. This model has its foundation in the Task Based Technological Change framework (Acemoglu & Autor, 2012; Autor, Levy, Murnane, 2003) and the associated Routine Replacing Technological Change framework (Gregory, Salomons & Zierahn, 2016). This model is expanded upon to include demographic labour force dynamics, labour reallocation, re- and up-skilling, and spill-over effects as the identified most important associated mechanisms. The labour market sub-model is constructed based on the relation between labour skills and production tasks in the frameworks. Tasks and their required skills evolve over time due to technological progress and other factors (Acemoglu & Autor, 2012; Acemoglu & Restrepo, 2018; Autor, 2015; Autor, Dorn, & Hanson, 2015; DeCanio, 2016; IFR, 2017; Nedelkoska & Quintini, 2018). The process of re- and up-skilling is defined and an education sub-model is constructed based on literature on the causal relations that influence skill attainment. Lastly, the future development of technology in relation to labour substitution is explored to define plausible future substitution estimates. These sub-models are combined to create a conceptual system model.

Second, the conceptualisation is operationalised into one or multiple models and simulated to explore the behaviour of the system given the identified uncertainties. This also allows for candidate policy and strategy identification (Kwakkel, Haasnoot, & Walker, 2016). Therefore, the theoretical model is operationalised using System Dynamics (SD) modelling. The use of SD to explore (socio-) economic systems and provide decision support dates to the early complex system modelling efforts using SD (Forrester, Mass, & Ryan, 1976; Smith & Ackere, 2000). Economic models to analyse dynamic phenomena and the SD methodology are consistent due to their mathematical underpinnings (Smith & Ackere, 2000). As a result, various schools of economics have adopted SD to study economic dynamics (Radzicki, 2009), including neoclassical (Weber, 2010) and various forms of heterodox economics (Atkinson, 2004; Radzicki, 2008). Yet, the operational, complexity, and systems approach of SD contrasts with conventional economic methodologies and practices (Forrester, 2003, 2013; Saeed, 2014). In this respect, from an SD perspective the use of SD in this study is economically and, most importantly, methodologically substantiated due to the exploratory and future oriented nature of this study. Yet, from the perspective of economics, this approach diverges from the econom(etr)ic and expert methodologies applied in technological change and labour substitution studies. In this process, the Exploratory Modelling and Analysis (EMA) workbench is used in Python as a tool to simulate the experiments. This generates an ensemble of future scenarios (rather than a selection of manually defined scenarios or predictive models) (Kwakkel & Pruyt, 2013). *'The main purpose of this combination of EMA and SD is to gain insight into what kinds of surprising dynamics can occur given a variety of uncertainties and a basic understanding of the system.'* (Kwakkel & Pruyt, 2013, p. 419). The advantage of exploratory modelling (step two and three of RDM) and the use of EMA, is that it provides the opportunity to gain new insights in system behaviour and strategy options when strict validation is impossible and/or when faced uncertainty problems.

Third, scenario discovery is performed using machine learning algorithms to simulate the model across the uncertainty space, assess the performance of the strategies, and identify conditions under which they perform inadequately (Bryant & Lempert, 2010). "*Scenario discovery provides a set of analytic tools that help decision makers identify such scenarios [internally consistent and challenging descriptions of possible futures] by focusing on those futures most important to the design of and choice among candidate robust strategies.*" (Bryant & Lempert, 2010, p. 35) This step relies on the Patient Rule Induction Method (PRIM) algorithm to sample from the individual uncertainty ranges to create uncertainty spaces in which plausible futures are located that are statistically significance to the outcomes of interest (Kwakkel, Haasnoot, & Walker, 2016). In relation with the main research question, these outcomes of interest concern unemployment and potential labour reallocation and re- and up-skilling policy levers. Note, that the fourth step of the RDM framework is not performed and that step three is used for policy identification and potential of policy intervention. Therefore, the application of RDM in the context and purpose of this study deviate from the slightly from conventional application of the framework.

2.2.3 Flow

The outline, research questions, and methodology are graphically depicted in the flow diagram (Figure 1).

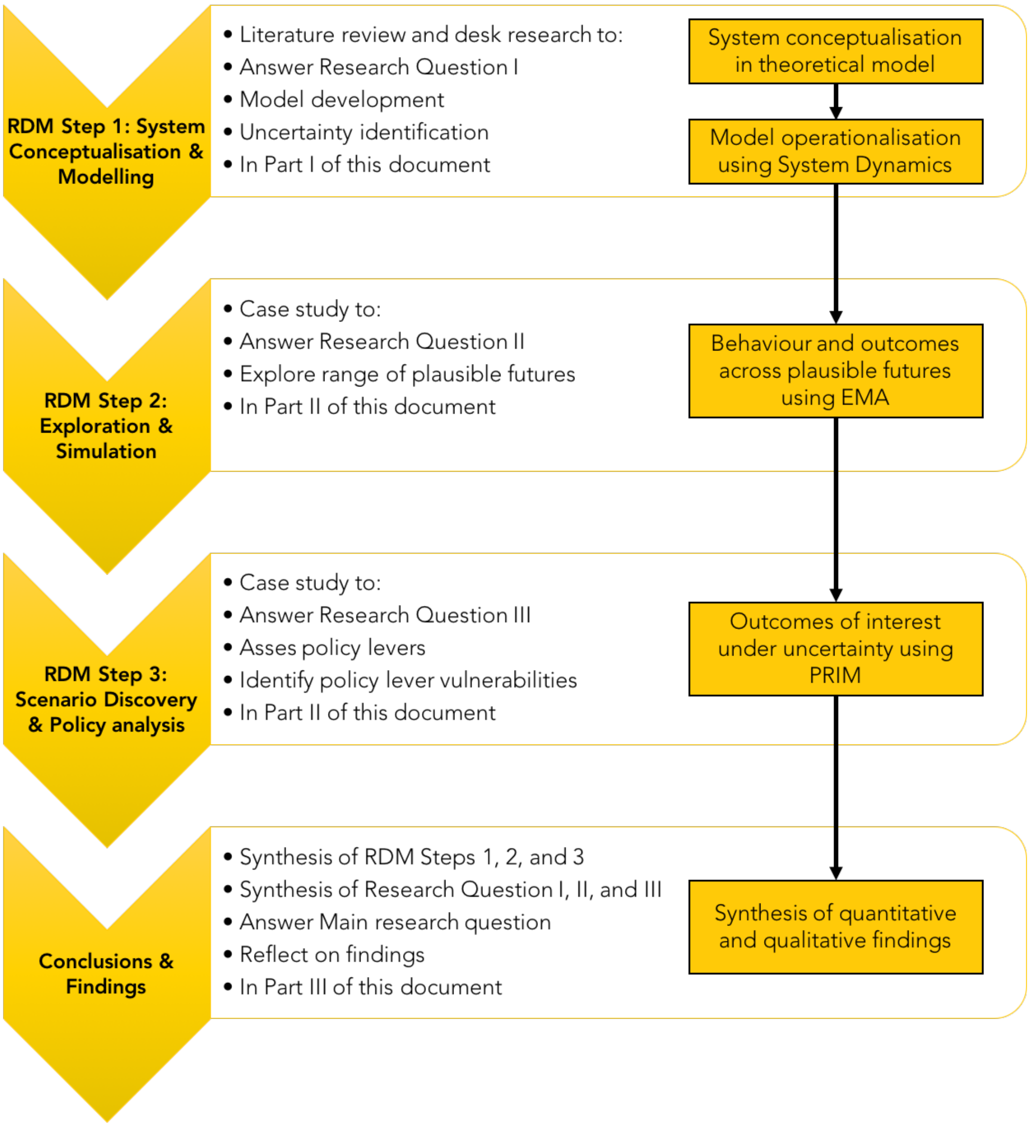

Figure 1 Research Flow Diagram

Part I Production, Demographics, Labour, Education, and Technology: a complex systems model

A model is constructed to simulate the plausible future co-development of technology and the labour market. To do so, the model is structured according five to interrelated sub-models, namely, economic production, demographic, labour market, education, and technology. In this part, the process of labour substitution is defined based on substitution frameworks. Economic models developed to study the impact of technology from a posterior perspective are adopted to define the SD model for future oriented analysis. Associated systems are defined to study the adaptability of the labour force in response to labour substitution. More specifically, how the labour force (as part of the demographic model) reallocates supply (labour market model) and adapts to changing skill demand (education model). Lastly, the plausible future scenarios of technological progress and associated uncertainties are defined and the complete conceptual model constructed using SD software.

3 The balance between substitution and spill-overs

Technology is increasingly capable of substituting labour in production processes (Frey & Osborne, 2017). Before being able to determine how technology and labour will co-develop, it is important to understand the underlying mechanisms. Labour substitution frameworks describe how technological change impacts the labour market across economies, industries, and occupations with mechanisms derived from econometric analysis and economic models. The mechanisms through which substitution manifests itself also give rise to counteractive effects. Technology will stimulate economic growth and can, via spill-over effects, offset the loss in labour. This chapter will introduce the labour substitution frameworks and associated spill-over effects. The state-of-art paradigmatic frameworks are adopted as the foundation of the production model in the consequent chapter.

3.1 Labour substitution frameworks – How technology replaces labour

Over time, economists and econometrists have argued that, statistically, the impact of technology on employment can be explained through various frameworks. In this approach, production function models and regression analysis are used to estimate the impact of technology based on causal relations. The perception that technology is replacing humans in production is not new. However, the relevant question is how substitution manifests itself. The frameworks attempt to theorise this manifestation and provide proof of explanatory consistency using posterior empirical comparison across different time-frames and economic scopes. The theoretical production and labour structure of the frameworks provide opportunity to define complementary models to explain and inform about the observed phenomena. Therefore, they provide a substantiated starting point in the exercise of modelling future substitution.

3.1.1 Skilled Biased Technological Change (SBTC)

In the past, scholars observed a decline in lower income and education jobs and an increase in the college-premium[6]. This resulted in the hypothesis that technology mainly substituted non-college educated labour (Autor, 2013). The outcome was the Skilled Biased Technological Change (SBTC) framework – also known as the canonical model by Acemoglu and Autor (Mishel, Shierholz & Schmitt, 2013). The framework examined the impact of technology at the occupational level based on a dichotomy between college and non-college employment. Technological substitution was argued to be biased towards non-college labour input. Critique from less aggregate analysis revealed that this correlation and the causal relation behind it did not hold universally over time, sectors, and economies (Mishel, Shierholz & Schmitt, 2013). The observed skill-biased labour market development was the dependent variable, not the independent. Implying that technology mainly substitutes occupations that employ the non-college labour force but not because of the traits of the employees, but because of the characteristics of their jobs. More importantly, the framework was unable to account for shifts technological change manifestation and associated effects on labour and wages (Autor & Dorn, 2013; Card & Dinardo, 2002).

3.1.2 Task-Based Technological Change (TBTC)

Autor, Levy, and Murnane (2003) introduced the foundations of the Task-Based Technological Change (TBTC) framework which argues that specific tasks are substituted since they are/can be routinized following structured and well-understood procedures. Therefore, such "routine tasks" can be captured in computer

[6] Difference between college or higher educated employment in wages and labour hours compared to non-college educated labour.

code via explicit programmed rules and executed by technology (Autor, 2015; Autor, Levy, Murnane, 2003; Goos, Manning, & Salomons, 2009). These routine tasks include physical and cognitive activities, respectively termed routine manual and routine abstract tasks (Autor & Dorn, 2013; Cortes, Jaimovich, Nekarda & Siu, 2014; Frey & Osborne, 2017). Conversely, "non-routine tasks" comprise cognitively and physically flexible, reactive, and adaptive tasks that are significantly harder to capture in procedures. As of such, tasks relying on sensorimotor, social, communicative, creative, problem-solving, and reasoning capabilities can (so far) not be executed by technology and remain human domain – at most complemented by technology (Autor, 2015; Autor, Levy, Murnane, 2003; IFR, 2017). Non-routine tasks are divided into two categories: "abstract" tasks and "manual" tasks. Respectively the tasks require problem-solving, inductive reasoning, intuition, creativity, and persuasion versus situational adaptability, recognition, and communicative interaction (Autor, 2015). Therefore, the impact of technology is studied at a task level whereby occupations consist of a combination of routine (cognitive and physical), abstract, and manual tasks (Autor, 2015; Mishel, Shierholz & Schmitt, 2013). Within the economy, businesses utilise a set of those tasks to produce products (goods or services[7]) which in turn utilise labour and (technological) capital production factors (Gregory, Salomons & Zierahn, 2016). In the process of technological substitution, former labour input in tasks is executed by capital and new labour tasks emerge due to restructuring of production processes.

Following this logic, substitution takes place at a disaggregate level compared to the SBTC framework. In contrast to SBTC, TBTC disconnects the absolute relation between skill level and occupation level (and consequently wage level) by analysing individual tasks within occupations and their required skill level (Autor, 2013; Mishel, Shierholz & Schmitt, 2013). To do so, the framework utilises a three-tier classification of labour demand and supply: low, middle, and high skilled (Autor, Levy, Murnane, 2003). In relation to tasks, abstract tasks demand high skill levels and cognitive capabilities, while manual tasks can be performed with relatively low skill levels[8] (Autor, 2015; Cortes, Jaimovich, Nekarda & Siu, 2014; Mishel, Shierholz & Schmitt, 2013). Therefore, occupations consisting of exclusively abstract or exclusively manual tasks are at the opposite ends of a continues skill spectrum (Autor, 2015). Similarly, high (low) wage occupations are synonymous to high (low) skill and abstract (manual) task-rich occupations (Goos, Manning, & Salomons, 2009). In relation to the dichotomy between goods and services, non-routine tasks are generally associated to the production of services and routine tasks to the production of goods. The variety of task compositions/structures and the change of these structures due to substitution shape the labour market, wages, and skill relevance. The distinction and relation between skills and tasks is well summarised by Acemoglu and Autor (2012), whom write,

> *'Many of the shortcomings of the canonical model can, we believe, be overcome by relaxing the implicit equivalence between workers' skills and their job tasks in the model. In our terminology, a task is a unit of work activity that produces output. A skill is a worker's stock of capabilities for performing various tasks. Workers apply their skills to tasks in exchange for wages. Thus, the task-based approaches emphasize that skills are applied to tasks to produce output—skills do not directly produce output. The distinction between skills and tasks is irrelevant if workers of a given skill always perform the same set of tasks. The distinction becomes important, however, when the assignment of skills to tasks is evolving with time, either because shifts in market prices mandate reallocation of skills to tasks or because the set of tasks demanded in the economy is altered by technological developments, trade, or offshoring'* (p. 444-445)

The TBTC framework has demonstrated more consistent statistical and empirical explanatory power of observed labour market phenomena than SBTC (Mishel, Shierholz & Schmitt, 2013). Consistent with empirical data, the TBTC task categorisation self-explains the observed polarising nature of technological substitution: the middle skilled are employed in occupations with a significant share of routine tasks (Autor, 2015). Therefore, at the opposite sides of the skill-spectrum, occupations rich in high skilled abstract tasks or

[7] Respectively defined as tangible hard-ware or soft-ware items and intangible benefits. In this document, products refer to both goods and services and production to the creation/manufacturing of both goods and services, unless specifically stated otherwise.
[8] Hence, manual tasks can be performed by a very large share of the labour force as middle and high skilled labour is equally capable of performing the tasks (Autor, 2015).

rich in low skilled manual tasks remained non-automated. Although TBTC is not completely uncriticised (see Mishel, Shierholz & Schmitt (2013)), later refinement to the framework and growing evidence[9] have established TBTC as the standard because of its explanatory consistency. Especially the works of scholars like Acemoglu, Autor, and Dorn have contributed to this status.

3.1.3 Routine Replacing Technological Change (RRTC)

Goos, Manning, and Salomons (2011) and Gregory, Salomons, Zierahn (2016) revised the TBTC framework into the Routine Replacing Technological Change (RRTC)[10] framework based on model and regression alternatives (Gregory, Salomons & Zierahn, 2016). Similar to the TBTC framework, the model is defined at the task level (Goos, Manning, & Salomons, 2011). However, the model uses task-level CB production functions whereby '*industry output is produced from a common set of 'tasks', used in different proportions by different industries*.' (Goos, Manning, & Salomons, 2011, p. 2). Consequently, the labour market is established wherein the occupations comprise a combination of those tasks. In contrast with TBTC, a dual substitution effect is introduced. That is, exogenous reduction of capital prices incentivises businesses to not only substitute labour directly but also to restructure production processes through routinisation[11] (Frey & Osborne, 2017; Gregory, Salomons & Zierahn, 2016). '*Recent technological breakthroughs are, in large part, due to efforts to turn non-routine tasks into well-defined problems*' (Frey & Osborne, 2017, p. 259). The routinisation effect implies that businesses substitute tasks for routine tasks following a CES production function. As a result, there is an emphasis on the balance between spill-over effects and substitution effects (Goos, Manning, & Salomons, 2011). Hence, the framework is more production-oriented compared to the more labour market-oriented TBTC.

The current status of TBTC among scholars and added production structure of RRTC provide the starting point to model future substitution. Therefore, in contrast to prior studies, the time-frame is shifted from posterior to a prior evaluation of the plausible future effect of technology. In this respect, the TBTC and RRTC framework determine the structure of the labour market, the production process, the effects of technological change, and the labour force's ability to adapt to changing tasks.

3.2 Spill-over effects – How we benefit from technology

The substitution of labour for more productive technology does not necessarily need to imply a loss of labour demand. The productivity growth will reduce the production costs of a task and create spill-over effects depending on the allocation of the costs benefits. These spill-over effects can offset the initial loss of labour demand via feedback mechanisms (Gregory, Salomons & Zierahn, 2016). The productivity growth can be allocated to different purposes, which eventually will determine to what extend substitution is offset. If used purely competitively, the reduction in production costs (per unit) is fully allocated to price reduction (thus constant wage and profit mark-up). Alternatively, strict allocation towards profitability implies that the reduction in production costs is purely used for profit (thus constant wage and product price). This would be the case if the companies are strictly profit maximising. Conversely, the reduction in production costs can also be completely transferred to wages (thus constant profit mark-up and product price). The effects of each of the distribution channels feed back to the economy via spill-over effects.

> '*one cannot obtain an adequate understanding of the changing structure of employment if one ignores the channels by which a change affecting the demand for one type of labor is likely to spill over to every other type of labor.*' (Goos, Manning, & Salomons, 2011, p. 3)

[9] The evidence empirically confirmed the existence of the phenomenon of job-polarisation from 1980's to the financial crisis in 2007. Therefore, providing a theoretically and empirically consistent framework and giving technology driven job-polarisation a paradigmatic status (see Autor (2015) for extensive list of studies).
[10] Initially named the Routine Biased Technological Change (RBTC) framework by Goos, Manning, and Salomons (2011)
[11] Defined as the *Substitution effects* by Gregory, Salomons, and Zierahn (2016).

Technological substitution studies argue that spill-over effects can offset the substituted labour tasks and labour hours altogether within the organisation, along the supply chain, and across sectors (Autor & Salomons, 2017; Goos, Manning, & Salomons, 2011; Gregory, Salomons & Zierahn, 2016; IFR, 2017). First, competitive allocation results in increased product demand (given the price elasticity of demand) followed by increased production and thus increased labour demand of the remaining labour in the organisation and in the supply chain of complementary sectors. Therefore, the reduction of prices can result in more overall labour demand[12] (Goos, Manning, & Salomons, 2011; Graetz & Michaels, 2017; Gregory, Salomons & Zierahn, 2016; IFR, 2017). Moreover, if the increase in remaining labour and associated increase in income exceeds the substituted labour income, additional product demand is created across sectors via consumption[13] (Gregory, Salomons & Zierahn, 2016; IFR, 2017). Therefore, the increase in product demand due to competitive allocation has a dual nature: increasing exogenous demand for tradable products due to declining (relative[14]) prices and increasing endogenous demand for tradable and non-tradable products due to reducing prices and increased total labour income[15] (Gregory, Salomons & Zierahn, 2016).

Second, allocation towards profits can be retained in the business or distributed as dividend. Profits that are retained within the company can be invested in business activities and innovation. This can create additional labour demand within the organisation or at the supplier (IFR, 2017). Moreover, investment in technological innovation can result in a second-order effect whereby further productivity growth is realised. This implies that a new round of spill-over effects is set in motion in the distant future. Distribution of dividend across shareholders increases their non-wage income and, therefore, possibly their product demand (given the propensity to consume and to save of the shareholders). However, part of this spill-over effects may leak away if the additional income flows out of the economy to foreign capital owners and expenditure (Gregory, Salomons & Zierahn, 2016).

Third, allocation towards wages will directly increase consumption (given the propensity to consume and income elasticity of demand) resulting in growing product demand across sectors, growing production, and so forth (IFR, 2017). In addition, a second order spill-over effect may arise when the additional labour demand creates a shortage of labour supply and result in higher wages (IFR, 2017). Conversely, limitations in (adequately equipped) labour supply compared to labour demand can also inhibit additional production and hinder the spill-over effects. Therefore, the dynamics of the labour market influence the realisation of the spill-over effects. As a result, the interactions between production, product markets, and labour markets are essential to determine the effects of technological change (e.g. robotics and artificial intelligence) on employment (Gregory, Salomons & Zierahn, 2016).

Overall, the ability to offset labour substitution depends on the relative allocation of the productivity gains to the spill-over mechanisms and the elasticities within the spill-over mechanisms (Gregory, Salomons & Zierahn, 2016). It is certain that technological substitution will result in productivity and output growth. However, it is uncertain whether spill-over effects are continuously and universally able to offset the effects of substitution on labour. As Graetz and Micheals conclude, '*the effect on hours worked is ambiguous'* (2017, p.12). This ambiguous nature is the result of the relative strength and dominance of spill-over effects on labour versus the substituted labour (Gregory, Salomons & Zierahn, 2016). If the feedback effect of spill-over mechanisms are weak, product demand does not react strongly and hence labour demand does not increase significantly enough:

> *'the size of the product demand spillover depends critically on where the gains from the increased productivity of technological capital accrue*.' (Gregory, Salomons & Zierahn, 2016, p. 1)

[12] Defined as the *Product demand effect* by Gregory, Salomons, and Zierahn (2016)
[13] Altogether, the effect of consumption spill-over to other sectors can result in an additional net increase of 1,4 to 1,6 jobs per job created in the sector of technological substitution (See Gregory, Salomons and Zierahn (2016 for details)
[14] In comparison to the price development of product substitutes produced abroad.

In this regard, the allocation of the gains is not monotonous. Evidence from robot driven productivity growth suggests that approximately two thirds of the labour productivity gains are used competitively and a tenth goes to wages (Graetz & Michaels, 2017). Therefore, the relative share of competitive, profit, or wage allocation determines the initial strength of the spill-over effects.

3.3 Framework and spill-over synthesis and current situation

Current evidence suggests that the spill-over effects are dominant over substitution effects and off-set the substituted labour at an aggregate level. Gregory, Salomons, and Zierahn (2016) demonstrate overall growth of labour demand at a regional level as productivity growth results in higher wage and non-wage incomes which feed back via product demand. However, the growth in labour demand is dispersed across the regional economy (Gregory, Salomons & Zierahn, 2016). Similarly, Salomons and Autor (2017) find spill-over dominance at an industry level where industry specific productivity growth increases aggregate labour demand across sectors. However, at a disaggregate level, the technology adopting industries that actually realise higher productivity growth experience falling labour hours themselves. Therefore, the spill-over effects end up in the remaining industries of the economy (Autor & Salomons, 2017). Likewise, Michaels and Graetz (2015) indicate that disaggregation at the labour force level is required since technological progress affects groups heterogeneously across sectors, occupations, and skill levels (Michaels & Graetz, 2015; IFR, 2017). Moreover, technologies affect the labour market in heterogeneous ways (Michaels & Graetz, 2015). Which implies that aggregation of substitution technologies, as if a single force acting upon labour, overlooks underlying effects. Therefore, an incomplete image may arise when only considering the aggregate macro-level impact of technology as a whole (i.e. all technological advancement have the same impact) on employment as a whole (i.e. all tasks are influenced in the same way) (Mishel, Shierholz & Schmitt, 2013).

4 Complex systems model introduction

A conceptual model is constructed based on the substitution frameworks and associated systems according five interrelated sub-models, namely, economic production, demographic, labour market, education, and technology (Figure 2). The conceptual model depicts the interrelations between the sub-models and the connection between the labour demand and labour supply side of the socio-economic system. In the subsequent chapters, each of the sub-models and their interrelations is defined. Here after, this conceptual model is operationalised using SD. Additionally, the three spill-over effects are included. The profit spill-over is divided in two flows, one towards (additional) innovation investment and one leaking out of the economy (note: financialisation is introduced in a subsequent chapter). The price spill-over is internalised and results in additional demand. Lastly, the wage spill-over results in additional household income and feeds back via consumption.

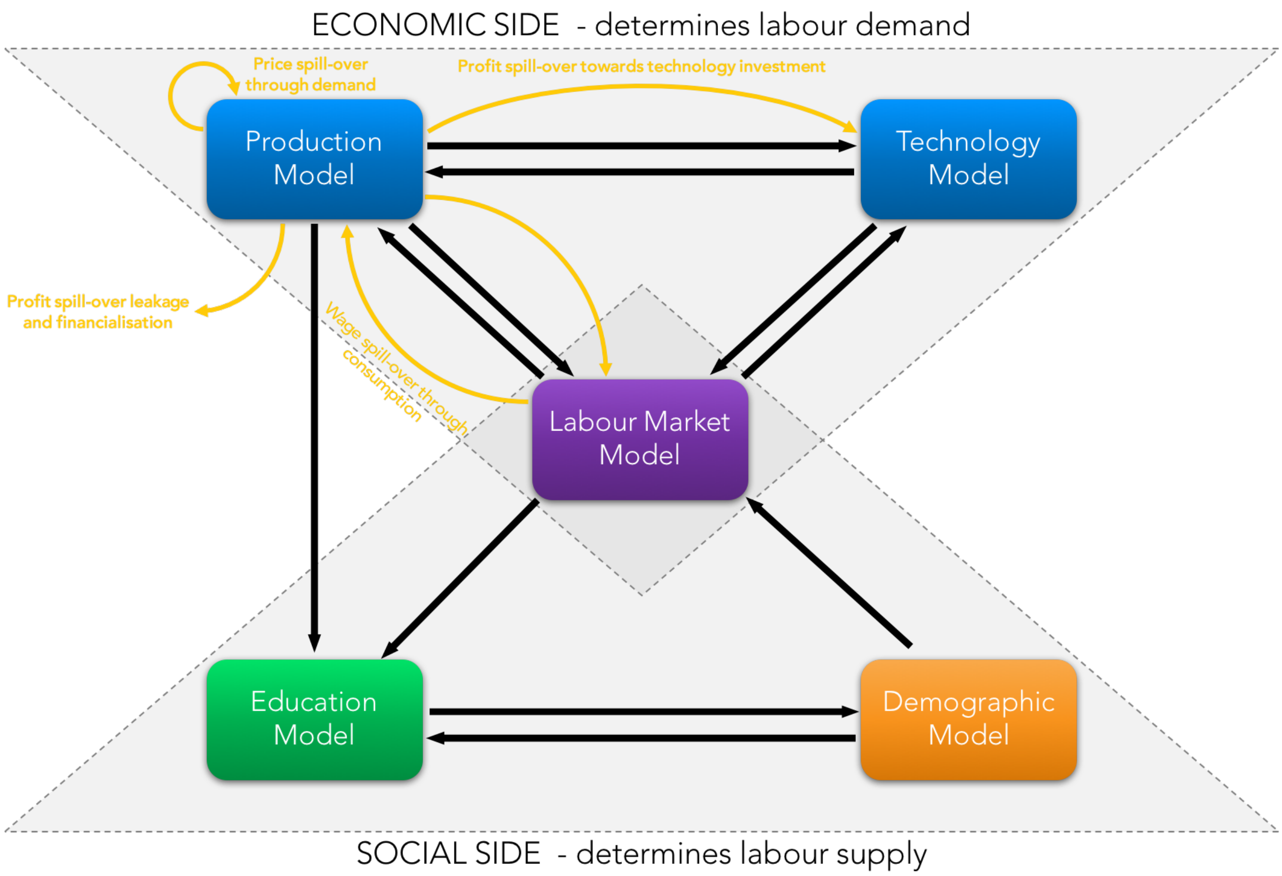

Figure 2 Conceptual model overview

5 Production model

The models associated with the presented substitution frameworks form the foundation of the economic component of the model. This economic production model represents a country's economy based on a nested set of production functions. Technological substitution is implemented via shifts in the composition of tasks and input within the production functions. This chapter will introduce the process of substitution, derive a macro-economic production model based on the labour substitution frameworks, and provide a synthesis of the relations with the socio-economic system. The effect and impact of and on labour, education, and technology is covered in separate subsequent chapters.

5.1 A basic production function model

Following TBTC and RRTC, occupations and production consist of a combination of routine, abstract, and manual tasks types performed by low, middle, and high skilled employees (Autor, 2015; Mishel, Shierholz & Schmitt, 2013). Overall production [X] consists of a specific composition of tasks [$X = \{T_1, T_2, \dots, T_n\}$] and employees perform a part of those tasks depending on their occupation [O] (Figure 3). Therefore, occupations comprise a subset of all the tasks in production [$O \subset X$] (Autor, 2013). Tasks are defined in accordance with Acemoglu and Autor (2012), namely *'a task is a unit of work activity that produces output'* (p. 445). Therefore, each task is separately identifiable and categorisable responsibility/activity with distinct output that contributes to the overall output of a production process. Each of the tasks [T] is characterised as a type (routine [$\mathcal{R}$], abstract [$\mathcal{A}$], or manual [$\mathcal{M}$]) with an individual share in total production [a, b, c] such that [$\sum\ a, b, c\ = 1$ and $0 < a, b, c < 1$] with a representing the share of routine tasks, b the share of abstract tasks, and c the share of manual tasks. Therefore, the overall production function is defined at the tasks level. Tasks themselves have individual production functions defined at the factor input level, as is conventionally done with production functions.

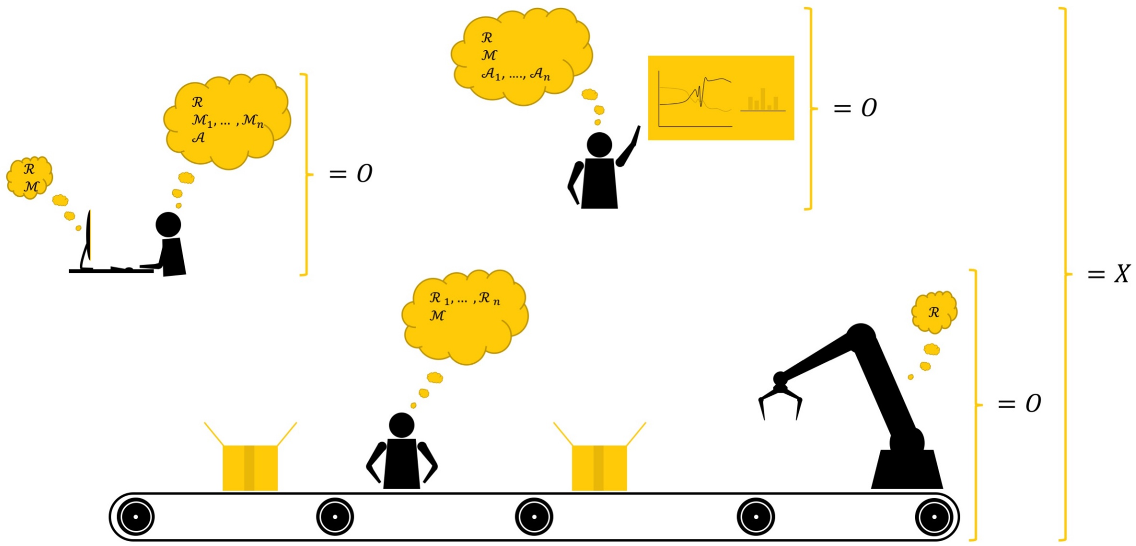

Figure 3 Production is a combination of occupations comprising a set of tasks

Following RRTC, each task [T] requires certain labour factor input [L_T] and task-specific[16] capital factor input [K_T] (Goos, Manning, & Salomons, 2011; Gregory, Salomons & Zierahn, 2016). The inputs respectively introduce factor specific costs, namely the labour costs [W_T] and capital costs [Π_T] of production (Gregory,

[16] Implying that non-specific capital in the businesses is not relevant. In this respect, capital is only referred to as specific capital utilised to perform a task.

Salomons & Zierahn, 2016). The share of the inputs is expressed via the capital share of production [α] and the labour share of production [$\beta = 1 - \alpha$] such that [$0 \leq \alpha \leq 1$]. Herein, the labour input factor requires a level of skill [ε] and the capital factor depends upon technology [τ]. The overall task productivity operates as the Total Factor Productivity (TFP) of the task [A_T], which is defined as the aggregate of the labour productivity [λ_T] and capital specific productivity [κ_T]. Therefore, production relies on a set of tasks which, in turn, utilise a combination of labour and capital. The result is a set of equations wherein input level production functions are nested inside the task level production function.

5.1.1 Input Substitution

Technology does not simply substitute the labour production factor by replacing it for capital – which would imply that former tasks utilising labour input are replaced one-on-one by tasks only requiring capital input. Rather, labour input within tasks is substituted for capital input to raise the overall productivity (Autor, 2015; IFR, 2017). This implies that substitution shifts the input from labour towards capital in the task level production function (e.g. $\delta\alpha = -\mathrm{i} \mid \delta\beta = \mathrm{i}$). Therefore, it does not necessarily imply that labour input is replaced all together. Complementary technology replaces existing capital input for more productive capital and/or replaces part of the labour input with more productive capital. Therefore, labour input is still required but the execution of the task and the interaction with the technology has changed. As a result, the skills required to perform the task [$\varepsilon_{t=1}$] may have changed and so does the relevance of prior skills [$\varepsilon_{t=0}$]. To accommodate this difference, a human capital factor is added [ξ_τ] which is skill- and technology-specific. In other words, it depicts the additionally required technological skills introduced by the substituted input(s). The increase in task productivity improves labour performance and, with it, increases the potential for labour augmenting spill-over effects. In which case, technology complements the labour factor and results in labour augmentation – albeit possibly with different skill requirements and in different tasks.

5.1.2 Task Substitution (routinisation)

The routinisation of processes does imply that the tasks themselves are reorganised and substituted for commutable routine alternatives. Businesses are incentivised to substitute abstract and manual tasks for routine tasks since especially routine labour can be (and will be) substituted when financially and technologically feasible (Autor, 2015; Goos, Manning, & Salomons, 2011; Gregory, Salomons & Zierahn, 2016; Michaels & Graetz, 2015). Therefore, technological progress is task type specific (note: not type exclusive) and the effects of technologies are different. This introduces a dual substitution effect: (1) input substitution within tasks (if labour input is substituted) and (2) task substitution across tasks (if routinisation takes place). Since routinisation substitutes the task altogether, the type-factor shares change accordingly in the overall production function. Evidence suggests that routinisation deteriorates labour input demand and thus substitutes employment (Gregory, Salomons & Zierahn, 2016). However, the adoption of new technology may introduce new associated tasks in support of the new capital and process. This would suggest that additional, albeit different, labour input is required which may offset the substituted labour. Unfortunately, this is only possible if the employees providing the former labour input have the newly required skills or if they are capable of attaining those skills in a reasonable time (Autor, Dorn, & Hanson, 2015; IFR, 2017). This attainment aspect equally applies to skill changes induced by input substitution.

5.1.3 Substitution Elasticity

Input and task substitution occurs in reaction to relative price developments of labour and capital - given the technological automatibility possible. Hence, '*Firms' technology choice is simple: adopt robots when profits from doing so exceed profits from using the labor-only technology by at least the fixed setup cost'* (Graetz & Michaels, 2017, p. 11). The rate of substitution depends on the respective elasticity of substitution [η] for input and tasks. Therefore, at the input level, the ratio of capital input over labour input follows the change in capital costs over labour costs (effectively nominal wage of the task). The value of the input substitution elasticity has been under debate since the first definition of the product function, but is estimated between 0.4 to 0.6 according to DeCanio (2016). Similarly, at the task level, the ratio of routinized tasks over non-routine tasks follows the change in routinized tasks costs over non-routine task costs. Gregory, Salomons, and Zierahn (2016) estimate the elasticity of task substitution [η_X] at 0.66 (with standard error of 0.175), while Goos at al. estimate a substitution elasticity of 0.9 (according to Gregory, Salomons & Zierahn (2016))[17]. This suggests that there are inhibiting factors to substitution outside of financial feasibility since the elasticities are not equal to unity (Gregory, Salomons & Zierahn, 2016) (that will be covered in the Technology model sections). However, the substitution elasticities need not be static and can change due to technological advancement (Schneider, 2011).

5.1.4 Production composition and substitution

The substitution of input is defined using a CB production function (following the TBTC and RRTC frameworks (Goos, Manning, & Salomons, 2011, 2014; Gregory, Salomons & Zierahn, 2016)) and nested Leontief function. The input production function (Eq. 1) and substitution of input (Eq. 2) *within* tasks, to the extent of input elasticity $[\eta_T]$, requiring skill level $[\varepsilon]$, and depending on task specific technology $[\tau]$ are expressed as,

$$T = A_T(\alpha K_{\tau_T}^{\eta_T} + \beta L_{\varepsilon_T}^{\eta_T})^{\frac{1}{\eta_T}}, \qquad \alpha + \beta = 1 \qquad \text{Eq. 1}$$

$$\frac{\delta\left(\frac{K_{\tau_T}}{L_{\varepsilon_T}}\right)}{\delta t} = \eta_T * \frac{\left(\frac{K_{\tau_T}}{L_{\varepsilon_T}}\right)}{\left(\frac{W_{\varepsilon_T}}{\Pi_{\tau_T}}\right)} * \frac{\delta\left(\frac{W_{\varepsilon_T}}{\Pi_{\tau_T}}\right)}{\delta t}$$

$$\left(\frac{K_{\tau_T}}{L_{\varepsilon_T}}\right)_{t=1} = \left(\frac{K_{\tau_T}}{L_{\varepsilon_T}}\right)_{t=0} + \eta_T * \frac{\left(\frac{K_{\tau_T}}{L_{\varepsilon_T}}\right)_{t=0}^2 * \left(\left(\frac{W_{\varepsilon_T}}{\Pi_{\tau_T}}\right)_{t=1} - \left(\frac{W_{\varepsilon_T}}{\Pi_{\tau_T}}\right)_{t=0}\right)}{\left(\frac{W_{\varepsilon_T}}{\Pi_{\tau_T}}\right)_{t=0}^2} \qquad \text{Eq. 2}$$

Note that the substitution function corresponds to Solow's capital intensity of production $[K/L]$ (Weber, 2010). A nested Leontief function is defined to accommodate the co-development of human capital $[\xi_\tau]$ as a requirement to operationalise new technology in the specific task $[\tau_T]$. The Leontief alternative is used since technology and the associated skills would not be utilised/are not operational without the other (Acemoglu & Restrepo, 2018). Human capital is technology dependent and an extension of the pre-attained skill level, hence $[\varepsilon_{T_\xi}]$ or simplified to $[L_{\xi_T}]$. Since technological progress is task specific, the Leontief function (Eq. 3) with relative weights $[\mathcal{w}]$ is expressed as,

$$A_T = min\left(\frac{L_{\xi_T}}{\mathcal{w}_L}, \frac{\tau_T}{\mathcal{w}_\tau}\right) \qquad \text{Eq. 3}$$

The model incorporates task-biased technological progress via task specific technology $[\tau_T]$ and task dependent productivities $[A_T]$. Therefore, the model follows Goos, Manning, and Salomons (2011, 2014) whom simplify the model by assuming non-industry specific technology (and provide substantiation why this assumption holds). The relative weights $[\mathcal{w}]$ set the amount of labour hours and technological development required to realise the associated productivity growth.

5.2 A nested task-based production function model

The substitution of tasks requires a more elaborate definition than proposed above in order to accommodate routinisation. The substitution of abstract and manual tasks for routine alternatives introduces four complications. First, the routine alternative still requires the skill level of, respectively, the prior abstract $[\varepsilon_{\mathcal{A}}]$ or manual $[\varepsilon_{\mathcal{M}}]$ task. Hence, substitution with conventional routine tasks $[\varepsilon_{\mathcal{R}}]$ would be incorrect. Second, routinisation is fundamentally incentivized by the possibilities for substitution. Therefore, routinized tasks have an automatibility ratio in line with routine tasks (further defined and discussed in the

[17] The estimated real world task substitution elasticities $[\eta_X]$ are used as input in the model.

Technology model sections). Third, the technology used for routinisation differs from both conventional routine tasks and the prior abstract or manual task. Otherwise, routinisation would be identical to input substitution from a technological point of view. Lastly, an overall production function with routine, abstract and manual tasks would result in an identical substitution elasticity between all task types. However, manual and abstract tasks are not substitutable with each other. In addition, a routinised alternative of routine tasks is introduced. This may seem counterintuitive, but new technologies will require additional skills (as is described in subsequent chapters). This also applies to routine tasks. As a result, a system of nested production functions (Eq. 4 A-D) is introduced with routinised routine [$\mathcal{R}_{\mathcal{R}}$], abstract [$\mathcal{R}_{\mathcal{A}}$], and manual [$\mathcal{R}_{\mathcal{M}}$] tasks and associated variables,

$$T \in \{\mathcal{V}_{\mathcal{R}}, \mathcal{V}_{\mathcal{A}}, \mathcal{V}_{\mathcal{M}}\}, \quad \mathcal{V}_{\mathcal{R}} = \{\mathcal{R}, \mathcal{R}_{\mathcal{R}}\}, \quad \mathcal{V}_{\mathcal{A}} = \{\mathcal{A}, \mathcal{R}_{\mathcal{A}}\}, \quad \mathcal{V}_{\mathcal{M}} = \{\mathcal{M}, \mathcal{R}_{\mathcal{M}}\}$$

$$X(T) = A_X \prod_{i=1}^{|T|} T_i^{\eta_i}, \quad \eta_i = (a, b, c), \quad \sum_{i=1}^{3} \eta_i = 1 \qquad \text{Eq. 4}$$

$$\begin{aligned} \mathcal{V}_{\mathcal{R}} &= (\alpha_{\mathcal{R}}\mathcal{R}^{\eta_X} + (1-\alpha_{\mathcal{R}})\mathcal{R}_{\mathcal{R}}^{\eta_X})^{\frac{1}{\eta_X}} \\ \mathcal{V}_{\mathcal{A}} &= (\alpha_{\mathcal{A}}\mathcal{A}^{\eta_X} + (1-\alpha_{\mathcal{A}})\mathcal{R}_{\mathcal{A}}^{\eta_X})^{\frac{1}{\eta_X}} \\ \mathcal{V}_{\mathcal{M}} &= (\alpha_{\mathcal{M}}\mathcal{M}^{\eta_X} + (1-\alpha_{\mathcal{M}})\mathcal{R}_{\mathcal{M}}^{\eta_X})^{\frac{1}{\eta_X}} \end{aligned} \qquad \text{Eq. 4 B}$$

$$\begin{aligned} \mathcal{R} &= A_{\mathcal{R}}\left(\alpha K_{\tau_{\mathcal{R}}}^{\eta_{\mathcal{R}}} + \beta L_{\varepsilon_{\mathcal{R}}}^{\eta_{\mathcal{R}}}\right)^{\frac{1}{\eta_X}} & \mathcal{R}_{\mathcal{R}} &= A_{\mathcal{R}_{\mathcal{R}}}\left(\alpha K_{\tau_{\mathcal{R}}}^{\eta_{\mathcal{R}}} + \beta L_{\xi_{\mathcal{R}}}^{\eta_{\mathcal{R}}}\right)^{\frac{1}{\eta_X}} \\ \mathcal{A} &= A_{\mathcal{A}}\left(\alpha K_{\tau_{\mathcal{A}}}^{\eta_T} + \beta L_{\varepsilon_{\mathcal{A}}}^{\eta_T}\right)^{\frac{1}{\eta_T}}, & \mathcal{R}_{\mathcal{A}} &= A_{\mathcal{R}_{\mathcal{A}}}\left(\alpha K_{\tau_{\mathcal{R}_{\mathcal{A}}}}^{\eta_T} + \beta L_{\xi_{\mathcal{A}}}^{\eta_T}\right)^{\frac{1}{\eta_T}} \\ \mathcal{M} &= A_{\mathcal{M}}\left(\alpha K_{\tau_{\mathcal{M}}}^{\eta_T} + \beta L_{\varepsilon_{\mathcal{M}}}^{\eta_T}\right)^{\frac{1}{\eta_T}}, & \mathcal{R}_{\mathcal{M}} &= A_{\mathcal{R}_{\mathcal{M}}}\left(\alpha K_{\tau_{\mathcal{R}_{\mathcal{M}}}}^{\eta_T} + \beta L_{\xi_{\mathcal{M}}}^{\eta_T}\right)^{\frac{1}{\eta_T}} \end{aligned} \qquad \text{Eq. 4 C}$$

$$A_{\mathcal{R}} = min\left(\frac{L_{\xi_{\mathcal{R}}}}{w_L}, \frac{\tau_{\mathcal{R}}}{w_\tau}\right) \qquad \begin{aligned} A_{\mathcal{A}} &= min\left(\frac{L_{\xi_{\mathcal{A}}}}{w_L}, \frac{\tau_{\mathcal{A}}}{w_\tau}\right) & A_{\mathcal{M}} &= min\left(\frac{L_{\xi_{\mathcal{M}}}}{w_L}, \frac{\tau_{\mathcal{M}}}{w_\tau}\right) \\ A_{\mathcal{R}_{\mathcal{A}}} &= min\left(\frac{L_{\xi_{\mathcal{A}}}}{w_L}, \frac{\tau_{\mathcal{R}_{\mathcal{A}}}}{w_\tau}\right) & A_{\mathcal{R}_{\mathcal{M}}} &= min\left(\frac{L_{\xi_{\mathcal{M}}}}{w_L}, \frac{\tau_{\mathcal{R}_{\mathcal{M}}}}{w_\tau}\right) \end{aligned} \qquad \text{Eq. 4 D}$$

For notation convenience and comprehensibility, the notation of the time variable has been left. The nested production function includes four levels. The first is the overall production function at the task level (Eq. 4 A) that defines the economic composition of routine, abstract, and manual tasks. In the nested task level (Eq. 4 B), the routinisation of abstract and manual tasks is incorporated depending on the task substitution elasticity [η_X], resulting in six task factor $\mathcal{R}, \mathcal{R}_{\mathcal{R}}, \mathcal{A}, \mathcal{R}_{\mathcal{A}}, \mathcal{M}, \mathcal{R}_{\mathcal{M}}$. At the input level (that is nested in the task level) (Eq. 4 C), each task has a specific production function composition, introducing six capital inputs [$K_{\tau_{\mathcal{R}}}, K_{\tau_{\mathcal{R}_{\mathcal{R}}}}, K_{\tau_{\mathcal{A}}}, K_{\tau_{\mathcal{R}_{\mathcal{A}}}}, K_{\tau_{\mathcal{M}}}, K_{\tau_{\mathcal{R}_{\mathcal{M}}}}$] and six labour inputs of which three human capital extended [$L_{\varepsilon_{\mathcal{R}}}, L_{\varepsilon_{\mathcal{A}}}, L_{\varepsilon_{\mathcal{M}}}, L_{\xi_{\mathcal{R}}}, L_{\xi_{\mathcal{A}}}, L_{\xi_{\mathcal{M}}}$][18]. Lastly, nested within the input level, productivity growth is realised through technological progress that requires adequately skilled labour input and specific technology (Eq. 4 D).

[18] The labour input notation has been simplified. The full notation would be: $L_{\varepsilon_{T_{\xi_\tau}}}$ with ε_T expressing the task-dependent skill level, ξ_τ the technology depended human capital factor, wherein the τ is tasks specific. However, since skill level and technology are task specific and human capital is technology specific the notation is simplified to L_{ε_T} and L_{ξ_T}.

The use of production function variants (CES and CD) corresponds to the RRTC framework and models based on the TBTC framework (see Goos, Manning, & Salomons, 2011, 2014; Gregory, Salomons & Zierahn, 2016) [19]. In addition, the model draws from multi-factor nested production function literature to confirm the structural integrity (Koesler & Schymura (2012) for substitution elasticities variation, Frieling & Madlener (2016) for nesting). Furthermore, the model definition is consistent and operationalisable with economic System Dynamics models to allow for simulation (Weber, 2010; Radzicki, 2009). Therefore, the task production functions (Eq. 4 B) are defined as CES functions and the input production functions (Eq. 4 C) are defined as CB functions (since $[\alpha + \beta = 1]$) - as is done in the RRTC framework (Goos, Manning, & Salomons, 2011, 2014; Gregory, Salomons & Zierahn, 2016). The model is extended to accommodate relevant empirical and framework principles. Firstly, the model is extended to explicitly include the skill levels as proposed by Acemoglu and Autor (2011) and Autor (2013) to enable labour market dynamics (Eq. 4 C and D). Moreover, the labour division is expanded via the introduction of technology dependent human capital/skill factor $[\xi_\tau]$ to resemble the dynamics of skills required to operate new technology (Acemoglu & Restrepo, 2018; IFR, 2017). Secondly, the explicit separation and pooling of task types differs from Goos, Manning, and Salomons (2011, 2014) since the macro-level is studied and not industries or regions (whom may use a disaggregation within the types). Therefore, the model is consistent with the RRTC and TBTC framework and expands on existing models to facilitate dynamic modelling.

5.2.1 Production costs

The input factor costs $[K_{\tau_T} \rightarrow \Pi_{\tau_T}$ and $L_T \rightarrow W_T]$ for task production sum to the task-specific costs $[P_T]$. Businesses are naturally costs minimising by reducing the overall costs of the factor input depending on the relative marginal costs of labour versus capital (Graetz & Michaels, 2017; Gregory, Salomons & Zierahn, 2016). The production costs follow the input CB production function as done by Gregory, Salomons, and Zierahn (2016) with $[\varphi]$ indicating the cost share of the input factors (Eq. 5). Developments in input price influence substitution as expressed in Eq. 2. The relative change in production price $[\delta P_T]$ can be allocated to the various spill-over effects (see 3.2): competitive allocation towards the product price $[p_{so}]$, profitability allocation towards the profit mark-up $[\phi_{so}]$[20], and wage allocation $[W_{so}]$. The so notation indicates that it concerns the spill-over quantity depending on the allocation fraction. Respectively, the spill-over allocation fractions $[f]$ for the three options are expressed as $[\varrho]$, $[\varpi]$, and $[\omega]$ such that $[f = \{\varrho, \varpi, \omega\}, \sum f_i = 1$, and $0 \leq f_i \leq 1]$. Evidence from robot driven productivity growth suggests that approximately two thirds of the labour productivity gains are used competitively and a tenth goes to wages (Graetz & Michaels, 2017). Therefore, ϱ=0.667, ω=0.1, and ϖ=0.233. Therefore, the spill-over effects are expressed as a product of the derivative of task-specific costs (Eq. 6). The price of products $[p_t]$ is defined as the task-specific costs prior to input costs changes $[P_{T_{t-1}}]$ increased with the conventional profit-mark-up $[\phi_c]$ and price spill-over effects (Eq. 7).

$$P_{T_t} = \Pi^{\varphi}_{\tau_{T_t}} W_{T\ t}^{1-\varphi} \qquad \text{Eq. 5}$$

$$p_{so} = \varrho \frac{\delta P_{T_t}}{\delta t}, \quad \phi_{so} = \varpi \frac{\delta P_{T_t}}{\delta t}, \quad W_{so} = \omega \frac{\delta P_{T_t}}{\delta t} \qquad \text{Eq. 6}$$

$$p_t = P_{T_{t-1}}(1 + \phi_c) + \frac{\delta P_{T_t}}{\delta t}(\varpi - \varrho) \qquad \text{Eq. 7}$$

The task specific profit $[\psi_{T_t}]$ is the summation of the conventional profit mark-up $[\phi_c]$ over input costs and the profitability spill-over $[\phi_{so}]$. The generated profit can be retained in the business or distributed as dividend (Eq. 8). The prior is assumed to fully contribute to growth of the respective productivity factor $[A_T]$. Whereas the latter is assumed to be relocated to capital owners and the financial markets outside the model

[19] Goos, Manning, and Salomons (2011) provide a more detailed evaluation of the use of production functions (CES and CB). The principle of nested functions is however not explicitly mentioned. Hence, multi-factor nested production function literature has been referred.

[20] The spill-over effect mark-up $[\phi_{so}]$ is financial, while the conventional mark-up $[\phi_c]$ is a dimensionless fraction.

[D_t]. The share of both is respectively expressed as the innovation investment share [ι_T] and the dividend share [$\nu_T = 1 - \iota_T$] such that [$0 \leq \iota_T \leq 1$].

$$\psi_{T_t} = P_{T_{t-1}}\phi_c + \phi_{so}, \quad I_{T_t} = \iota_T\psi_{T_t}, \quad D_{T_t} = (1 - \iota_T)\psi_{T_t} \qquad \text{Eq. 8}$$

The wage allocation spill-over effect is not included in the equations since it feeds back in the Labour market model where the wages are established. Productivity growth stands at the centre of living standard improvement (Dew-Becker & Gordon, 2005; OECD, 2015b). Yet, if wages do not proportionally grow with economic outcomes and productivity growth, this well-established paradigm becomes questionable. *'The failure of the productivity growth revival to boost the real incomes and wages of the median family and median worker calls into question the standard economic paradigm that productivity growth translates automatically into rising living standards'* (Dew-Becker & Gordon, 2005, p. 1-2). As a result, the conventionally parallel growth of productivity and wages resulting in a constant wage share is no longer present (Dew-Becker & Gordon, 2005). The fact that wages do not benefit from economic and productivity growth is demonstrated by the consistent decline in the wage share across OECD countries over the past three decades (OECD, 2015b; Stockhammer, 2013). In relation with the production model, the wage share, also referred to as labour share, acts as an indicator of the income distribution between labour and capital.

5.2.2 Wage share and profit share

From the production function (Eq. 4), the overall wage share [w_X] and per tasks [w_T] are determined as follows (Schneider, 2011),

$$w_X = \sum_{i=1}^{|T|} w_T * \frac{T}{X}, \quad w_T = \frac{W_T L_{\varepsilon_T}}{P_T T} \qquad \text{Eq. 9}$$

And thus, the profit share is as follows (Schneider, 2011),

$$\pi_X = \sum_{i=1}^{|T|} \pi_T * \frac{T}{X}, \quad \pi_T = 1 - w_T \qquad \text{Eq. 10}$$

Therefore, the shares depend on labour supply, labour demand, the level of output, and the mechanisms of production, wage setting, and employment (Schneider, 2011). Following the CB production function at the task level, the wage shares would be equal to the respective marginal product of labour and stable in the long term (Schneider, 2011). Yet, this only holds under balanced growth and/or the assumption that the wage and capital bills sum to the total output, which does not necessarily need to be the case (Schneider, 2011). Shifts in the wage share stem from unbalanced growth across sectors, changing sectoral compositions, globalisation, financialisation, market interventions, (market) institutions, financial markets, bargaining, and technological advancement shift the factor shares away from their steady state and marginal products (OECD, 2015b; Schneider, 2011; Stockhammer, 2013).

The wage-share of national income was often perceived as a constant ratio or used a stylised fact in macro-economic theories and models (Autor & Salomons, 2017; OECD, 2015b; Schneider, 2011). However, short to medium term fluctuations countercyclical to the business cycle are present (OECD, 2015b; Schneider, 2011). The fluctuations have been allotted to various factors and rigidities depending on the economic school and the model definition (Schneider, 2011). Furthermore, measurement of the real-world wage share is more complicated due variation in the measurement and definition of the variables (OECD, 2015b; Schneider, 2011). Most of the attention for the wage share and its behaviour stems from Neo-classical approach (Schneider, 2011). Yet, the factors explaining the behaviour of the wage share have not reached a definitive state of consensus (OECD, 2015b; Schneider, 2011). These discussions are beyond the scope of this study. Yet, the relation with technological change and its impact on labour and spill-over effects is relevant as are financialisation and bargaining.

In contrast with the constant wage share trend in the past, developments over the past three decades demonstrate a consistent decline in the wage share in relation with technological change across OECD countries (OECD, 2015b; Stockhammer, 2013)[21]. This secular trend concerns scholars and policy makers since '*main macroeconomic aggregates, namely household consumption, private sector investment, net exports and government consumption (ILO 2012; Wolf 2014)'* (OECD, 2015b, p. 2) deteriorate. Therefore, a feedback mechanisms is present from economic outcomes, to wages, to demand, to economic outcomes. Moreover, inequality grows and political support for economic policy declines (OECD, 2015b). More importantly, the current rate at which AI and advanced robotics are increasingly capable of substituting labour sparks debates whether the balance between wage-share and profit-share is becoming ever-in favour of capital owners (Autor & Salomons, 2017). This would imply that the declining trend of the wage share since the 1990's of approximately 0.3% annually (OECD, 2015b) will continue or even accelerate.

The nature of technological change (i.e. labour or capital augmenting or saving) together with the associated productivity growth determines the shift in factor input and output (Schneider, 2011; Stockhammer, 2013). In combination with the relative factor prices this determines the rate of substitution and thus the factor input demand. In respect of productivity growth, '*when the growth in average wages lags the growth in labour productivity, the result is a decline in the labour share.'* (OECD, 2015b, p. 7). The OECD determined that *'total factor productivity (TFP) growth and capital deepening – the key drivers of economic growth – accounted for most of the average within-industry decline of the labour share in OECD countries between 1990 and 2007'* (OECD, 2015b, p. 9). Therefore, the spill-over effect whereby productivity growth is allocated towards wages influences the wage share. Furthermore, the spill-over effect whereby productivity growth is allocated towards prices should result in additional demand from consumption and export. Yet, materialisation of this consumption growth lacks when wages do not grow proportionally with productivity and economic growth. Moreover, wage allocation is not necessarily equally distributed across skill levels (Dew-Becker & Gordon, 2014). Over the past decades, most of the productivity growth allocated towards wages has accrued to high skilled wage incomes (Dew-Becker & Gordon, 2014). Therefore, the distribution within the wage allocation is skewed towards high skilled labour input. As a result, disproportionate and unequal wage share growth can be the result of technological change.

Stockhammer (2013) finds that financialisation is the single most important factor of the decline in the wage share and refutes the prevailing claimed importance of technological change[22] (based on empirical findings and the fact that it is based on Neo-classical assumptions and over-stylised properties[23]). Although the financial market is outside of the model, profit allocation of productivity growth and utilization of the capital share of income are within the boundaries of the model. This implies that the increase in capital income leaking to the financial markets [D_t] results in a reduction of the wage share. Theoretically, an economy can benefit from a growing capital share if it is invested in the economy. Yet, financialisation has prevented this mechanism from occurring: '*It might be argued that lower wages are necessary to boost profits in order to increase investment and, in turn, job creation. However, in developed economies, the shift in income away from labour towards capital has not produced the expected results on investment*.' (OECD, 2015b, p. 11-12). According to the OECD (2015b) this is for three reasons, for one, profits mainly accrued in the financial sector; second, profits have increasingly been used to pay dividends and invest in financial assets; and third, productive investment has declined due to declining household, government, and export consumption and stricter credit provision. The latter can directly be accredited to the reducing wage share. The income from growing capital share predominantly ends up in the hands of the top 10, 1, and mainly 0.1 percent of incomes (wage and capital) (OECD, 2015b; Stockhammer, 2013). Which, in turn, is mostly used for saving and subsequent investment instead of consumption (OECD, 2015b; Stockhammer, 2013). Therefore, this development catalyses the inequality growth and restraints productivity growth. In the model, the spill-over

[21] Note: in developing countries technological change is positively related with technological change, see Stockhammer (2013).

[22] Stockhammer (2013) even goes as far to say, *'the view that changes in income distribution in advanced economies have mainly been driven by technological change. This is not correct. While technological change has had a negative effect on wage shares in developed economies, this effect is smaller than that of other factors and it is less robust.'* (p. viii)

[23] *'In a world of complete markets, perfect competition, full employment and well behaved aggregate production functions, income shares are determined by technology. This is the core of the neoclassical theory of income distribution. However, none of these assumptions is likely to hold in the real world*.' (Stockhammer, 2013, p. 5)

effect whereby productivity growth is allocated towards profits in combination with the ratio of profits used for investment [ι_T] determines the leakage towards the financial markets.

In addition, a deteriorating (collective) wage bargaining position of employees in combination with declining union density negatively influences the wage level. The OECD (2015b) concludes that *'Among institutional factors, empirical evidence suggests that the role of factors that affect the bargaining power of workers is largest (OECD, 2012).'* (p. 10). The wage setting process is defined in the Labour market model (see 7).

5.3 Production model synthesis

To synthesize, substitution will increase the aggregate productivity of tasks and overall production giving rise to spill-over effects. The relative strength of the spill-over effects and where they will accrue depends on the allocation pattern (i.e. the values of the allocation fractions [ϱ, ϖ, ω]) and the values of associated variables along feedback mechanisms (Autor & Salomons, 2017; Goos, Manning, & Salomons, 2014; Graetz & Michaels, 2017; Gregory, Salomons & Zierahn, 2016). In this sense, labour substitution impoverishes the position of labour but can be countered by the effects of spill-overs. Therefore, the effect of technology on the labour market depends on the relative dominance and accumulation of the substitution effects versus the spill-overs (Goos, Manning, & Salomons, 2011; Gregory, Salomons & Zierahn, 2016). Consequentially, technology that enabled substitution can complement or displace labour input and, respectively, result in labour-augmentation or capital-augmentation on the labour market[24]. Hence, the effect of technology on labour is not predetermined to be negative or positive (Autor, 2015).

Technological progress facilitates cost reduction via productivity growth. The extent to which substitution takes place depends on the relative price development of capital and wages and the extent to which technology is capable of replacing humans (Autor, 2015; Gregory, Salomons & Zierahn, 2016; Weber, 2010). The latter is determined in the Technology model (see 9). In the process, substitution changes the task and skill composition and sets labour market dynamics in motion. The development of the dynamics depends on the market's clearing ability in response to the change in skill demand. In this respect, technological progress, wage dynamics, consumption, and skill attainment influence the substitution effects and spill-over effects. Therefore, the balance between substitution and spill-over is influenced by the dynamics of the labour and capital factor.

The reason to refer to the sub-model as the *Production model* instead of the *Economic model* is because it is restricted to include only a part of a macro-economy in line with the scope of the TBTC and RRTC frameworks to study the plausible impact of technological change and, in this study, the effects of labour force adaptability. Therefore, capital and financial markets, interest rates, exchange rates, import and export, economic and technological competitive position, globalisation, government consumption, monetary and fiscal policy, sectoral composition, and exogenous factors/shocks are not considered which are part of conventional macro-economic models depending on the economic school and scope. In this respect, the model and this study are, as far as the literature available at the time of writing, the first attempt to (dynamically) model labour adaptability in reaction to technological substitution in the context of future technological change and associated uncertainties. This also implies that the model can benefit from extensions that reach beyond the TBTC and RRTC based production model and incorporate and endogenise more sectors, markets, and factors. Therefore, the results should be considered within these limitations. The production model forms the foundation for the operationalisation with SD and describes the interrelations, composition, and processes in/of the economy, economic growth, labour demand, and labour substitution. In relation with the production model, wages are determined in the labour market model and feedback to the economic outcomes via consumption. In addition, the technological change variables of the production model are determined in the Technology model.

[24] E.g. technology substitutes labour input for capital input and enables routinisation which in turn can have a labour-augmenting effect (complementary technology = if the labour hour input does not decrease and benefits from the increase in productivity) or capital-augmenting effect (displacing technology = if the labour hour input is reduced as a result of the increase in productivity).

6 Demographic model

Labour input is supplied by the labour force which includes all population members whom participate in the labour market. However, labour input and supply are not homogenous. Firstly, different skill levels exist which participate in different activities in the economy. Secondly, different age cohorts[25] can be identified in the population with difference participation rates across skill levels and sex. Lastly, the age cohorts have distinct societal and social roles and position (e.g. children or parenthood). The population members age over time and flow (horizontally) from age cohort to age cohort, from birth to death. Moreover, the members can climb the social-economic ladder by attaining a higher skill level via re-skilling and up-skilling. The population model is structured accordingly to study socio-economic outcomes of technological substitution including (un-)employment, inequality, incomes, and participation across cohorts. In this sense, demographic dynamics resonate in the labour force and therefore influence labour input and economic processes. Moreover, the economic conditions feedback to the population and labour force via the labour market, wages, and skill attainment. In this paragraph, the population model is developed by defining its structure, the process of skill attainment, and defining the demographic processes. In the subsequent chapter the process of skill attainment is covered.

6.1 Structure of the population and labour force

The TBTC and RRTC frameworks simplify the population and labour force in three categories, namely low, middle, and high skilled. However, the definition of each skill level is rather ambiguous since education systems vary across countries. This results in country specific skill level definitions which complicate comparison of labour market effects and studies (Autor & Salomons, 2017; Graetz & Michaels, 2017). Therefore, the 2011 Unesco International Standard Classification of Education (ISCED) is adopted in this study (see UNESCO Institute for Statistics (2012)). The low skilled group [$\varepsilon_{\mathbb{L}}$] is defined as individuals that completed primary education or the first years of/lower secondary education - i.e. level 1 and 2 of ISCED 2011. Middle skilled [$\varepsilon_{\mathbb{M}}$] includes individuals whom completed (upper) secondary or profession-specific education – i.e. level 3, 4 and 5 of ISCED 2011. The latter [$\varepsilon_{\mathbb{H}}$] consists of individuals whom completed tertiary education and have a bachelor, master, or doctoral degree – i.e. level 6, 7 and 8 of ISCED 2011. This enables effective comparison between studies[26] and countries, and conforms with the TBTC and RRTC frameworks[27].

The population and labour force are structured accordingly [$\varepsilon_{\mathbb{L}}, \varepsilon_{\mathbb{M}}, \varepsilon_{\mathbb{H}}$] and are related via the participation rate [ρ]. However, as defined in the production model, the labour force is expanded with a technology specific human capital factor [ξ_τ] to incorporate skill dynamics. This implies that the ISCED categorisation still applies but a human capital extended variant exists for each skill level ($\varepsilon_{\mathbb{L}}$ and $\xi_{\mathbb{L}}$, $\varepsilon_{\mathbb{M}}$ and $\xi_{\mathbb{M}}$, and $\varepsilon_{\mathbb{H}}$ and $\xi_{\mathbb{H}}$). Therefore, the population and labour force consist of six levels [$\varepsilon_{\mathbb{L}}, \varepsilon_{\mathbb{M}}, \varepsilon_{\mathbb{H}}, \xi_{\mathbb{L}}, \xi_{\mathbb{M}}, \xi_{\mathbb{H}}$]. The participation rate is defined as the share of individuals of working age (15 to 64 years[28]) in the population offering their labour supply in the labour market - independent of the number of contracted hours. The rate is different for each skill level [ε], different between male [♂] and female [♀] populations, and different for each age cohort [$\mathbb{AC}$] within the working age population. Therefore, the population model consists of an identical male and female sub-model with six skill levels and separate age cohorts.

The age cohorts [$\mathbb{AC}$] can be organised according to various criteria, including demographic, biological, or - as in this study – professional age categories. Prior to entering the working age population, individuals are

[25] i.e. a group of persons sharing a particular statistical or demographic characteristic

[26] The definitions used in literature often refer to the US education system of high-schools and colleges and fits these classifications to the production function labour input (Autor & Salomons, 2017; Goos, Manning, & Salomons, 2011).

[27] Although not explicitly stated, Arntz, Gregory, and Zierahn (2016) also use the ISCED standardisation., among others

[28] Following the OECD Definition of Working age population (https://data.oecd.org/pop/working-age-population.htm)

born and are children [$\mathbb{CH}$] up to the age of 15. Since secondary and tertiary education expands into the working age population, the first professional age cohort is defined as students [$\mathbb{ST}$]. The age span of this group depends on the skill level since the education levels have different durations [$\Delta t_{\mathbb{ST}_\varepsilon}$]. Some students may already enter the labour market within the timespan of the student age cohort [$\mathbb{ST}_\varepsilon$], for example to work part-time or during a full-time gap year. This depends on the students' participation rate per skill level [$\rho_{\mathbb{ST}_\varepsilon}$]. Hereafter, individuals enter their professional life consisting of three age cohorts: young adults or *junior professionals* [$\mathbb{YA}_\varepsilon$] with duration [$\Delta t_{\mathbb{YA}_\varepsilon}$], mature adults [$\mathbb{MA}_\varepsilon$] for [$\Delta t_{\mathbb{MA}_\varepsilon}$] years; and senior adults or *senior professionals* [$\mathbb{SA}_\varepsilon$] for [$\Delta t_{\mathbb{SA}_\varepsilon}$] years. Logically, retirement [$\mathbb{RE}$] follows professional life as the last phase in life from the retirement age [$t_{\mathbb{RE}}$] up until the average life expectancy per skill level [$t_{\dagger_\varepsilon}$]. This structuring creates a skill level-based population model for males and females organised according the six age cohorts. The result is a population flow per skill-level per sex that entails the whole national population when summed (Figure 3 for each skill level).

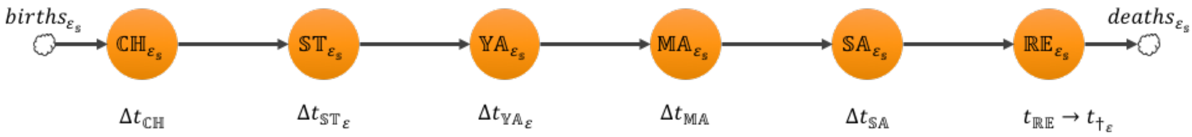

Figure 4 Universal population model per skill level

Note in Figure 3 that the duration of the student and young adult age cohorts is different for the various skill levels since the education duration is different while the transition to mature adults occurs at an identical age. Secondly, note that the diagram is sex independent [$\mathbb{s} \in \{♀, ♂\}$] and that the average life expectancy is different for the skill levels. Lastly, the participation rate [$\rho_{\mathbb{AC}_\varepsilon}$], age cohort duration [$\Delta t_{\mathbb{AC}_\varepsilon}$], and life expectancy [$t_{\dagger_\varepsilon}$] are identical for the respective normal and extended skill levels (e.g. $\rho_{\mathbb{AC}_{\varepsilon_{\mathbb{L}}}} = \rho_{\mathbb{AC}_{\xi_{\mathbb{L}}}}$ etcetera).

6.1.1 Skill attainment, labour adaptation, and adaption delay

Technological progress is expected to significantly change labour in the future (Arntz, Gregory, Zierahn, 2016; Frey & Osborne, 2015, 2017; Nedelkoska & Quintini, 2018). Adaptation of the labour force can only be realized through attainment of new skills (Acemoglu & Restrepo, 2018). The importance of skill attainment is commonly recognized among scholars (see Acemoglu & Restrepo (2018)) as well as institutes and interest groups (e.g. IFR, 2017, OECD, 2017b, EU Skills Panorama 2014, 2015). However, labour skill adaptation is not friction-less and constant across society (Acemoglu & Restrepo, 2018; Gregory, Salomons & Zierahn, 2016). In general, adjustments within the labour force in reaction to labour market demand shifts are a slow and incomplete process (Autor, Dorn, & Hanson, 2015). More importantly, these adjustments depend on the ability of the labour force to adapt to new tasks and learn new skills, which is not homogenous among the labour force (Autor, Dorn, & Hanson, 2015). Less educated members have been less successful in adjusting to new labour market conditions after technological shocks (Autor, Dorn, & Hanson, 2015). In this respect, the labour adaptation elasticity increases with skill level. As a result, especially the low-skilled labour force is vulnerable if they are unable to adjust and to keep up with the more demanding and different skill sets in time. Simultaneously, routinisation and job-polarisation put pressure on the middle-skilled labour force since their jobs are most likely to be substituted (Autor, 2015). Moreover, recent technological substitution has universally been in favour of high-skilled employment (IFR, 2017; Mishel, Shierholz & Schmitt, 2013). Therefore, education and training are essential for a successful transition towards a highly-automated and digitalised society and economy. Moreover, unsuccessful attainment and provision of newly demanded skills may catalyse inequality.

Education and training of the labour force includes (1) *re-skilling* [$\mathbb{R}$], which is attainment of the extended skill set at the same skill level (e.g. [$\varepsilon_{\mathbb{L}}$] to [$\xi_{\mathbb{L}}$]), and (2) *up-skillin g* [$\mathbb{U}$], which is defined as attainment of a higher skill level to adjust to more demanding tasks (e.g. [$\varepsilon_{\mathbb{L}}$] to [$\varepsilon_{\mathbb{M}}$]) (Arntz, Gregory, Zierahn, 2016; IFR, 2017; OECD, 2017b). Therefore, the constructed population model has flows from normal to extended skill levels and between the skill levels where individuals climb the socio-economic ladder. Note, that the age cohort to which an individual belongs defines the highest attained skill level. This may not be the actual level at which the individual participates in the labour market. When considering the six levels and the intermediate flows, a 6x3x2 matrix of age cohort stocks appears per sex (Figure 5). The process of skill attainment depends on the relative economic conditions of the skill levels (and associated tasks) and the education and training system. The labour market model and education and training model is developed in subsequent paragraphs (Labour market model).

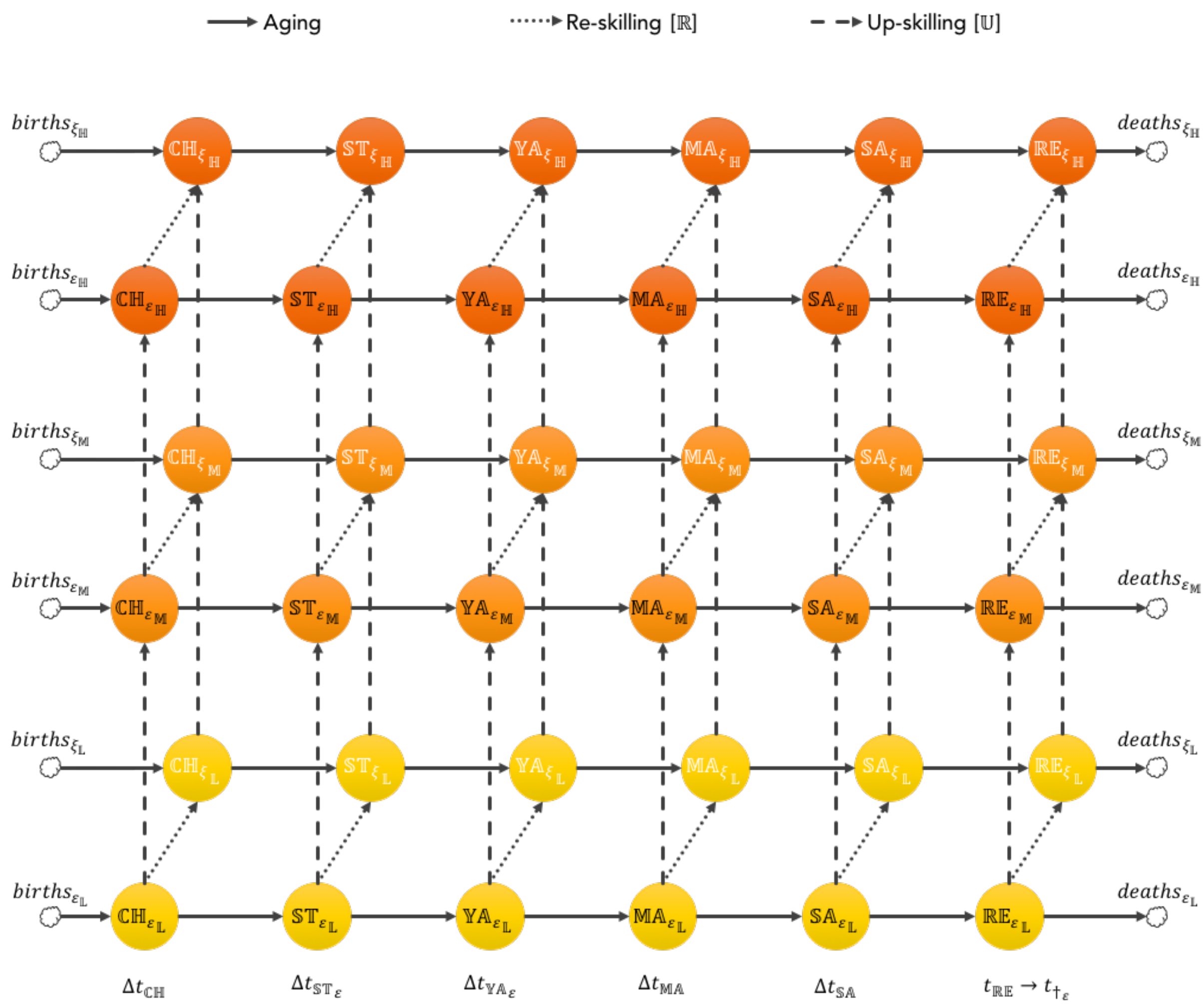

Figure 5 Schematic population model including natural aging flows, re-skilling, and upskilling for six skill levels

6.1.2 Demographic expansion of the model

The schematic population model presented (Figure 5) is a simplified form that needs to be expanded to realistically represent demographic behaviour. The different age cohort are based on professional stages of the working age population. However, the population structure also represents the stages of household life. Young adults get children and children leave the household around the transition from mature adult to senior adults of their parents. This introduces births and creates shifts in participation and full-time versus part-time labour supply across age cohorts. Another addition to the model is deaths $[\mathbb{D}]$ for age cohort other than the retired depending on the death rate per age cohort $[\dagger_{\mathbb{AC}}]$.

The births per education level are determined based on two sets of parameters. The first set determines the ratios of children's skill level in respect to the parents' skill level for all combinations $[\varepsilon_{\mathbb{L}}, \varepsilon_{\mathbb{M}}, \varepsilon_{\mathbb{H}}]$ and $[\mathbb{YA}\ \mathbb{s}$ and $\mathbb{CH}\ \mathbb{s}]$. The second set operationalises these ratios to determine the actual births per skill level. The outcome is combined with the normal rate of extended skill $[\mathbb{a}_\xi]$ to determine the actual births for the six skill levels. Firstly, the skill ratios are based on three parameters, namely:

(1) young adult couple ratios [$\mathbb{c}_{\varepsilon_{\mathbb{YA}♀}\varepsilon_{\mathbb{YA}♂}}$] across all combinations of low, middle and high skill level of mother [$\mathbb{YA}♀$] and father [$\mathbb{YA}♂$][29];
(2) parent-child skill level relation ratios [$\mathbb{e}_{\varepsilon_{\mathbb{YA}\,\mathbb{s}}\varepsilon_{\mathbb{CH}\,\mathbb{s}}}$] across all combinations of mother and father [$\mathbb{YA}\,\mathbb{s}$] in ration to daughter and son [$\mathbb{CH}\,\mathbb{s}$][30]; and
(3) relative dominance ratios [$\mathbb{d}_{\mathbb{YA}_{\mathbb{CH}\,\mathbb{s}}}$] of the mother or the father on the skill level of a daughter or son (identical for all skill levels)[31].

These normalised parameters result in the effective ratio of children per skill level per female young adult per skill level [$\mathbb{r}_{\varepsilon_{\mathbb{YA}♀}\varepsilon_{\mathbb{CH}\,\mathbb{s}}}$] (Eq. 11)[32].

$$\mathbb{r}_{\varepsilon_{\mathbb{YA}♀}\varepsilon_{\mathbb{CH}\,\mathbb{s}}} = \mathbb{d}_{\mathbb{YA}_{\mathbb{CH}\,\mathbb{s}}}\left(\mathbb{c}_{\varepsilon_{\mathbb{YA}♀}\varepsilon_{\mathbb{YA}♂}} * \mathbb{e}_{\varepsilon_{\mathbb{YA}♀}\varepsilon_{\mathbb{CH}\,\mathbb{s}}}\right) + \left(1-\mathbb{d}_{\mathbb{YA}_{\mathbb{CH}\,\mathbb{s}}}\right)\left(\mathbb{c}_{\varepsilon_{\mathbb{YA}♀}\varepsilon_{\mathbb{YA}♂}} * \mathbb{e}_{\varepsilon_{\mathbb{YA}♂}\varepsilon_{\mathbb{CH}\,\mathbb{s}}}\right), \quad with$$

$$\mathbb{c}: \quad \varepsilon_{\mathbb{YA}♀} \in \left\{\varepsilon_{\mathbb{L}_{\mathbb{YA}♀}}, \varepsilon_{\mathbb{M}_{\mathbb{YA}♀}}, \varepsilon_{\mathbb{H}_{\mathbb{YA}♀}}\right\}, \quad and \quad \varepsilon_{\mathbb{YA}♂} = \left\{\varepsilon_{\mathbb{L}_{\mathbb{YA}♂}}, \varepsilon_{\mathbb{M}_{\mathbb{YA}♂}}, \varepsilon_{\mathbb{H}_{\mathbb{YA}♂}}\right\},$$

$$\rightarrow \sum_{x\in\varepsilon_{\mathbb{YA}♂}}^{|\varepsilon_{\mathbb{YA}♂}|} \mathbb{c}_{\varepsilon_{\mathbb{YA}♀}x} = 1, \quad 0 < x < 1$$

Eq. 11

$$\mathbb{e}: \quad \varepsilon_{\mathbb{YA}\,\mathbb{s}} \in \left\{\varepsilon_{\mathbb{L}_{\mathbb{YA}♀}}, \varepsilon_{\mathbb{M}_{\mathbb{YA}♀}}, \varepsilon_{\mathbb{H}_{\mathbb{YA}♀}}, \varepsilon_{\mathbb{L}_{\mathbb{YA}♂}}, \varepsilon_{\mathbb{M}_{\mathbb{YA}♂}}, \varepsilon_{\mathbb{H}_{\mathbb{YA}♂}}\right\}, \quad \mathbb{s} \in \{♀, ♂\}, \quad and$$
$$\varepsilon_{\mathbb{CH}\,\mathbb{s}} = \left\{\varepsilon_{\mathbb{L}_{\mathbb{CH}\,\mathbb{s}}}, \varepsilon_{\mathbb{M}_{\mathbb{CH}\,\mathbb{s}}}, \varepsilon_{\mathbb{H}_{\mathbb{CH}\,\mathbb{s}}}\right\},$$

$$\rightarrow \sum_{y\in\varepsilon_{\mathbb{CH}\,\mathbb{s}}}^{|\varepsilon_{\mathbb{CH}\,\mathbb{s}}|} \mathbb{e}_{\varepsilon_{\mathbb{YA}\,\mathbb{s}}y} = 1, \quad 0 < y < 1$$

$$\mathbb{d}: \quad \mathbb{s} \in \{♀, ♂\}, \quad 0 \le \mathbb{d}_{\mathbb{YA}_{\mathbb{CH}\,\mathbb{s}}} \le 1$$

Secondly, this dimensionless number is multiplied by three population properties to determine the births for each of the non-extended skill levels [$\varepsilon_{\mathbb{L}}, \varepsilon_{\mathbb{M}}, \varepsilon_{\mathbb{H}}$], which are:
(4) the birth rate of young adult females for each of the three skill levels [$\mathbb{b}_{\varepsilon}$];
(5) the ratio male and female children [$\mathbb{g}$]; and
(6) the female young adult population per skill level [$\mathbb{YA}_{\varepsilon_{♀}+\xi_{♀}}$].

$$births_{\varepsilon_{♀}} = \mathbb{r}_{\varepsilon_{\mathbb{YA}♀}\varepsilon_{\mathbb{CH}\,\mathbb{s}}} * \mathbb{b}_{\varepsilon} * (1-\mathbb{g}) * \mathbb{YA}_{\varepsilon_{♀}+\xi_{♀}} * \left(1-\mathbb{a}_{\xi}\right),$$
$$births_{\xi_{♀}} = \mathbb{r}_{\varepsilon_{\mathbb{YA}♀}\varepsilon_{\mathbb{CH}\,\mathbb{s}}} * \mathbb{b}_{\varepsilon} * (1-\mathbb{g}) * \mathbb{YA}_{\varepsilon_{♀}+\xi_{♀}} * \mathbb{a}_{\xi},$$

Eq. 12

$$births_{\varepsilon_{♂}} = \mathbb{r}_{\varepsilon_{\mathbb{YA}♀}\varepsilon_{\mathbb{CH}\,\mathbb{s}}} * \mathbb{b}_{\varepsilon} * \mathbb{g} * \mathbb{YA}_{\varepsilon_{♀}+\xi_{♀}} * \left(1-\mathbb{a}_{\xi}\right),$$
$$births_{\xi_{♂}} = \mathbb{r}_{\varepsilon_{\mathbb{YA}♀}\varepsilon_{\mathbb{CH}\,\mathbb{s}}} * \mathbb{b}_{\varepsilon} * \mathbb{g} * \mathbb{YA}_{\varepsilon_{♀}+\xi_{♀}} * \mathbb{a}_{\xi}$$

This multiplication provides the actual births for each of the three skill levels and encompasses all combinations of parent couples, parents to child combinations, and parent influences. However, the number is still only divided over the basic three skill levels. Therefore, the division between conventional and

[29] This results in a 3x3 matrix for all combinations of $\mathbb{YA}♀$ and $\mathbb{YA}♂$.
[30] This results in 4 3x3 matrices for all combinations of mother [$\mathbb{YA}♀$] and daughter [$\mathbb{CH}♀$], mother [$\mathbb{YA}♀$] and son [$\mathbb{CH}♂$], father [$\mathbb{YA}♂$] and daughter [$\mathbb{CH}♀$], and father [$\mathbb{YA}♂$] and son [$\mathbb{CH}♂$].
[31] This results in 2 values, one for daughters [$\mathbb{CH}♀$] and one for sons [$\mathbb{CH}♂$] wherein a value over 0.5 makes the mother dominant and vice versa.
[32] For high skilled female with high skilled daughter this results in the equation:

$$\mathbb{r}_{\mathbb{H}_{\mathbb{YA}♀}\mathbb{H}_{\mathbb{CH}♀}} = \mathbb{d}_{\mathbb{YA}_{\mathbb{CH}♀}}\left(\mathbb{c}_{\mathbb{H}_{\mathbb{YA}♀}\varepsilon_{\mathbb{YA}♂}} * \mathbb{e}_{\mathbb{H}_{\mathbb{YA}♀}\mathbb{H}_{\mathbb{CH}♀}}\right) + \left(1-\mathbb{d}_{\mathbb{YA}_{\mathbb{CH}♀}}\right)\left(\mathbb{c}_{\mathbb{H}_{\mathbb{YA}♀}\varepsilon_{\mathbb{YA}♂}} * \mathbb{e}_{\varepsilon_{\mathbb{YA}♂}\mathbb{H}_{\mathbb{CH}♀}}\right)$$
$$= \mathbb{d}_{\mathbb{YA}_{\mathbb{CH}♀}}\left(\mathbb{c}_{\mathbb{H}_{\mathbb{YA}♀}\mathbb{L}_{\mathbb{YA}♂}} * \mathbb{e}_{\mathbb{H}_{\mathbb{YA}♀}\mathbb{H}_{\mathbb{CH}♀}}\right) + \left(1-\mathbb{d}_{\mathbb{YA}_{\mathbb{CH}♀}}\right)\left(\mathbb{c}_{\mathbb{H}_{\mathbb{YA}♀}\mathbb{L}_{\mathbb{YA}♂}} * \mathbb{e}_{\mathbb{L}_{\mathbb{YA}♂}\mathbb{H}_{\mathbb{CH}♀}}\right)$$
$$+ \mathbb{d}_{\mathbb{YA}_{\mathbb{CH}♀}}\left(\mathbb{c}_{\mathbb{H}_{\mathbb{YA}♀}\mathbb{M}_{\mathbb{YA}♂}} * \mathbb{e}_{\mathbb{H}_{\mathbb{YA}♀}\mathbb{H}_{\mathbb{CH}♀}}\right) + \left(1-\mathbb{d}_{\mathbb{YA}_{\mathbb{CH}♀}}\right)\left(\mathbb{c}_{\mathbb{H}_{\mathbb{YA}♀}\mathbb{M}_{\mathbb{YA}♂}} * \mathbb{e}_{\mathbb{M}_{\mathbb{YA}♂}\mathbb{H}_{\mathbb{CH}♀}}\right)$$
$$+ \mathbb{d}_{\mathbb{YA}_{\mathbb{CH}♀}}\left(\mathbb{c}_{\mathbb{H}_{\mathbb{YA}♀}\mathbb{H}_{\mathbb{YA}♂}} * \mathbb{e}_{\mathbb{H}_{\mathbb{YA}♀}\mathbb{H}_{\mathbb{CH}♀}}\right) + \left(1-\mathbb{d}_{\mathbb{YA}_{\mathbb{CH}♀}}\right)\left(\mathbb{c}_{\mathbb{H}_{\mathbb{YA}♀}\mathbb{H}_{\mathbb{YA}♂}} * \mathbb{e}_{\mathbb{H}_{\mathbb{YA}♂}\mathbb{H}_{\mathbb{CH}♀}}\right)$$

extended skills needs to be established. This division is determined based on the normal rate of extended skill [$\mathbb{a}_\xi$] per skill level. Subsequent paraphrases of education provide a more detailed definition of extended skills, re-skilling, and the normal rate of extended skills. Multiplication with this ratio provides the final births per skill level for male and female children (Eq. 12). This results in the complete schematic population model with births, deaths, re-skilling, and up-skilling (Figure 6).

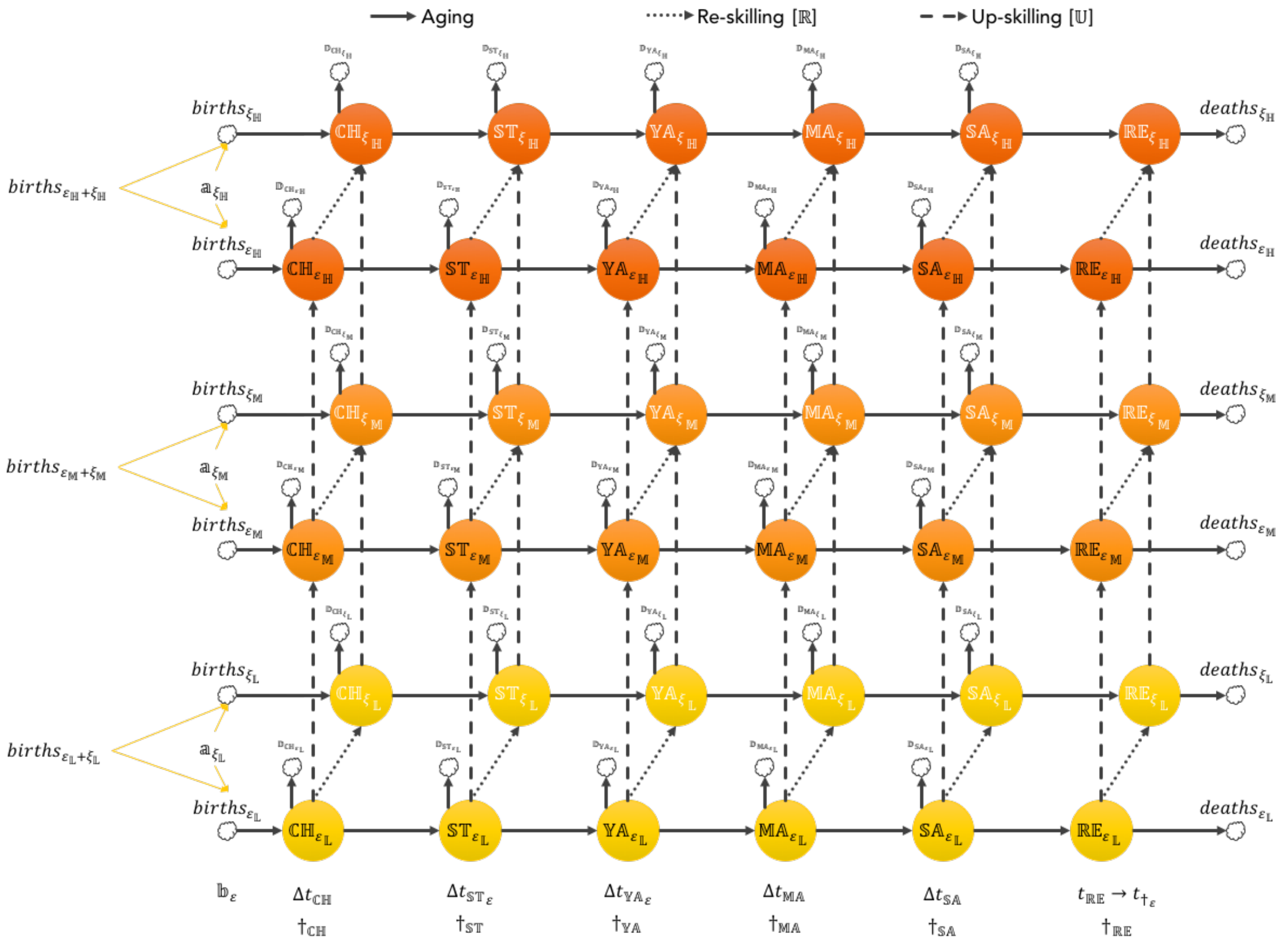

Figure 6 Expanded schematic population model for the male and female population

6.2 Demographic development in relation with technological change

Demographic developments are associated to labour market dynamics through direct and indirect mechanisms. Aging of the population and labour force has two distinct economic effects. First, '*an aging population creates an excess of savings relative to investments*' (Acemoglu & Restrepo, 2017c, p. 174), which results in lower demand and economic growth. Secondly, '*an older population will reduce labor force participation and productivity*' (Acemoglu & Restrepo, 2017c, p. 174), thus reducing the total output from labour, ceteris paribus. The negative effect of aging populations can result in a reduced economic growth of half a percent annually and suppressed employment demand (IFR, 2017).

However, these causal mechanisms do not show up in real world data of aging OECD countries. Contrarily, societal aging and GDP are statistically positively correlated. According to Acemoglu and Restrepo (2017c), this is the result of the simultaneous significant correlation between aging populations and industrial robotics adoption. Therefore, '*the scarcity of younger and middle-age labor can trigger sufficient adoption of robots (and other automation technologies) so as to actually increase aggregate output, despite the reduced* *labor input.'* (Acemoglu & Restrepo, 2017c, p. 177). In essence, robots do not influence the demo-economic causal mechanisms but are able to offset the negative effects. One can argue that innovation and technology therefore provide a solution to increasing economic and budgetary demographic pressures.

6.3 Demographic model synthesis

The demographic model relies heavily on national demographic and statistical data. Especially the birth component of the model is based on the statistical data and causal relations between parent couples' highest achieved skill levels and between parent's and children's highest completed skill levels. Therefore, the births represent the highest attained skill level of the children when they enter the labour force. In this sense, the dynamic flows of re- and up-skilling children and student age cohorts is simplified such that the highest achieved skill level is set at birth rather than over an individual's youth. This is for three reasons. Firstly, detailed modelling of all specific flows of an education system would inhibit reusability of the model and analysis across countries (e.g. see UNESCO-IBE (2012)). This constraint is further explicated in the subsequent section on education. Secondly, it would complicate the model significantly, while the outcomes when entering the professional age cohorts are identical. Thirdly, the additionally required data may not be available for all the countries or time-frames of interest. Moreover, in the current configuration of the model, any re-skilling and up-skilling of children and students represent additional skill attainment over the normal values due to policies and investment. Hence, the effects of additional skill attainment can be more easily assessed and the robustness of policies evaluated.

7 Labour market model

Recent studies demonstrate that technologies put pressure on the labour market and create shifts in skill demand (see for example Autor and Salomons (2017), Graetz and Michaels (2017), and Michaels and Graetz (2015)). The labour market is not frictionless nor perfectly clearing. Tasks require different types of labour input and associated skills. The introduction of technological progress changes the task composition and skills to fulfil those tasks (Acemoglu & Restrepo, 2017b, 2018). Therefore, mismatches continuously exist between labour demand and supply, resulting in reallocation and wage dynamics. The satisfaction of changing labour demand depends on skill attainment of the labour force, which in turn determines the financial and employment stability of labour force members (Autor & Salomons, 2017; IFR, 2017). Taken all together, the labour market is structured according to supply and demand resulting in flows between and within employment, unemployment, and non-participation across skill levels.

7.1 Participation of the population, income, and income utilisation

Population members participate in production processes to earn a living, for social inclusion, social status, and personal fulfilment. Economically speaking, employees receive a nominal wage $[W]$ - that depends on the skill level and market situation - in return for providing labour input (Acemoglu & Autor, 2012). However, employment is not simply a rational means to generate income and satisfy expenditure needs and utility. The utility gained from employment extends to an emotional and social level. The process of labour substitution introduces (perceived) employment uncertainty resulting in a societal sense of fear for deteriorating income and unemployment (IFR, 2017; Mishel, Shierholz & Schmitt, 2013). Later sections will provide a more in depth analysis on the qualitative social and societal implications. In addition, the model results will be reflected upon from this qualitative perspective. However, model formulation is restricted to the quantitative (financial and employment) perspective of labour[33]. Therefore, it is assumed that labour force members strive for employment stability and wage maximisation without concern for emotional and social utility.

The embedded mechanisms for wage setting (also named formation or determination) in an economic model influences the wage level and the wage share. These mechanisms depend on the wage determination regime, of which various forms exist across perfect competition and imperfect competition labour market models[34] (Booth, 2014). The extensive literature concerning labour market theory, models, and their representative and statistical accuracy is beyond the scope of this study. Yet, the wage setting processes in the models and the feedback of income via consumption to economic outcomes are relevant and explored. An imperfectly competitive model is adopted since delays in labour market information, imperfect information, delays in labour reallocation, skill and wage barriers, and wage and task preferences are included in the model in line with the TBTC and RRTC frameworks and findings.

7.1.1 Wage income from labour

Occupations consist of a combination of different tasks requiring a certain skill level which contribute towards a certain wage level. Dynamics in wages are created by mismatches between labour supply and demand and wage bargaining. Concerning mismatches, a deficit (excess) in labour supply with the required

[33] In this respect, the labour and consumption decisions to create utility are based on relevant variables and concepts only. The implication of, and concepts associated to, rationality, decision making, cognitive limitation, preference, marginalism, and utility will only briefly be discussed since such level of detail exceeds the model attempt made.

[34] *'Perfectly competitive markets are described in economic theory as those in which no participants (buyers or sellers) have the market power to set the price of a homogeneous product. The conditions for perfect competition are strict; for example, an infinite number of agents, no barriers to entry or exit, perfect factor mobility, perfect information, and no transactions costs.'* (Booth, 2014, p. 54)

skill will shift the wage distribution upwards (downward) (Autor, 2013). In reaction, labour supply is reoriented to the relative increase or decrease unemployment and wages – whereby labour supply is attracted towards higher wages and employment opportunities (DeCanio, 2016). This operates as a balancing feedback mechanism since the additional labour supply will counteract the prior shortage. However, labour market adjustment mechanisms are slow and incomplete (Autor, Dorn, & Hanson, 2015) due to imperfect information, employment substitution elasticity, employment relation rents, and heterogeneous preferences (Booth, 2014). Moreover, wage developments lag behind economic developments (OECD, 2015b; Schneider, 2011). Furthermore, technological progress introduces new skills which the labour force may not have attained (to a satisfactory degree) yet (IFR, 2017). Therefore, flow delays are present and deficit or excess fluctuations may continue to exist. As a result, the labour market is not clearing, not frictionless and wage dynamics are present.

Contrarily, wage dynamics do not naturally follow labour supply and demand dynamics, e.g. job-polarisation does not necessarily lead to wage-polarisation (Goos, Manning, & Salomons, 2011; Mishel, Shierholz & Schmitt, 2013). The strength of this relation is country specific and depends on the institutional arrangement. Various studies demonstrate a consistent significant positive correlation between labour polarisation and wage inequality developments in the US. Yet, this correlation does not hold for Europe, most probably due to protective institutions[35] that result in relatively rigid wages (Goos, Manning, & Salomons, 2011; Gregory, Salomons & Zierahn, 2016). Wages have barely reacted to mismatches in labour markets across countries, sectors, and in reaction to substitution (Autor & Salomons, 2017). Most evidently, lower skilled occupations have seen a larger reduction in labour force then a loss of labour demand, yet the wages have reduced (Autor & Salomons, 2017). In contrast, the high skilled labour force benefits disproportionally from recent technology when it comes to wages and the wage share (Graetz & Michaels, 2017; Mishel, Shierholz & Schmitt, 2013; OECD, 2015b). Due to these counterintuitive developments and the rigidity of wages in Europe, the RRTC framework assumes homothetic preferences (no change in relative product demand and expenditure patterns following changing wages)[36] and simplified wage dynamics since *'In sum, the evidence does not strongly support the idea that changes in aggregate income or income dispersion – possibly following technological progress and globalization– play an important part in explaining changes in relative employment.'* (Goos, Manning, & Salomons, 2011, p. 21). In the model, it is assumed that mismatches do not result in wage dynamics. Wage setting through bargaining does.

The wage bargaining process depends on the relative position of the agents involved and the balance between wages, employment, and profits (Schneider, 2011). Pareto optimal outcomes can be reached based on the utility curves of firms and unions/employees on the wage-employment balance. In this case, wages exceed the marginal product of labour (Schneider, 2011). There are, however, conflicting theories whether collective bargaining (with unions) and deviation from the marginal product results in inefficiencies or efficiency and productivity losses or gains (Booth, 2014). Deteriorating union positions and bargaining strength of employees results in downward shift of wages and the wage share (in the direction of the marginal product) (Schneider, 2011). This implies that, both firms and unions/employees have a simultaneous bargaining position on the balance between wages and employment (Schneider, 2011). As a result, the relative power of the actors determines the factor shares due to conflict of interests between wages, profits, and employment (Booth, 2014; OECD, 2015b; Schneider, 2011).

In respect of the bargaining process, wage adjustments are slow and relatively rigid to economic outcomes and factors input changes (OECD, 2015b; Schneider, 2011). The bargaining process does not react immediately to changes in substitution, input demand, productivity growth, and economic outcomes (Schneider, 2011). Moreover, bargaining is decentralised, periodic, and independent for each wage or

[35] Minimum wage legislation and collective bargaining (Goos, Manning, & Salomons, 2011)

[36] *'The assumption of homotheticity implies that changes in both the level and the distribution of aggregate income have no effect on the distribution of demand across industries. This might be thought unduly restrictive because it has been argued (Manning 2004; and Mazzolari and Ragusa 2013) that job polarization might be caused by increasing inequality leading to increased demand for low-skill service sector jobs from high-wage workers to free up more of their time for market work. However, we cannot find evidence for non-homotheticity at our level of industry aggregation (Autor and Dorn 2013 arrive at similar conclusions).'* (Goos, Manning, & Salomons, 2014, p. 2518)

collective wage level (Schneider, 2011). In this process, unions act in behalf of employees to bundle bargaining power into a collective effort (Booth, 2014; Hirsch, Merkl, Mueller, & Schnabel, 2014). The wage formation regime differs from firm to firm and economy to economy (Hirsch, Merkl, Mueller, & Schnabel, 2014). Therefore, wages can be collectively bargained for, yet, this effort occurs per firm or industry (and thus is still decentralised, periodic, and independent, although to a lesser degree). The preferred wage formation regime depends on the firms relative TFP[37] and the relative bargaining process efficiency given national labour institutions (Hirsch, Merkl, Mueller, & Schnabel, 2014). These regime dynamics occur at the micro-level (Hirsch, Merkl, Mueller, & Schnabel, 2014) and are, therefore, beyond the scope of this study. Currently, collective bargaining is the main wage formation regime in Europe (Hirsch, Merkl, Mueller, & Schnabel, 2014). This implies, that in the model it is assumed that bargaining occurs at the task level (since the sectoral composition is not included in the model, as explicated later in this work) and is delayed.

The bargaining process is more complicated in the defined production model (Eq. 4) due to the disaggregation in tasks and skill levels compared to aggregate production functions. First, technological change is task specific and therefore the capital factor price, substitution elasticity, and productivity growth are heterogeneous. Second, each task and skill level has an associated wage which develops independently based on bargaining and institutions, yet depends on the overall economic outcomes across tasks (Schneider, 2011). Last, the sectoral composition of the economy continuously changes (OECD, 2015b; Schneider, 2011). Therefore, the aggregate and disaggregate wages and wage share at the industry level need not necessarily be equal or develop in parallel (OECD, 2015b; Schneider, 2011). In the model, this materialises as differences between tasks. The wage share of the low and medium skilled labour force has declined while the high skilled labour force's wage share has increased (OECD, 2015b). As a result, inequality has grown across skill levels (OECD, 2015b; Stockhammer, 2013). In this respect, the factors that influence wages and the wage share are heterogeneous across tasks and result in within and between task and skill level variation (OECD, 2015b). In the model this implies that even though CB functions are used, the wage share various across tasks, does not need to be equal to the marginal product of labour per tasks, and does not need to be stable in the long term (as set forth in 5.2).

> *'At a basic level, the distinction between high, middle and low skills adds an important degree of freedom to the model, allowing for non-monotone movements in wage levels and wage inequality as seen in the data.'* (Autor, 2013, p. 9)

The bargaining process is incorporated in the model through the share of productivity growth that is allocated towards wages. This implementation is a simplified and rather quantitative approach to the bargaining process. The process itself is not included. Future research can expand on this limitation by adopting an (agent based) bargaining model that simulates and represents agent interaction and incorporates various wage setting regimes. In terms of policies related to the actors, labour institutions such as unemployment benefits, minimum wages, transaction costs, wages taxes, and firing costs influence wage setting and the wage share (OECD, 2015b; Hirsch, Merkl, Mueller, & Schnabel, 2014; Schneider, 2011). Arguably, such instruments could be used to counteract the declining wage share. However, these instruments may function in the short to medium term, but stimulate technological substitution in the long term due to an increasing relative price of labour compared to capital (Schneider, 2011). The effects of different wage allocation distributions across tasks is simulated to determine the effect of wages, the wage share, and inequality.

7.1.2 Income from capital

Other forms of income exist in addition to wage and stem from the capital share. Non-wage income mainly comprises returns from assets and investment including divided, rent, and profits. This form of income has grown because of an increasing profit share and increasing accumulation of capital returns with a limited number of capital holders (Autor, 2015). The latter is especially relevant since it reinforces inequality

[37] In relation with production technology, Hirsch, Merkl, Mueller, and Schnabel (2014) demonstrate that, in Germany, firms with larger TFPs are inclined to "hide" behind collective bargaining schemes, arguably, to benefit profit- and competitive-wise from their relative productivity advantage in the industry.

developments and increases employment uncertainty across generations (see studies by Sachs and Kotlikoff (2012) and Sachs, Benzell, and LaGarda (2015) according to Autor (2015)). Thereby, older generations whom have been able to build up wealth over their lifetime and hold a portfolio of capital assets/investment benefit, while younger generations face increasing employment pressure and uncertainty. For the labour force this implies that productivity and economic output increase but they do not share in the benefits.

7.1.3 The utilisation of income

Income from wages and capital feedback to the economy via utilisation. Income is utilised in various ways, depending on the demographic and socio-economic conditions of the household. Generally, the expenditures can be categorised in two forms: consumption by immediately utilising earnings in return for products, or saving for later utilisation and investment. The balance between the share of income utilised for consumption [c] and savings [s] is defined by the propensity to save [σ] and propensity to consume [$\gamma = 1 - \sigma$]. Economy-wide, household consumption has developed in parallel to historic income development (Autor, 2015). Therefore, the aggregate propensity to consume across incomes has remained stable. However, a large share of the income from capital is used for saving (OECD, 2015b; Stockhammer, 2013). As a result, the increase of the capital share and reduction of income share results in reduced consumption (OECD, 2015b; Stockhammer, 2013). This loss in consumption can be offset by investment from capital income. However,

> '*It might be argued that lower wages are necessary to boost profits in order to increase investment and, in turn, job creation. However, in developed economies, the shift in income away from labour towards capital has not produced the expected results on investment*.' (OECD, 2015b, p. 12)

This is mainly the result of financialisation (see 5.2). This implies that in the model, a reduction of the wage share results in a decline of consumption and, concequentially, a relative proportional reduction of economic growth (i.e. relative w_{X_t} compared to $w_{X_{t=0}}$). On the other hand, the effect of an increasing profit share depends on the ratio of profits used for investment [ι_T] which determines the flow out of the model for use in the financial market [D_t] (see 5.2).

The income utilised for consumption is distributed across different products. In the model, this materialises in a demand distribution across tasks. The relevance of the consumption distribution followed from suggestions that higher income groups mainly consume additional services (See Goos, Manning, and Salomons (2011, 2014) and Autor (2015) for studies and argument). As a result, the task composition would change in favour of manual tasks. However, there is no evidence available that confirms this theory (Goos, Manning & Salomons, 2011, 2014). Hence, in line with the RRTC framework, it is assumed that demand growth is equally distributed across the tasks in the model. Moreover, the impact of changes in income appear to be relatively limited compared to price changes due to productivity growth (Goos, Manning & Salomons, 2011). Changes in output price and (consequential) changes in demand have the ability to weaken job-polarisation effects (Goos, Manning & Salomons, 2011). In relation with the spill-over effects, this implies that competitive utilisation of productivity growth results in additional demand, offsetting labour substitution. Therefore, competitive allocation per task in the model results in a reduction of the output price of a task and, consequentially, increasing task output demand given the price elasticity of demand per task [η_{p_T}] (as defined in 3.2). It is assumed that the price elasticity of demand is constant over time.

7.2 The labour market

The dynamic nature of labour is created by changes in economic production on one hand, and demographic and skill changes on the other. These dynamics meet on the labour market. It is here that labour demand stemming from the production model [$L_{\varepsilon_\mathcal{R}}, L_{\varepsilon_\mathcal{A}}, L_{\varepsilon_\mathcal{M}}, L_{\xi_\mathcal{R}}, L_{\xi_\mathcal{A}}, L_{\xi_\mathcal{M}}$] and labour supply stemming from the population model [$L_{\varepsilon_\mathbb{L}}, L_{\varepsilon_\mathbb{M}}, L_{\varepsilon_\mathbb{H}}, L_{\xi_\mathbb{L}}, L_{\xi_\mathbb{M}}, L_{\xi_\mathbb{H}}$] need to be matched to create economic value and incomes for households. This process depends on the labour market structure which dictates which skill levels and tasks match. In this paragraph, the labour market model is developed by defining labour supply, demand, and market structure prior to implementation in an operational model.

7.2.1 Labour supply [$\boldsymbol{S}$]

The labour force [$\mathbb{LF}_{\varepsilon_{\mathbb{s}}}$] includes all individuals who participate in the labour market, depending on the participation rate [$\rho_{\mathbb{WA}_{\varepsilon_{\mathbb{s}}}}$] per age cohort per skill level for each sex. This participating population stems from all working age cohorts [$\mathbb{WA}_{\varepsilon}$] plus retired and includes both part-time [$\mathbb{p}$] and full-time [$\mathbb{f}$] participants (Eq. 13). The actual part-time [$L_{\varepsilon_{\mathbb{LF}\,\mathbb{p}}}$] and full-time [$L_{\varepsilon_{\mathbb{LF}\,\mathbb{f}}}$] labour supply per skill level is established based on the fulltime ratio of employment [$\varsigma_{\mathbb{WA}_{\varepsilon_{\mathbb{s}}}}$] and the participation rate [$\rho_{\mathbb{WA}_{\varepsilon_{\mathbb{s}}}}$] per age cohort per skill level for each sex (Eq. 14). The participation rate is assumed to remain stable since the prior trend of increasing female participation (due to social and societal changes in the position of woman in households and society across generations) has slown down and will not continue in the future (Euwals, Knoef, & Van Vuuren, 2011; ILO, 2018). Note that the aggregate participation rate (and the labour force size) are still variable due to demographic shifts in the age cohort size and composition. Identical male and female skill levels feed into the same labour market supply groups. Therefore, no distinction is made between age cohorts and sex resulting into twelve labour supply groups – one full-time and one part-time for each skill level [$\varepsilon_{\mathbb{L}}, \varepsilon_{\mathbb{M}}, \varepsilon_{\mathbb{H}}, \xi_{\mathbb{L}}, \xi_{\mathbb{M}}, \xi_{\mathbb{H}}$][38].

$$\begin{aligned} \mathbb{WA}_{\varepsilon_{\mathbb{s}}} &= \left\{\mathbb{ST}_{\varepsilon_{\mathbb{s}}}, \mathbb{YA}_{\varepsilon_{\mathbb{s}}}, \mathbb{MA}_{\varepsilon_{\mathbb{s}}}, \mathbb{SA}_{\varepsilon_{\mathbb{s}}}, \mathbb{RE}_{\varepsilon_{\mathbb{s}}}\right\}, \quad \mathbb{WA}_{\varepsilon_{\mathbb{s}}} \subset \mathbb{AC}_{\varepsilon_{\mathbb{s}}} \\ \mathbb{LF}_{\varepsilon_{\mathbb{s}}} &= \left\{\mathbb{ST}_{\varepsilon_{\mathbb{s}}} * \rho_{\mathbb{ST}_{\varepsilon_{\mathbb{s}}}}, \mathbb{YA}_{\varepsilon_{\mathbb{s}}} * \rho_{\mathbb{YA}_{\varepsilon_{\mathbb{s}}}}, \mathbb{MA}_{\varepsilon_{\mathbb{s}}} * \rho_{\mathbb{MA}_{\varepsilon_{\mathbb{s}}}}, \mathbb{SA}_{\varepsilon_{\mathbb{s}}} * \rho_{\mathbb{SA}_{\varepsilon_{\mathbb{s}}}}, \mathbb{RE}_{\varepsilon_{\mathbb{s}}} * \rho_{\mathbb{RE}_{\varepsilon_{\mathbb{s}}}}\right\} \end{aligned} \qquad \textit{Eq. 13}$$

$$\begin{aligned} L_{\varepsilon_{\mathbb{LF}\,\mathbb{f}}} &= \sum_{x \in \mathbb{WA}_{\varepsilon_{\mathbb{s}}}}^{|\mathbb{WA}_{\varepsilon_{\mathbb{s}}}|} \varsigma_x * \rho_x * x &&= \sum_{y \in \mathbb{LF}_{\varepsilon_{\mathbb{s}}}}^{|\mathbb{LF}_{\varepsilon_{\mathbb{s}}}|} \varsigma_y * y, \\ L_{\varepsilon_{\mathbb{LF}\,\mathbb{p}}} &= \sum_{x \in \mathbb{WA}_{\varepsilon_{\mathbb{s}}}}^{|\mathbb{WA}_{\varepsilon_{\mathbb{s}}}|} (1 - \varsigma_x) * \rho_x * x &&= \sum_{y \in \mathbb{LF}_{\varepsilon_{\mathbb{s}}}}^{|\mathbb{LF}_{\varepsilon_{\mathbb{s}}}|} (1 - \varsigma_y) * y \end{aligned} \qquad \textit{Eq. 14}$$

The production sector requires task specific labour input [$L_{\varepsilon_{\mathcal{R}}}, L_{\varepsilon_{\mathcal{A}}}, L_{\varepsilon_{\mathcal{M}}}, L_{\xi_{\mathcal{R}}}, L_{\xi_{\mathcal{A}}}, L_{\xi_{\mathcal{M}}}$] which is matched to labour force's skill levels. Hereby, the labour supply per skill level [$L_{\varepsilon_{\mathbb{LF}}}$] (e.g. $L_{\varepsilon_{\mathbb{L}}}$) is linked to the appropriate tasks [$L_{\varepsilon_{T}}$], resulting in the task specific labour supply [$L_{\varepsilon_{\mathbb{LF} \to T}}$] per skill level per task (e.g. $L_{\varepsilon_{\mathbb{L} \to \mathcal{M}}}$ indicating the low skilled labour supply to manual tasks). The task specific labour supplies are summed to create the total labour supply per task [$L_{\varepsilon_{T\,S}}$]. In this respect, studies use different labour market structures that dictate which skill levels match which tasks (and therefore how labour supply is distributed and which supplies should be summed).

7.2.2 Labour demand [$\boldsymbol{D}$]

On the demand side, the task production functions dictate how many labour hours are required per task type [$L_{\varepsilon_{\mathcal{R}}}, L_{\varepsilon_{\mathcal{A}}}, L_{\varepsilon_{\mathcal{M}}}, L_{\xi_{\mathcal{R}}}, L_{\xi_{\mathcal{A}}}, L_{\xi_{\mathcal{M}}}$]. This total amount of labour input is divided between part-time hours [$h_{\mathbb{p}}$] and full-time hours [$h_{\mathbb{f}}$] given the fulltime ratio [ς_T] per task. Hence, the demanded labour hours are converted into a specific quantity of full-time and part-time jobs per tasks (Eq. 15). These positions are filled with linked labour supply. The difference between the demanded labour [$L_{\varepsilon_{T\,D}}$] and total supplied labour [$L_{\varepsilon_{TS}}$] per task (for full-time and part-time) results in the unemployed labour force per task type [u_T] and unemployment rate [υ_T]. All unemployment is involuntary and all non-participation is voluntary.

[38] This implies that the working age [$\mathbb{WA}_{\varepsilon_{\mathbb{s}}}$] population comprises five age cohorts across six skill levels and two sexes. The labour force [$\mathbb{LF}_{\varepsilon_{\mathbb{s}}}$] comprises all population members active on the labour market out of the working age population whom flow into the actual labour supply across six skill levels and two contract types (part-time and full-time), e.g. the full-time extended high skilled labour supply:

$$\begin{aligned} L_{\xi_{\mathbb{H}\,\mathbb{f}}} = {} & \varsigma_{\mathbb{ST}_{\xi_{\mathbb{H}\,\mathbb{f}\,♂}}} * \rho_{\mathbb{ST}_{\xi_{\mathbb{H}\,\mathbb{f}\,♂}}} * \mathbb{ST}_{\xi_{\mathbb{H}\,\mathbb{f}\,♂}} + \varsigma_{\mathbb{YA}_{\xi_{\mathbb{H}\,\mathbb{f}\,♂}}} * \rho_{\mathbb{YA}_{\xi_{\mathbb{H}\,\mathbb{f}\,♂}}} * \mathbb{YA}_{\xi_{\mathbb{H}\,\mathbb{f}\,♂}} + \varsigma_{\mathbb{MA}_{\xi_{\mathbb{H}\,\mathbb{f}\,♂}}} * \rho_{\mathbb{MA}_{\xi_{\mathbb{H}\,\mathbb{f}\,♂}}} * \mathbb{MA}_{\xi_{\mathbb{H}\,\mathbb{f}\,♂}} + \varsigma_{\mathbb{SA}_{\xi_{\mathbb{H}\,\mathbb{f}\,♂}}} * \rho_{\mathbb{SA}_{\xi_{\mathbb{H}\,\mathbb{f}\,♂}}} * \mathbb{SA}_{\xi_{\mathbb{H}\,\mathbb{f}\,♂}} + \varsigma_{\mathbb{RE}_{\xi_{\mathbb{H}\,\mathbb{f}\,♂}}} * \rho_{\mathbb{RE}_{\xi_{\mathbb{H}\,\mathbb{f}\,♂}}} * \mathbb{RE}_{\xi_{\mathbb{H}\,\mathbb{f}\,♂}} + \\ & \varsigma_{\mathbb{ST}_{\xi_{\mathbb{H}\,\mathbb{f}\,♀}}} * \rho_{\mathbb{ST}_{\xi_{\mathbb{H}\,\mathbb{f}\,♀}}} * \mathbb{ST}_{\xi_{\mathbb{H}\,\mathbb{f}\,♀}} + \varsigma_{\mathbb{YA}_{\xi_{\mathbb{H}\,\mathbb{f}\,♀}}} * \rho_{\mathbb{YA}_{\xi_{\mathbb{H}\,\mathbb{f}\,♀}}} * \mathbb{YA}_{\xi_{\mathbb{H}\,\mathbb{f}\,♀}} + \varsigma_{\mathbb{MA}_{\xi_{\mathbb{H}\,\mathbb{f}\,♀}}} * \rho_{\mathbb{MA}_{\xi_{\mathbb{H}\,\mathbb{f}\,♀}}} * \mathbb{MA}_{\xi_{\mathbb{H}\,\mathbb{f}\,♀}} + \varsigma_{\mathbb{SA}_{\xi_{\mathbb{H}\,\mathbb{f}\,♀}}} * \rho_{\mathbb{SA}_{\xi_{\mathbb{H}\,\mathbb{f}\,♀}}} * \mathbb{SA}_{\xi_{\mathbb{H}\,\mathbb{f}\,♀}} + \varsigma_{\mathbb{RE}_{\xi_{\mathbb{H}\,\mathbb{f}\,♀}}} * \rho_{\mathbb{RE}_{\xi_{\mathbb{H}\,\mathbb{f}\,♀}}} * \mathbb{RE}_{\xi_{\mathbb{H}\,\mathbb{f}\,♀}} \end{aligned}$$

$$L_{\varepsilon_{T\,D\mathbb{f}}} = \frac{L_{\varepsilon_{T\,D}} * \varsigma_T}{h_{\mathbb{f}}}, \quad L_{\varepsilon_{T\,D\mathbb{p}}} = \frac{L_{\varepsilon_{T\,D}} * (1-\varsigma_T)}{h_{\mathbb{p}}},$$
$$\upsilon_T = 1 - \frac{L_{\varepsilon_{T\,S}} - L_{\varepsilon_{T\,D}}}{L_{\varepsilon_{T\,S}}}, \quad u_T = \upsilon_T * L_{\varepsilon_{T\,S}}$$

Eq. 15

7.2.3 Labour market structure

The most simplified structure would reduce the labour market to an isolated relation between skill level and task type as is done within the SBTC framework (Acemoglu & Autor, 2012). This implies that the low skilled labour force can only supply labour to manual tasks [$L_{\varepsilon_{\mathbb{L}}} \rightarrow L_{\varepsilon_{\mathcal{M}}}$], middle skilled to routine tasks [$L_{\varepsilon_{\mathbb{M}}} \rightarrow L_{\varepsilon_{\mathcal{R}}}$], and high skilled to abstract tasks [$L_{\varepsilon_{\mathbb{H}}} \rightarrow L_{\varepsilon_{\mathcal{A}}}$]. This relation between skill and tasks is referred to as the *natural task.* However, Acemoglu and Autor (2012) emphasize that this practise, although commonly adopted and statistically well representative of real-world outcomes, is only accurate under static skill and task relations. This implies that the same skill level would always perform the same tasks across the labour force and over time. However, tasks and associated skills evolve over time, due to technological progress and other factors (Acemoglu & Autor, 2012; Acemoglu & Restrepo, 2018; Autor, 2015; Autor, Dorn, & Hanson, 2015; DeCanio, 2016; IFR, 2017; Nedelkoska & Quintini, 2018). Moreover, labour force members shift their supply to other task types in reaction to labour market developments (Arntz, Gregory, Zierahn, 2016; Frey & Osborne, 2017). Therefore, technology-driven dynamics and labour allocation dynamics need to be included. Hence, the TBTC and RRTC use different labour market structures that accommodate these dynamics.

The extended skill set [ξ] was introduced in the model to accommodate the dynamics associated to technology-driven skill development within tasks. However, the dynamics associated to the reallocation of labour supply across task types mainly determines the labour market structure. TBTC and RRTC studies have adapted the prior SBTC structure into more free-flowing market that disconnects the isolated relations (Mishel, Shierholz & Schmitt, 2013). Generally speaking, three market structures can be identified in literature.

The most elaborate structure includes all combinations of skill level and task type to create a fully open market. As defined earlier, occupations consist of a combination of manual, routine, and abstract tasks. The most extreme cases are occupations consisting exclusively of tasks of one type and the most moderate occupations have an even share of the task types. As a result, each task type is performed by each skill level depending on the intensity of task types within the occupations in the economy. Therefore, some abstract tasks within manual-task intense occupations will be performed by low skilled employment and vice versa. However, statistical and labour market evidence suggests that the relations between task type and skill level are rather robust – especially for high skill levels (Autor, Dorn, & Hanson, 2015; Frey & Osborne, 2017). Therefore, the low, middle, and high skilled labour force tends to be employed in occupations with a high intensity of the natural task type. Since occupations consists of a combination of task types, abstract-intense occupations require highly skilled employees and manual-intense occupations can be performed by the low skilled labour force (Autor, 2015; Autor, Dorn, & Hanson, 2015; Cortes, Jaimovich, Nekarda & Siu, 2014; Mishel, Shierholz & Schmitt, 2013). Therefore, occupations can be placed in a continues space with opposite extremes of abstract, routine, and manual task exclusive occupations (Figure 7) and a strong relation between natural type-intensity and skill level (Colours in the corners of the triangle). Examples of jobs in the extremes are hairdressers (for $\mathcal{M}$), product manufacturing (for $\mathcal{R}$), and academic analysists (for $\mathcal{A}$).

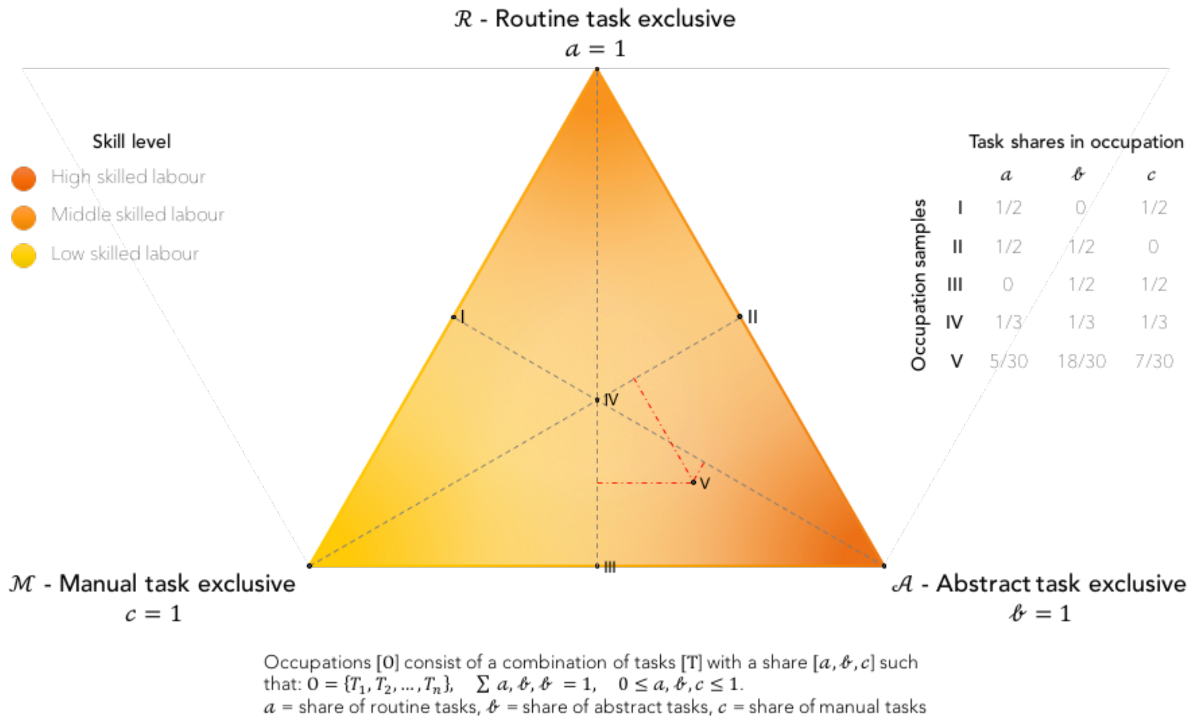

Figure 7 Occupations and the relation between skill levels and tasks on an open market

Various scholars argue that there is a significant difference between the cognitive capabilities of the high skilled labour forces compared to the other two skill levels (Acemoglu & Restrepo, 2017b, 2018; Autor, Levy, Murnane, 2003). Moreover, the definition of the task types suggests that a revision in the relation between middle and low skilled labour and routine and manual tasks is required. Given these two observations, two alternative market structures have been identified. Both structures incorporate an overlap between routine and manual labour markets. However, the position of the high skilled labour force is different.

Manual tasks are mainly service oriented and routine tasks are predominantly associated to production (Autor, 2015; Autor, Dorn, & Hanson, 2015). In contrast with the isolated labour market structure, manual task intense services may require a middle skill education background and routine task intense production may operate equally well with low skilled input. Moreover, labour force members shift their supply to other task types in reaction to labour market developments. For example, recent labour market flows suggest that part of the middle skilled labour force, formerly employed in routine-intense occupations, shift to manual task intense service jobs in reaction to automation (Frey & Osborne, 2015, 2017). Therefore, the isolated relation between low skilled labour supply and manual tasks $[L_{\varepsilon_{\mathbb{L}}} \rightarrow L_{\varepsilon_{\mathcal{M}}}]$ and middle skilled labour supply and routine tasks $[L_{\varepsilon_{\mathbb{M}}} \rightarrow L_{\varepsilon_{\mathcal{R}}}]$ is incomplete. Hence, the low and middle skilled labour force share the market for manual and routine tasks.

The cognitive capabilities of the high skilled labour force create a distinct comparative advantage (Autor, Levy, Murnane, 2003). In this respect, limited cognitive means and human capital inhibit middle and lower skilled individuals from performing abstract task intense occupations (Acemoglu & Restrepo, 2017b, 2018; Autor, Levy, Murnane, 2003). Therefore, Acemoglu and Restrepo (2017b, 2018) argue that all tasks and occupations can be performed by the high skilled labour force while the other skill levels run into an upper limit above which the abstract-task intensity is too high. This results in a semi-open labour market where all skill levels can perform manual and routine intense occupations while abstract tasks remain the exclusive domain of the high skilled labour force (Figure 8). Other scholars isolate the abstract market altogether, resulting in a semi-isolated labour market in which the high skilled labour force is exclusively employed in abstract intense occupations as is done by Autor, Katz and Kearney (2006)[39], Acemoglu & Autor (2011), Gregory, Salomons & Zierahn (2016), and Goos, Manning, & Salomons (2009) (Figure 9).

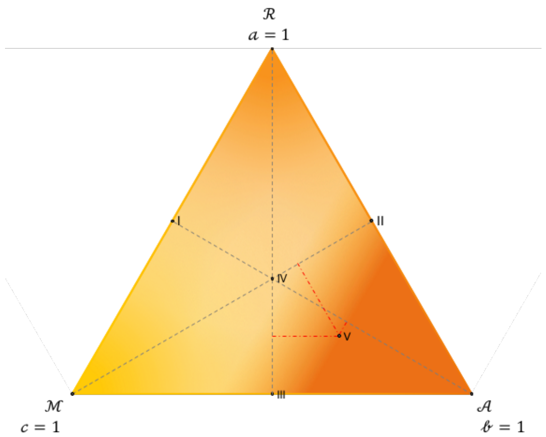

Figure 8 Semi-open labour market

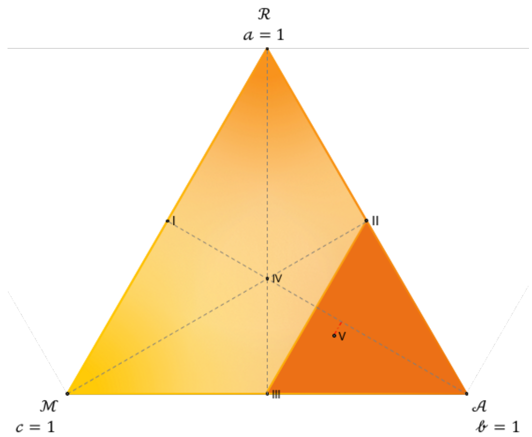

Figure 9 Semi-isolated labour market[40]

7.3 The Labour market model

Essentially, all these market structures (isolated, open, semi-open, semi-isolated) can be modelled with the current methodology. However, the semi-open labour market structure is adopted since the model is task-based (thus not occupation-based), is developed to consider the allocation possibilities (as highlighted by Acemoglu & Autor (2012) in the section on Task-Based Technological Change (TBTC) (see 3.1)) and fits within the TBTC and RRTC framework. The task-based approach results in a simplified representation of the real-world occupation-based labour market[41]. As stated before, businesses utilise a specific combination and particular quantity of tasks to produce output (be it goods or services) (Figure 3). Occupations consists of a coherent set of tasks that are part of the overall set of tasks in production. Each of those tasks can be characterised according the TBTC task types $[\mathcal{R}, \mathcal{A}, \mathcal{M}]$ and the RRTC routinized alternatives $[\mathcal{R}_{\mathcal{A}}, \mathcal{R}_{\mathcal{M}}]$. Therefore, the occupations can be placed in the continues space presented in Figure 7 and Figure 8 depending on the share of the task types (only including the three TBTC levels for illustrative clarity). In turn, the production of the tasks requires specific labour and capital input (Eq. 4). Therefore, a particular quantity of every occupation is demanded given the quantity of task input required for the intended production - which equates to the number of job positions. Consequently, a corresponding tasks-specific labour input is demanded given the labour market structure.

In this sense, the task approach simplifies the continues space of occupations (as presented in Figure 7 and Figure 8) into a polarised market of discrete categories - namely the tasks within occupations that characterise the labour input required. The advantage of using a systematic categorisation of tasks is that it provides a robust approach across different time-frames and economies at the macro level (Arntz, Gregory, Zierahn, 2016). Occupations and sectors continuously develop, emerge, and fade over time. However, the components (i.e. tasks) that make up those occupations and labour input do not fundamentally change. In this respect, the changes are captured in the input-level production functions of the tasks. On the other hand, shifts of labour supply are captured at the task level. Therefore, the dynamics of occupations and sectoral labour input can be captured with a simplified task-based model[42]. The semi-open labour market

[39] According to Goos, Manning, & Salomons (2011)

[40] The rate of abstract tasks in the high skilled labour market domain is set at $b = 0.5$ for convenience and visual purposes.

[41] Which would also require sector-specific and experience-specific human capital (e.g. junior and senior functions) to be considered.

[42] Occupations emerge, develop, and fade over time Acemoglu and Restrepo (2017b). These new occupations have become a larger fraction of the US labour market over the past three decades Acemoglu and Restrepo (2017b). An occupation-based model would need to be able to predict and adapt to the unforeseen future occupations and consider sectoral economic dynamics (Frey & Osborne, 2015). This would require a sub-model for every occupation type across all sectors including sectoral interaction and dynamics, Therefore, severely complicating the model.

results in the relations between skill levels and task types as presented in Table 1. The inner matrix matches supply and demand to define all task specific labour supplies [$L_{\varepsilon_{\mathbb{LF}\to T}}$]. These relations are noted such that [N] notes the natural relation between skills and tasks and [Q] notes the additional labour supply possibilities per skill level for which the individuals are qualified.

Table 1 Labour market skill (supply) - task (demand) relation $\mathbb{LF} \to T$

Labour supply [$L_{\varepsilon_{\mathbb{LF}}}$]	Labour demand [L_{ε_T}] →	$L_{\varepsilon_\mathcal{M}}$	$L_{\xi_\mathcal{M}}$	$L_{\varepsilon_\mathcal{R}}$	$L_{\xi_\mathcal{R}}$	$L_{\varepsilon_\mathcal{A}}$	$L_{\xi_\mathcal{A}}$
	$L_{\xi_\mathbb{H}}$	Q	Q	Q	Q	Q	N
	$L_{\varepsilon_\mathbb{H}}$	Q		Q		N	
	$L_{\xi_\mathbb{M}}$	Q	Q	Q	N		
	$L_{\varepsilon_\mathbb{M}}$	Q		N			
	$L_{\xi_\mathbb{L}}$	Q	N	Q	Q		
	$L_{\varepsilon_\mathbb{L}}$	N		Q			

The actual structure of the labour market connects the production model and demographic model via labour demand and supply. The prior labour supply equitation (Eq. 14) is expanded to incorporate the semi-open labour market including the dual relation between low and middle skilled labour and manual and routine tasks. It is assumed that employees are normally oriented towards their natural tasks type [N], avoid tasks with higher unemployment rates [υ], and strive to maximise wages [W]. This implies that employees will supply labour to the natural task type, unless another task type has a lower unemployment rate, but only if the loss in wage is acceptable [ϑ] or an increase in wage is realised. The relative strength of the labour allocation reaction to unemployment depends on the reallocation sensitivity [$0 \leq \eta_\upsilon \leq 1$] and on the utility elasticity of wages [$0 \leq \eta_W \leq 1$]. This reactive adjustment process is delayed [Δt_L] because of legal resignation period constraints, job application process duration, and the period before the labour market trends are recognised and picked up as common knowledge. Therefore, the task specific labour supply [$L_{\varepsilon_{\mathbb{LF}\to T}}$] per skill level (Eq. 16) are summed per task to get the labour supply per task [$L_{\varepsilon_{T\,S}}$] (Eq. 17) and summed per skill level to the total labour supplied per skill level [$L_{\varepsilon_{\mathbb{LF}}}$] (Eq. 18).

The labour demand equations remain unchanged since demand stems from the task production functions. However, since the relation between skill and task has been established, the unemployment equations can be extended to calculate the age cohort specific unemployment [$u_{\mathbb{LF}_{\varepsilon_\mathbb{S}}}$]. Thereby, the distribution of unemployment among the supplying age cohorts is determined. Since the model treads males and females across all age cohorts as equals, the unemployment rate per task equal across participating age cohorts. In other words, unemployment is normally distributed relative to the share of each supplying age cohort to the total labour supply of the task. However, higher educated labour supply and demand are shifting towards lower requirement tasks (Autor & Salomons, 2017). *'They [res. Beaudry et al. (2013)] show that high-skilled workers have moved down the occupational ladder, taking on jobs traditionally performed by low-skilled workers, pushing low-skilled workers even further down the occupational ladder and, to some extent, even out of the labour force.'* (Frey & Osborne, 2017, p. 258). This aspect is incorporated in the model via a labour supply skill level selection order.

$$L_{\varepsilon_{\mathbb{LF}\to T}} = \sum_{y\in \mathbb{LF}_{\varepsilon_{\mathbb{S}}}}^{|\mathbb{LF}_{\varepsilon_{\mathbb{S}}}|} y * a_{y_{\mathbb{LF}\to T}} * \frac{b_{y_{\mathbb{LF}\to T}}}{\sum b_{y_{\mathbb{LF}\to T}}} * \frac{c_{y_{\mathbb{LF}\to T}}}{\sum c_{y_{\mathbb{LF}\to T}}}, \quad with \quad \mathbb{LF}\to T = \{N, Q\}$$

$$a_{y_{\mathbb{LF}\to T}} = \begin{cases} \varsigma_y & , \quad \mathbb{f} \\ (1-\varsigma_y), & \mathbb{p} \end{cases}$$

$$b_{y_{\mathbb{LF}\to T}} = \begin{cases} 0 & , \quad W_Q < W_N * (1-\vartheta) \\ 1 - \left(\frac{W_Q}{W_N * (1-\vartheta)}\right)^{1-\eta W} & , \quad W_N * (1-\vartheta) < W_Q < W_N \\ 1 - \left(\frac{W_N}{W_N * (1-\vartheta)}\right)^{\eta W} & , \quad W_Q = W_N \\ 1 - \left(\frac{W_Q}{W_N}\right)^{\eta W} & , \quad W_Q > W_N \end{cases} \qquad \text{Eq. 16}$$

$$c_{y_{\mathbb{LF}\to T}} = \begin{cases} 1 - \left(\frac{\upsilon_Q}{\upsilon_N}\right)^{\eta_\upsilon}, & \upsilon_Q < \upsilon_N \wedge b_{y_{\mathbb{LF}\to T}} > 0 \\ 0 & , \quad \upsilon_Q < \upsilon_N \vee b_{y_{\mathbb{LF}\to T}} \leq 0 \end{cases}$$

$$L_{\varepsilon_{T\,S}} = \sum_{z\in L_{\varepsilon_{\mathbb{LF}\to T}}}^{|L_{\varepsilon_{\mathbb{LF}\to T}}|} z\,, \quad with \quad L_{\varepsilon_{\mathbb{LF}\to T}} = \{L_{\varepsilon_{\mathbb{L}\to T}}, L_{\xi_{\mathbb{L}\to T}}, L_{\varepsilon_{\mathbb{M}\to T}}, L_{\xi_{\mathbb{M}\to T}}, L_{\varepsilon_{\mathbb{H}\to T}}, L_{\xi_{\mathbb{H}\to T}}\} \qquad \text{Eq. 17}$$

$$L_{\varepsilon_{\mathbb{LF}}} = \sum_{z\in L_{\varepsilon_{\mathbb{LF}\to T}}}^{|L_{\varepsilon_{\mathbb{LF}\to T}}|} z\,, \quad with \quad L_{\varepsilon_{\mathbb{LF}\to T}} = \{L_{\varepsilon_N}, L_{\varepsilon_{Q_n}}\} \qquad \text{Eq. 18}$$

7.4 Labour market model synthesis

The labour market model is task-based and semi-open whereby all skill levels can perform manual and routine intense occupations while abstract tasks remain the exclusive domain of the high skilled labour force. The task specific labour input [$L_{\varepsilon_{\mathcal{R}}}, L_{\varepsilon_{\mathcal{A}}}, L_{\varepsilon_{\mathcal{M}}}, L_{\xi_{\mathcal{R}}}, L_{\xi_{\mathcal{A}}}, L_{\xi_{\mathcal{M}}}$] stemming from the production model is converted into the task specific labour demand [$L_{\varepsilon_{T\,D}}$] (i.e. the number of jobs demanded). Given the matched labour skills in Table 1, the total labour supply per task [$L_{\varepsilon_{T\,S}}$] is determined via summation of the task specific labour supplies [$L_{\varepsilon_{\mathbb{LF}\to T}}$]. This labour market is identical for both part-time [$\mathbb{p}$] and full-time [$\mathbb{f}$] jobs. Simplification of the labour market implies that quantitative and qualitative information at the occupation and sector level is stripped from the input data to satisfy the task-based structure. As a result, part of the information will be lost and simulation of the model may generate polarised quantitative outcomes. However, in similar fashion to the social analysis of the quantitative results, the outcomes are analysed from the perspective of the broader initial conditions. Thus, the results are analysed from an occupation-based frame of reference given the broader initial context of the simulation. Therefore, the specific and distinguishable impact of various technologies provide opportunity to induce the quantitative data into broader informed conclusion.

8 Education model

The required and relevant skills in the economy change as technology enables substitution of input and tasks. Some skills are rendered obsolete while new skill requirements emerge (Autor, 2015; DeCanio, 2016). From an economic perspective, management of the skill set of the current and future labour force is essential to ensure continuation of the economic advantages provided by technology (Acemoglu & Restrepo, 2018; Arntz, Gregory, Zierahn, 2016; IFR, 2017). From the perspective of employees, there is consensus that equipping the labour force with the relevant skills is essential to ensure employment and income stability (Autor & Salomons, 2017; Frey & Osborne, 2017; IFR, 2017); *'The reason why human labour has prevailed relates to its ability to adopt and acquire new skills by means of education.'* (Frey & Osborne, 2017, p. 258). The ability of the labour force to adapt to the evolving labour markets determines their future employment certainty and wage level (Autor, 2015). Consequently, the rate of successful adjustment to new skill sets determines the realisation of feasible productivity growth, welfare stability, and inequality control (Acemoglu & Restrepo, 2018; Autor, 2015; OECD, 2017b; IFR, 2017). In this respect, the labour force, government, and employers have a shared interest and responsibility (IFR, 2017). Problematically,

> *'Given the gravity of the technological transformation we are undergoing, there is astonishingly little research effort in understanding the subsequent response through skill adjustment.'* Yet, the authors continue based on the little research that *'re-qualification and upskilling play a key role in mitigating the difficult transitions awaiting workers whose skills have been rendered obsolete by technological progress.'* (Nedelkoska & Quintini, 2018, p. 36)

The education and training model is an attempt to narrow this gap. Education and training systems are critical for skill attainment. The process of skill attainment (re-skilling and up-skilling) depends on the facilities and resources (made) available to the population by government education spending, employers' human capital investment, and personal expenditure. However, a lack of awareness, information, mandate, and action can inhibit timely skill adjustment even if the financial resources are sufficient (OECD, 2017b). The education and training system comprises all facilities and resources for skill attainment. The system itself can be separated in compulsory (primary and secondary) education for the children age cohort, optional (secondary, post-secondary, vocational, and tertiary) education for the student age cohort, and professional/adult training for the working population age cohorts. Together, these sub-systems determine the skill attainment and adaptability of the labour force. In this process, the quality and quantity of skill attainment is influenced by critical factors in education and training systems. Combining these factors with the financial supports results in the skill attainment model for children, students and the working age population. In this paragraph, the skill attainment model is developed by defining the financial resources, the critical factors across the cohort-specific sub-systems ($\mathbb{CH}$, $\mathbb{ST}$ and $\mathbb{WA}$), and structure of the education and training systems.

8.1 Funding of education and training

Both governments and companies have a roll in the skill adaptation process (IFR, 2017; OECD, 2017b). Herein, governments should focus on economy wide skill adjustment with policies, programmes and incentive creation (IFR, 2017). These initiatives should not be static in time but consider life-long learning (LLL) due to the continuously changing skill relevance on the labour market (IFR, 2017; Nedelkoska & Quintini, 2018). Moreover, governments should actively monitor the labour market and cooperate closely with the private sector to determine which low-skilled opportunities remain or emerge for employees not able to re-skill or up-skill (IFR, 2017). As a result, labour force education and training should not be isolated to re- and up-skilling, but should also safeguard future low-skilled opportunities that emerge as an indirect or spill-over result of substitution (IFR, 2017).

Simultaneously, companies carry responsibility over their employees to provide relevant skill training. Conflictingly, the current trend among businesses demonstrates declining investment in employee training and knowledge-intensive capital and development (IFR, 2017). This trend should be reversed to mitigate possible skill mismatches and sustain the possible productivity growth path (Acemoglu & Restrepo, 2018; IFR, 2017). Therefore, the investment stream $[I_T]$ from profits is divided into employment training investment $[I_{T_L}]$ and technological innovation R&D investment $[I_{T_\tau}]$. If employment training is neglected, all investments fully contribute to technological innovation and thus the respective productivity factor $[A_T]$. However, as discussed before, the absence of adequately skilled employees may inhibit the realisation of this productivity growth since the technology cannot be implemented and operationalised (Acemoglu & Restrepo, 2018; IFR, 2017). The share of the investment streams $[I_{T_\tau}$ and $I_{T_L}]$ and dividend stream $[D_{T_t}]$ is respectively determined by the innovation investment share $[\iota_T]$, the employment investment share $[\epsilon_T]$, and the dividend share $[\nu_T]$ such that $[g = \{\iota_T, \nu_T, \epsilon_T\}, \sum g_i = 1,$ and $0 \leq g_i \leq 1]$. Therefore, Eq. 8 is expanded into (Eq. 19),

$$\psi_{T_t} = P_{T_{t-1}}\phi_c + \phi_{so}, \quad I_{T_\tau} = \iota_T\psi_T, \quad I_{T_L} = \epsilon_T\psi_T, \quad D_{T_t} = \nu_T\psi_T \qquad \textit{Eq. 19}$$

This implies that, the outcomes of the model in respect of re-skilling, up-skilling, and adequately skilled labour shortages will qualitatively support the current insistence concerning company training investment.

Company training investment is isolated to a task-level basis to tackle mismatches. Yet, companies use a combination of tasks to produce final output (Autor, 2013, 2015; Mishel, Shierholz & Schmitt, 2013). Hence employment investment is allocated towards re-skilling $[\mathbb{R}]$ and up-skilling $[\mathbb{U}]$. Government investment into education of the labour force $[G_{L_\varepsilon}]$ and labour force consumption of personal training $[c_{L_\varepsilon}]$ can be allocated toward re-skilling or up-skilling. The government has a triple mandate in this context: ensure economic wellbeing of the population, maximise economic returns $[X(T)]$ with the realisation of productivity growth $[A_T]$, and ensure a balanced government budget $[G]$. The first includes maintaining a healthy level of unemployment; realising a societally acceptable level of inequality between socio-economic groups; and ensuring economic welfare of the population via wage levels[43]. The second includes maintaining an adequately skilled population via the public education system and stimulating innovation via government investment in technological innovation $[G_{T_\tau}]$. Lastly, government expenditure, including investments and unemployment benefits $[G_U]$, needs to be minimised (Eq. 20) - within the minima set by the national unemployment institutions $[Z]$.

$$\min_G\left(G_{L_\varepsilon} + G_{T_\tau} + G_U\right) \qquad \textit{Eq. 20}$$

The routine biased nature of technological progress demands dichotomous and multidisciplinary education (EU Skills Panorama 2014, 2015; European Commission, 2015; IFR, 2017). On the one hand, the development of technology and its growing societal and economic importance demand for STEM (Science, Technology, Engineering and Mathematics), Technology Literacy (TL), and Digital Literacy (DL) competences (Bybee, 2010; EU Skills Panorama 2014, 2015; IFR, 2017; Sanders, 2009). In this context, taken together and termed STEM from here on foreword since STEM encompasses TL and DL in its approach (see Bybee (2010)). The earlier definition of the extended skill levels $[\xi_{\mathbb{L}}, \xi_M, \xi_H]$ are thus STEM trained individuals depending on the skill level. These individuals have an education background within the corresponding standardised ISCED-F 2013 fields (05, 06, or 07)[44] of education (UNESCO Institute for Statistics, 2015). In simplified words, the extended skill, 'STEM', labour force encompasses all individuals with adequate technological skills to operate, and make use of, the full extend off (productive) capabilities of new technology within a task.

However, these routine and systematic practises are most vulnerable to automation by computers (Autor, 2015). On the other hand, the inability of technology to substitute non-routine tasks increases the relevance and labour market value of social and cognitive skills (Frey & Osborne, 2017; IFR, 2017). Autor (2015) notes, *'many of the middle-skill jobs that persist in the future will combine routine technical tasks with the set of*

[43] Note that this only concerns the economic variables exogenous to the model.
[44] 05 = Natural Sciences, Mathematics and Statistics, 06 = Information and Communication Technologies, and 07 = Engineering, Manufacturing and Construction

nonroutine tasks in which workers hold comparative advantage: interpersonal interaction, flexibility, adaptability, and problem solving.' (p. 27). These tasks fit squarely in the abstract and manual domains. Moreover, the expected future impact of technology will increase the relevance of, demand for, and exclude substitution of, tasks requiring creative and social intelligence (Frey & Osborne, 2017). In this respect, the demand for multi-disciplinary STEM labour outgrows STEM exclusive labour demand growth by 50% in European countries and this trend is expected to continue (European Commission, 2015). Therefore, STEM education should focus on multi-disciplinarity and conventional education should increase basic STEM capability attainment (to ensure an adequate fundamental STEM understanding).

Hence, company training investment [I_{T_L}], government education investment [G_{L_ε}] and employee training expenditure [c_{L_ε}] need to be balanced across re-skilling and up-skilling in reaction to task-specific technological progress, shifts in labour demand, and task-specific unemployment. Moreover, the investments need to be balanced across age cohorts. The demographic groups have different labour market positions (i.e. how the group's labour supply is divided across the tasks) and rates of extended skill. Therefore, the impact of substitution is not homogenous across the groups. This implies that, education and training investment should be sensitive to both economic as well as socio-economic outcomes. This investment process and the consequential improvements are, however, delayed and reactive. Meaning that undesired developments in the labour market (shortages and excesses) result in investment. Hereafter, the population (and thus the labour force) will reorganise to the desired state. However, problem identification, funding, policy implementation, and finally education and training takes time (Bybee, 2010). Adjustments within the labour force in reaction to labour market demand are slow and incomplete (Autor, Dorn, & Hanson, 2015). The investment process itself is not incorporated in the model as it would extend beyond the scope of this study. Rather, the outcomes of the modelling exercise provide necessary guidance on allocation of resources to mitigate unemployment and materialise potential socio-economic benefits.

8.2 ℂℍ Primary and compulsory (secondary) education system

National education systems vary significantly from country to country, which not only complicates skill-level definition and labour outcome comparison (Autor & Salomons, 2017; Graetz & Michaels, 2017) but can also inhibit common problem and solution identification, and policy intervention (Hanushek & Woessmann, 2016; Ryan & Feller, 2009). A globalisation trend in education has popularised universal evaluation of critical resources and inputs versus evidence-based performance outcomes (Hanushek & Woessmann, 2016; Ryan & Feller, 2009)[45]. However, education systems differ in constitutional and legislative support and financing; the relative position of public and private education; system size; and historic system path-dependence (Ryan & Feller, 2009). Decentralised new management/governance methods and standardised parametric performance measurements provide a more localised, flexible, and demand-driven approach in combination with comparable indicators for education quality (Ryan & Feller, 2009). Among such standardisations is the OECD Program for International Student Assessment (PISA) (OECD, 2016)[46]. Hanushek and Woessmann (2016) emphasise the value of such tests,

> *'These common international assessments provide unique data for understanding both the importance of various factors determining achievement and the impact of skills on economic and social outcomes.' (p. 150)*

The standardised international assessments of student and education system performance have sparked an extensive literature on school effectiveness and the cause-effect relation between resources (e.g. class size) and schooling quality within and across countries (Hanushek & Woessmann, 2016; Levačić & Vignoles,

[45] See p.150-151 of Hanushek and Woessmann (2016), Ryan and Feller (2009), and Ryan and Cousins (2009)

[46] See The World Bank Education statistics (EdStats) Query database for an extensive dataset of standardized assessments at http://datatopics.worldbank.org/education/wQueries/qlearning. Also consider the UNESCO World Data on Education: Seventh edition 2010-11 for information on all associated national education systems at http://www.ibe.unesco.org/en/document/world-data-education-seventh-edition-2010-11.

2002)[47]. These causal relations provide opportunity to enrich the model with empirical evidence and construct a representative simplified education system model. A majority of literature uses an education production function in the form of Eq. 21 to describe and analyse the relations (Hanushek & Woessmann, 2016; Levačić & Vignoles, 2002; Woessmann, 2016).

$$T = a_0 + a_1 F + a_2 R + a_3 I + a_4 A + e \qquad \textit{Eq. 21}$$

> *'where T is the outcome of the educational production process as measured, e.g., by test scores of mathematics, science, and reading achievement. The vector F captures facets of student and family background characteristics, R is a vector of measures of school resources, I are institutional features of schools and education systems, and A is individual ability.'* (Hanushek & Woessmann, 2016, p. 152)

Note: the Fraktur notation is used from this point onward for the education system to separate it from the production model and population model notations. Therefore, $T = \mathfrak{T}$, $F = \mathfrak{F}$, $R = \mathfrak{R}$, $I = \mathfrak{I}$, and $A = \mathfrak{A}$ with the factors within being noted in lower-case.

In the model developed in this study, the student and family background characteristics [$\mathfrak{F}$] and individual ability vector [$\mathfrak{A}$] are incorporated in the population model via the birth mechanisms (Eq. 11 to Eq. 12). This incorporation is consistent with the methodology (with relative influence ratios) and the factors in the studies referred to by Hanushek and Woessmann (e.g. skill level relations and family composition) (see table 8.1 at p.154 of Hanushek & Woessmann (2016)). Moreover, the social factors are largely outside the influence of school systems (Woessmann, 2016). Hence, the education production function is simplified to a vector for school resources and institutional features ($\mathfrak{R}$ and $\mathfrak{I}$). It is important to note that the required aggregation of individuals' and exogenous characteristics within the education system only holds at a macro-level (Hanushek & Woessmann, 2016)[48]. Despite this, the model is still insensitive to unobserved cultural factors, cultural heterogeneity, and selection biases which poses problems for cross-country and micro-level comparison (Hanushek & Woessmann, 2016; Woessmann, 2016). However, these concerns are limited since the model developed in this study is an isolated macro-level model.

The four vectors in the education production function comprise a set of factors that influence education quality and, therefore, student skill level outcomes (Hanushek & Woessmann, 2016). A more detailed explanation is provided in Appendix I. The factors contribute to an overall score via their coefficient value multiplied by the factor value in the education system (e.g. factor coefficient of weekly instruction time in minutes per week times the number of minutes). The overall score on the assessment gives an insight in the quality of the education system and student performance between and within countries (Hanushek & Woessmann, 2016; Woessmann, 2016). Students (should) realise a 25-30 point (or one standard deviation) increase on the assessments for each year of education (scoring scale applies to nearly all national and international tests) (Woessmann, 2016). However, the variation in education quality between and within countries results in variation in the actual attained skills and thus accumulated points (Hanushek & Woessmann, 2016; Woessmann, 2016). The associated factors provide opportunity to establish strategies to improve education systems and resource allocation[49] (Hanushek & Woessmann, 2016; OECD, 2017a).

Improving the factors results in higher average student performance and, thus, a higher skill level when transitioning from the child age cohort [$\mathbb{CH}$] to student [$\mathbb{ST}$][50]. Factor and capacity improvement requires investments and depends on the availability of resources (e.g. shortage of certified teachers, wages,

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[47] See Hanushek & Woessmann (2016) for a comprehensive and rich overview of the field of science including methodological and scope variation as well as paradigmatic shifts and see Woessmann (2010) for summary of the origin of the international assessments.

[48] At the micro-level, the results need to be controlled for all relevant observable and unobservable factors as well as reversed causation (e.g. education systems where less-performing schools receive additional funding) to ensure comparative equivalence (Hanushek & Woessmann, 2016, Woessmann, 2016).

[49] Given awareness for the inherent limitations stemming from the aggregation and insensitivities when considering comparisons and micro-levels (see Hanushek & Woessmann (2016)

[50] This is methodologically consistent since the assessments are performed at the age of 15 (Hanushek & Woessmann (2016).

budgets, autonomy). The implementation of a representative and elaborate education system in the model would be required to realise such dynamics. However, this would extend the model outside the intended scope and would require extensive research into education systems, causal relations, and associated (financial) factors across countries (e.g. OECD (2017a)). The OECD PISA database and associated publications provide a systematic, empirical, and substantiated foundation (i.e. suitable for simulation for different countries) and extensive set of parameters for such an extension. The model developed in this study is simplified to a macro-level black box to determine the effects of factor inputs on skill attainment output based on Hanushek and Woessmann (2010, 2016) and Woesmann (2016). In other words, the relative skill attainment increase (based on the factor values) is used to determine how it effects the labour force and how it can change unemployment. Future expansion of the model could include a more complete, representative, and dynamic education sector model to replace this black box.

8.2.1 $\mathbb{CH}$ Education system structure and model

For each skill level $[\varepsilon_{\mathbb{L}}, \varepsilon_{\mathbb{M}}, \varepsilon_{\mathbb{H}}]$ an identical model is constructed, which is expanded to consider the extended skill levels. Improvement of the education quality will result in up-skilling of children. In this process, one standard deviation of difference in score $[\mathfrak{T}_{\mathbb{u}}]$ can be associated to one skill level difference (Feskens, Kuhlemeier & Limpens, 2016)[51]. The average national score at the initiation of the model is taken as the index value of 1. The score improvements associated to the factors are also normalized whereby an increase of one normalised standard deviation (25-30 points of conventional assessment score) results in a shift of the children to one skill level higher. This results in the rate of up-skilling of children $[\mathbb{u}_{\mathbb{CH}}]$ which is assumed to be identical for both sexes (Eq. 23).

However, a limited capacity $[\mathfrak{C}_{\varepsilon+1}]$ will create a temporary ceiling by inhibiting students from joining the higher skill level. The temporary nature follows from a delay in creating additional education facilities including classrooms, material, and teachers $[\Delta t_{\mathfrak{C}}]$. The increase in capacity after the delay time depends on the planning constant $[\mathfrak{x}]$ which determines for how many years to come additional capacity is created (Eq. 24). In this respect, the delay and planning constants are related, either plan for smaller increases that take less time, or plan larger increases that take longer. In the first case, constant adjustment may be required that could be costlier. On the other hand, a too long delay can result in a generation of students that did not have the opportunity to up-skill and therefore create a lasting disruption that trickles through the working age population. The up-skill rate function, up-skill population flow function (Eq. 23) and capacity generation function (Eq. 24) are provided below. For comprehensibility, the skill level to up-skill to is noted as $\varepsilon + 1$.

$$\mathfrak{T} = a_0 + a_1\mathfrak{R} + a_2\mathfrak{I} + e \qquad \textit{Eq. 22}$$

$$\mathbb{u}_{\mathbb{CH}_{\varepsilon_t}} = \frac{\mathfrak{T}_{\varepsilon_{t=0}} - \mathfrak{T}_{\varepsilon_t}}{\mathfrak{T}_{\mathbb{u}}}, \quad with \quad \mathbb{u}_{\mathbb{CH}_{t=0}} = 1$$

$$\mathbb{U}_{\mathbb{CH}_{\varepsilon_{\mathbb{s}}}} = \begin{cases} \mathbb{u}_{\mathbb{CH}_{\varepsilon_t}} * \mathbb{CH}_{\varepsilon_t} & , \quad \mathbb{CH}_{\varepsilon+1_t} + \mathbb{U}_{\mathbb{CH}_{\varepsilon_{t-1}}} < \mathfrak{C}_{\mathbb{CH}_{\varepsilon_t}} \\ \dfrac{\mathfrak{C}_{\mathbb{CH}_{\varepsilon+1_t}} - \mathbb{CH}_{\varepsilon+1_t}}{12}, & \quad \mathbb{CH}_{\varepsilon+1_t} + \mathbb{U}_{\mathbb{CH}_{\varepsilon_{t-1}}} \geq \mathfrak{C}_{\mathbb{CH}_{\varepsilon_t}} \end{cases} \qquad \textit{Eq. 23}$$

$$\frac{\delta\mathfrak{C}_{\mathbb{CH}_{\varepsilon+1}}}{\delta t} = \begin{cases} 0 & , \quad \mathbb{CH}_{\varepsilon+1_{t-\Delta t_{\mathfrak{C}}}} + \mathbb{U}_{\mathbb{CH}_{\varepsilon_{t-\Delta t_{\mathfrak{C}}-1}}} < \mathfrak{C}_{\mathbb{CH}_{\varepsilon_{t-\Delta t_{\mathfrak{C}}}}} \\ \left(\mathbb{u}_{\mathbb{CH}_{\varepsilon_{t-\Delta t_{\mathfrak{C}}}}} * \mathbb{CH}_{\varepsilon_{t-\Delta t_{\mathfrak{C}}}}\right) * \mathfrak{x}, & \quad \mathbb{CH}_{\varepsilon+1_{t-\Delta t_{\mathfrak{C}}}} + \mathbb{U}_{\mathbb{CH}_{\varepsilon_{t-\Delta t_{\mathfrak{C}}-1}}} \geq \mathfrak{C}_{\mathbb{CH}_{\varepsilon_{t-\Delta t_{\mathfrak{C}}}}} \end{cases} \qquad \textit{Eq. 24}$$

[51] Using the ISCED 2011 definition of skill levels, as is done by Feskens, Kuhlemeier & Limpens (2016) and the PISA assessment. For the Netherlands one standard deviation is equal to up-skilling from VMBO to HAVO or MBO to HBO and HAVO to VWO or HBO to WO.

8.2.2 $\mathbb{CH}$ Extended skill factors

The general education quality factors also apply to the attainment of extended skills, and thus re-skilling. The extended skills require STEM education. The PISA assessments, among others, cover multiple disciplines (e.g. literacy, mathematics, science) (Woessmann, 2016). Across the disciplines, the teachers' subject knowledge, access to subject-specific textbooks, and instruction time spend on the subject influences performance (Woessmann, 2016). Successful continuation in the STEM field is associated with strong performance in associated courses during compulsory education (Wang, 2013). Following the literature on improving performance, a similar set of factors, as introduced for overall education, is created for extended skills. Therefore, an extended factor is introduced for each factor in the resources vector, resulting in the extended resource vector $[\mathfrak{R}_\xi]$.

Especially the instruction time spend on science has a more substantial effect on performance compared to mathematics and literacy (OECD, 2016). However, the total instruction time in a curriculum and the number of teachers are limited (Gromada & Shewbridge, 2016; Masdeu Navarro, 2015). In this respect, the limited time needs to be allocated to different subjects and learning activities within each subject (Gromada & Shewbridge, 2016). The effectiveness of the subjects' allocated resources needs to be maximized to increase performance (Gromada & Shewbridge, 2016). However, there are diminishing returns on additional hours spent and students experience a (personal) maximum learning capacity across the day and over the years (Gromada & Shewbridge, 2016). The quality of the activities and provided support is vital. Learning supportive staff could provide this needed support (Masdeu Navarro, 2015). The teacher remains responsible for the learning process and lessons, but the supportive staff can ensure the students get the instruction time and (personal) subject support required (Masdeu Navarro, 2015). This will increase the productivity and effectiveness of the teachers without increasing the instruction time or workload on the students and teachers.

In the STEM education process, limited subject knowledge among teachers can inhibit re-skilling of students (Ottenbreit-Leftwich, Glazewski, Newby, & Ertmer, 2010). However, training the teachers in the subjects up to the desired level of STEM expertise and associated pedagogical content knowledge is unrealistic according to Sanders (2009). Rather, STEM trained educators and staff can assist integration of STEM in curriculums with the help of national programs. Such an approach is possible by involving existing STEM educators (Sanders, 2009) to provide implementable material for untrained teachers across skill levels and student ages (Bybee, 2010; Kearney, 2011). Practical, project oriented, and real-world problem associated lessons have been found to be most effective (Sanders, 2009). However, the actual implementation of such material and technology depends on the attitude, beliefs, and (practical) technological knowledge[52] of the teachers (Ottenbreit-Leftwich, Glazewski, Newby, & Ertmer, 2010; Polly, Mims, Shepherd, & Inan, 2010). [53]

Stimulating re-skilling $[\mathbb{R}]$ considering expected labour developments is not a walk in the park. The process is slow, *'Achieving higher levels of STEM literacy cannot be accomplished quickly; it will take a minimum of ten years.'* (Bybee, 2010, p. 33), and not all children with adequate STEM training pursue/succeed in subsequent STEM education and professions. Firstly, this implies that the effect of STEM stimulation requires a period over which the effect of $\mathfrak{R}_\xi$ improvement gradually materialise. The rate of students in STEM secondary and tertiary education at the moment of initialisation is used as the normal rate of extended skills $[\mathbb{a}_\xi]$. The additional extended skill attainment is determined by the rate of re-skilling $[\mathbb{r}_{\mathbb{CH}}]$ under influence of $\mathfrak{R}_\xi$. Secondly, this implies, that in the model, children do not necessarily have to continue in secondary and tertiary STEM education when flowing to the student age cohort $[\mathbb{ST}_\xi]$. This depends on the attitude towards, and interest in, a future career in associated occupations and tasks (Kearney, 2011). The STEM sensitivity factor $[\eta_{\mathbb{R}} \mid 0 \leq \eta_{\mathbb{R}} \leq 1]$ is introduced to determine the actual rate of re-skilling, i.e. the rate of children continuing to subsequent STEM secondary and tertiary education in the student age cohorts.

[52] Meaning, how to use computers, technology, and the materials provided (Polly, Mims, Shepherd, & Inan, 2010).

[53] These influences are implemented in the respective factors, meaning that the time spend on STEM is implemented in $[\mathbb{t}_\xi]$, the implementable material available in existing education system with $[\mathbb{i}_\xi]$, and technology/STEM knowledge and attitude of teachers via $[\mathbb{s}_\xi]$.

Multiple models exist to study the possibilities to increase re-skilling of the population (with STEM certificates and degrees) in the US using system dynamics, including the BHEF U.S. STEM Education Model (BHEF, 2010; BHEF, 2013; Wells, Sanchez & Attridge, 2007)[54] and Boeing's STEM model (Newton, Richey, Mojtahedzadeh, 2009), among others. As with the extension of the education model, the effect of STEM programs and education systems is implemented as a black box, since, as Wang (2013), concludes,

> *'the process leading to entrance into STEM fields of study is complex; numerous influences individual, psychological, contextual, and social—act together to shape, develop, and sustain one's interest and eventually turn it into an actual choice.'* (p. 1111)

$$\mathbb{r}_{\mathbb{CH}_{\varepsilon_t}} = \frac{\mathfrak{T}_{\xi_{t=0}} - \mathfrak{T}_{\xi_t}}{\mathfrak{T}_{\mathbb{r}}}, \quad \textit{such that} \quad 0 \leq \mathbb{r}_{\mathbb{CH}_{\varepsilon_t}} \leq 0{,}67, \quad \textit{and} \quad 0 \leq \mathbb{a}_{\xi} \leq 1$$

$$\mathbb{R}_{\mathbb{CH}_{\varepsilon_s}} = \begin{cases} \mathbb{r}_{\mathbb{CH}_{\varepsilon_t}} * \eta_{\mathbb{R}} * \mathbb{CH}_{\varepsilon_t}, & \mathbb{CH}_{\xi_t} + \mathbb{R}_{\mathbb{CH}_{\varepsilon_{t-1}}} < \mathfrak{C}_{\mathbb{CH}_{\xi_t}} \\ \dfrac{\mathfrak{C}_{\mathbb{CH}_{\xi_t}} - \mathbb{CH}_{\varepsilon_t}}{12}, & \mathbb{CH}_{\xi_t} + \mathbb{R}_{\mathbb{CH}_{\varepsilon_{t-1}}} \geq \mathfrak{C}_{\mathbb{CH}_{\xi_t}} \end{cases} \qquad \text{Eq. 25}$$

$$\frac{\delta \mathfrak{C}_{\mathbb{CH}_{\xi}}}{\delta t} = \begin{cases} 0, & \mathbb{CH}_{\xi_{t-\Delta t_{\mathfrak{C}}}} + \mathbb{R}_{\mathbb{CH}_{\varepsilon_{t-\Delta t_{\mathfrak{C}}-1}}} < \mathfrak{C}_{\mathbb{CH}_{\xi_{t-\Delta t_{\mathfrak{C}}}}} \\ \left(\mathbb{r}_{\mathbb{CH}_{\varepsilon_{t-\Delta t_{\mathfrak{C}}}}} * \eta_{\mathbb{R}} * \mathbb{CH}_{\varepsilon_{t-\Delta t_{\mathfrak{C}}}}\right) * \mathfrak{x}, & \mathbb{CH}_{\xi_{t-\Delta t_{\mathfrak{C}}}} + \mathbb{R}_{\mathbb{CH}_{\varepsilon_{t-\Delta t_{\mathfrak{C}}-1}}} \geq \mathfrak{C}_{\mathbb{CH}_{\xi_{t-\Delta t_{\mathfrak{C}}}}} \end{cases} \qquad \text{Eq. 26}$$

The maximum effect of multidimensional STEM programs is estimated at 1,67 times the normal extended skill rate based on BHEF findings[55] (BHEF, 2013). Which is assumed to be the ceiling for re-skilling by normalising the impact of STEM stimulation via $\mathfrak{R}_{\xi}$ on $[\mathfrak{T}_{\xi}]$ (Eq. 25). The sensitivity factor, $\eta_{\mathbb{R}}$, is normally set to 0,4 based on Wells, Sanchez & Attridge, 2007 findings of STEM educated versus STEM graduated students. Future expansion of the model could implement an extensive STEM system model similar to the models for the US, but universally applicable across education systems - see Wells, Sanchez & Attridge (2007) for BHEF model, Kelic & Zagonel (2008) for a hybrid variant, and Newton, Richey, Mojtahedzadeh (2009) for an overview of SD STEM models.

8.3 $\mathbb{ST}$ Higher education system structure and model

After primary (and compulsory secondary) education, students can continue following subsequent education and/or enter the labour force part-time or full-time. The population model is structured to determine the highest achieved form of education at birth based on various parameters that are consist with the vectors influencing compulsory education[56] and re-skilling and up-skilling during secondary and tertiary education (Leach & Zepke, 2005; Moktar Hossain & Robinson, 2012). In this respect, the secondary and tertiary education system model comprises the additional flow of re-skilling and up-skilling above the status quo. In similar fashion to the compulsory education system for children, multiple factors influence skill attainment in higher education. However, unlike compulsory education, this is mainly a personal process, including the skill level, specialisation (sector and/or occupation group), and institution(s) to apply. This process is influenced by interrelated factors in the personal background, preferences and interests, external influences, and prior achievement in (compulsory) education (Germeijs, Luyckx, Notelaers, Goossens, & Verschueren, 2012; Leach

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[54] An online version of the model is provided here: https://forio.com/simulate/bhef/u-s-stem-education-model/simulation/

[55] By using an identical method with a baseline prior to program implementation, i.e. $\mathbb{a}_{\xi}$ in this study, and a ratio increase due to STEM program implementation.

[56] This simplification has been made to facilitate modelling and simulation of various educations systems. Otherwise, a separate stock-flow structure across skill levels needs to be constructed for every country due to variation in the education system.

& Zepke, 2005; Moogan, Baron & Harris, 1999; Wang, 2013). Additionally, career prospects influence secondary and tertiary education decisions. These decisions are mostly related to specialisations within skill levels (sectoral and occupational) and therefore beyond the scope of this study. However, the rational factors influencing additional re-skilling and up-skilling are implemented to create the student education system within the skill attainment model.

A simplified secondary and tertiary education system is constructed to model re-skilling and up-skilling in the student age cohort. Unlike compulsory education, defining a consistent set of factors that determine the rate of re-skilling and up-skilling is complex. Ups-killing depends on *'a considerable array of psychological and social decision-making processes and factors. These create a very complex process.'* (p. 4) according to Leach and Zepke (2005), based on a review of the literature. Problematically, extending the model to incorporate the complex interdependencies of influential factors is beyond the scope of this study and model and would have limited value given the aggregation to a task-based model (i.e. instead of an occupation and sectoral based model). Moreover, it would extend beyond the intended goal of the model, namely to determine the effect on potential of the rate of re-skilling and up-skilling. The relation between up-skilling and income is mostly one of pursuing an identical socio-economic status (i.e. skill level and wage level) as an individual's parents (Leach & Zepke, 2005). The decision to re-skill (or pursue a STEM career directly) is influenced by a balance of labour market factors, personal preferences, and (external) influences (Moktar Hossain & Robinson, 2012). Also, in other specialisations, job opportunities (for 20,5% of students) and projected earnings (for 8,7% of students) are important factors in the motivation to pursue a particular sector and career (Kim, Markham, & Cangelosi, 2002). Strangely enough, STEM careers are better paid then non-STEM at the same skill level. Yet, this systematic difference does not draw enough students to counteract the shortage of STEM professionals (Moktar Hossain & Robinson, 2012). Hence, the relation between wages and career decisions is ambiguous and/or can be specialisation specific. However, students are drawn towards favourable opportunities on the labour market and are inclined to pursue a similar socio-economic status as their parents.

$$\mathbb{R}_{\mathbb{ST}_{\varepsilon_{\mathbb{S}}}} = \begin{cases} \left(1 - \dfrac{\upsilon_{\mathbb{YA}_{\xi_t}}}{\upsilon_{\mathbb{YA}_{\varepsilon_t}}}\right) * \mathfrak{y} * \mathbb{ST}_{\varepsilon_t}, & \mathbb{ST}_{\xi_t} + \mathbb{R}_{\mathbb{ST}_{\varepsilon_{t-1}}} < \mathfrak{C}_{\mathbb{ST}_{\xi_t}} \wedge \upsilon_{\mathbb{YA}_{\varepsilon_t}} > \upsilon_{\mathbb{YA}_{\xi_t}} \\ \dfrac{\mathfrak{C}_{\mathbb{ST}_{\xi_t}} - \mathbb{ST}_{\varepsilon_t}}{12}, & \mathbb{ST}_{\xi_t} + \mathbb{R}_{\mathbb{ST}_{\varepsilon_{t-1}}} \geq \mathfrak{C}_{\mathbb{ST}_{\xi_t}} \end{cases} \qquad \textit{Eq. 27}$$

$$\frac{\delta \mathfrak{C}_{\mathbb{ST}_{\xi}}}{\delta t} = \begin{cases} 0, & \mathbb{ST}_{\xi_{t-\Delta t_{\mathfrak{C}}}} + \mathbb{R}_{\mathbb{ST}_{\varepsilon_{t-\Delta t_{\mathfrak{C}}-1}}} < \mathfrak{C}_{\mathbb{ST}_{\xi_{t-\Delta t_{\mathfrak{C}}}}} \\ \left(1 - \dfrac{\upsilon_{\mathbb{YA}_{\xi_{t-\Delta t_{\mathfrak{C}}}}}}{\upsilon_{\mathbb{YA}_{\varepsilon_{t-\Delta t_{\mathfrak{C}}}}}}\right) * \mathfrak{y} * \mathbb{ST}_{\varepsilon_{t-\Delta t_{\mathfrak{C}}}} * \mathfrak{x}, & \mathbb{ST}_{\xi_{t-\Delta t_{\mathfrak{C}}}} + \mathbb{R}_{\mathbb{ST}_{\varepsilon_{t-\Delta t_{\mathfrak{C}}-1}}} \geq \mathfrak{C}_{\mathbb{ST}_{\xi_{t-\Delta t_{\mathfrak{C}}}}} \end{cases} \qquad \textit{Eq. 28}$$

$$\mathbb{U}_{\mathbb{ST}_{\varepsilon_{\mathbb{S}}}} = \begin{cases} \left(1 - \dfrac{\upsilon_{\mathbb{YA}_{\varepsilon+1_t}}}{\upsilon_{\mathbb{YA}_{\varepsilon_t}}}\right) * \mathfrak{y} * \mathbb{ST}_{\varepsilon_t}, & \mathbb{ST}_{\varepsilon_t} + \mathbb{U}_{\mathbb{ST}_{\varepsilon_{t-1}}} < \mathfrak{C}_{\mathbb{ST}_{\varepsilon_t}} \wedge \upsilon_{\mathbb{YA}_{\varepsilon_t}} > \upsilon_{\mathbb{YA}_{\varepsilon+1_t}} \\ \dfrac{\mathfrak{C}_{\mathbb{ST}_{\varepsilon_t}} - \mathbb{ST}_{\varepsilon_t}}{12}, & \mathbb{ST}_{\varepsilon_t} + \mathbb{U}_{\mathbb{ST}_{\varepsilon_{t-1}}} \geq \mathfrak{C}_{\mathbb{ST}_{\varepsilon_t}} \end{cases} \qquad \textit{Eq. 29}$$

$$\frac{\delta \mathfrak{C}_{\mathbb{ST}_{\varepsilon+1}}}{\delta t} = \begin{cases} 0, & \mathbb{ST}_{\varepsilon+1_{t-\Delta t_{\mathfrak{C}}}} + \mathbb{U}_{\mathbb{ST}_{\varepsilon_{t-\Delta t_{\mathfrak{C}}-1}}} < \mathfrak{C}_{\mathbb{ST}_{\varepsilon_{t-\Delta t_{\mathfrak{C}}}}} \\ \left(1 - \dfrac{\upsilon_{\mathbb{YA}_{\varepsilon+1_{t-\Delta t_{\mathfrak{C}}}}}}{\upsilon_{\mathbb{YA}_{\varepsilon_{t-\Delta t_{\mathfrak{C}}}}}}\right) * \mathfrak{y} * \mathbb{ST}_{\varepsilon_{t-\Delta t_{\mathfrak{C}}}} * \mathfrak{x}, & \mathbb{ST}_{\varepsilon+1_{t-\Delta t_{\mathfrak{C}}}} + \mathbb{U}_{\mathbb{ST}_{\varepsilon_{t-\Delta t_{\mathfrak{C}}-1}}} \geq \mathfrak{C}_{\mathbb{ST}_{\varepsilon_{t-\Delta t_{\mathfrak{C}}}}} \end{cases} \qquad \textit{Eq. 30}$$

It is assumed that re-skilling and up-skilling of the students age cohort only depends on the labour market since the initial distribution of the population among the skill levels at birth is based on the socio-economic, family and individual background and differences between individuals. Therefore, the relative unemployment rate of young adults between non-extended skill [$\upsilon_{\mathbb{YA}_{\varepsilon}}$] and extended skill [$\upsilon_{\mathbb{YA}_{\xi}}$] at the same level determines re-skilling (Eq. 27). Up-skilling is determined by the relative unemployment rate between the skill level and one skill level higher of young adults (e.g. $\upsilon_{\mathbb{YA}_{\varepsilon_{\mathbb{L}}}}$ and $\upsilon_{\mathbb{YA}_{\varepsilon_{\mathbb{M}}}}$) (Eq. 29). Both depend on the labour market prospect sensitivity factor [$\mathfrak{y}$] and are limited by the capacity [$\mathfrak{C}_{\mathbb{ST}_{\xi}}$] of the re-skilled and up-skilled level (Eq. 28 and Eq. 30). Similarly to compulsory education, each skill level of secondary and tertiary education has a maximum capacity which can inhibit students from up-skilling or re-skilling. Hence, the same mechanisms to capacity expansion of compulsory education apply (Eq. 24 and Eq. 26).

8.4 $\mathbb{WA}$ Training system structure and model

Potentially the most critical form of education is professional training of the working age population to counteract labour market mismatches (Nedelkoska & Quintini, 2018). It is expected the current shortage of multi-disciplinary STEM skilled employees is to continue to grow, reinforcing the associated socio-economic and economic difficulties (EU Skills Panorama 2014, 2015). These mismatches need to be counteracted across the labour force by creating more entry points to multi-disciplinary STEM professions and training possibilities (EU Skills Panorama 2014, 2015; Frey & Osborne, 2015). Moreover, there are mismatches on the labour market due to polarisation, creating an increasing demand for higher educated (Nedelkoska & Quintini, 2018; OECD, 2017b). However, the education mobility of the labour force is relatively low in the short-run since education is typically fixed prior to entering the labour force (i.e. during the child and student age cohorts) (Goos, Manning, & Salomons, 2011). In the long run, the work force is capable of adjusting to labour market mismatches via education (Goos, Manning, & Salomons, 2011). The question is, which factors contribute to the labour force re- and up-skilling?

The process of re-skilling and up-skilling is a multi-actor effort including governments, employers, employees, and skill development assessment bodies (OECD, 2017b). Depending on the national institutional arrangement, the actors are involved in different roles in education of the labour force. Unlike education prior to entering the labour force, this is not a process of performance and personal decisions. '*The theoretical training literature (see for instance Acemoglu and Pischke, 1998; Becker, 1962; Hashimoto, 1981) emphasizes that joint decisions by workers and firms are behind actual training participation*' (Maximiano, 2012, p. 2). Employers, employed individuals, unemployed individuals, and governments can initialise education (OECD, 2017b). Moreover, the influence of the labour market is not unilateral as with students (drawn to low unemployment). This emerges as a lack of incentive for both the employed and unemployed to participate in education and training to improve their job prospects, even though this would make sense given the labour market (OECD, 2017b). The OECD (2017b) provides an extensive set of policies in the hands of the actors to improve skill attainment of the labour force to counteract mismatches. Which includes financial support/investment/ subsidy, informing, career guidance, legislation, institutional reform/adaptation, and technological stimulus/innovation. Essentially, all policies aim at incentivising employees and employers to target mismatches by re-skilling and up-skilling[57].

From the perspective of the employee and employers, multiple factors are relevant[58]. The probability of attaining training increases with skill-level due to an advantage in learning capabilities and return of investment (Albert, García-Serrano & Hernanz, 2010; Maximiano, 2012; O'Connell & Byrne, 2010). Accordingly, a skill level specific training factor is introduced [$\mathfrak{u}_{\varepsilon}$]. Age, seniority, years of experience, and sex of employees does not influence training attainment significantly between the age of 25 and 55 across Europe according to Albert, García-Serrano, and Hernanz (2010). Evidence from Ireland confirms this finding

[57] Within the scope of this study and the task-based approach, only general training is considered and not firm or job specific training. This also implies that the conventional dichotomy between firm specific and general training and associated rent on the labour market is not considered (Konings & Vanormelingen, 2015). Moreover, the productivity growth associated with training (see Konings and Vanormelingen (2015)) and the productivity effect of relatively over or under educated labour (Mahy, Rycx, & Vermeylen, 2015) are not implemented.

[58] However, empirically determining the structure of these factors that lead to the (shared) decision to participate in training is difficult and the required empirical data has only become available relatively recently (Albert, García-Serrano & Hernanz, 2010; Maximiano, 2012).

(O'Connell & Byrne, 2010). However, employees above 55 are significantly less likely to receive/participate in training (O'Connell & Byrne, 2010). This is mainly due to an unwillingness of employers to provide or investment in training of older employees (Maximiano, 2012). This implies, that training is not evenly distributed across the working age cohorts. Hence, an age cohort specific training factor is introduced [$\mathfrak{v}_{\mathbb{LF}}$] that affects the $\mathbb{SA}$ and $\mathbb{RE}$ age cohorts. Moreover, full-time [$\mathbb{f}$] employees tend to receive or participate in more training possibilities then their part-time [$\mathbb{p}$] counterparts, as is the case with permanent versus temporary contracted employees (Almeida & Aterido, 2008; O'Connell & Byrne, 2010). This is mainly due to unwillingness of employees, although employers are more reluctant to provide training to part-timers (Maximiano, 2012). Therefore, a contract specific training factor is introduced [$\mathfrak{w}$]. Trained labour force members do not receive higher wages after attainment of additional skills when corrected for biases and endogeneity (Albert, García-Serrano & Hernanz, 2010). Without this correction, the increase after training is between 10 and 20 percent (Albert, García-Serrano & Hernanz, 2010; O'Connell & Byrne, 2010). However, this effect is undone when corrected for unobserved heterogeneous related factors (Albert, García-Serrano & Hernanz, 2010). Conversely, one could argue that, for that reason, re-skilling and up-skilling is not incentivised by wage differences from the perspective of the labour force. Re-skilling or up-skilling depends on the cooperative nature of training participation between employee and employer (Maximiano, 2012). Therefore, the balance between re-skilling and up-skilling is targeting tasks where a larger shortage is experienced, based on the relative task-specific unemployment rate.

$$\mathbb{R}_{\mathbb{LF}_{\varepsilon_{\mathbb{s}}}} = \mathbb{R}_{\mathbb{LF}_T} + \mathbb{R}_{\mathbb{LF}_u}$$

$$\mathbb{R}_{\mathbb{LF}_T} = \begin{cases} 0 & , \quad \upsilon_{T_\xi} > \upsilon_{T_\varepsilon} \\ \left(1 - \frac{\upsilon_{\mathbb{LF}_{T_\xi}}}{\upsilon_{\mathbb{LF}_T}}\right) * \mathfrak{u}_\varepsilon * \mathfrak{v}_{\mathbb{LF}} * \mathfrak{w} * L_{\varepsilon_{\mathbb{LF}\to T}} * \left(1 - \upsilon_{\varepsilon_{\mathbb{LF}\to T}}\right), & \upsilon_{T_\xi} < \upsilon_{T_\varepsilon} \end{cases} \quad \text{Eq. 31}$$

$$\mathbb{R}_{\mathbb{LF}_u} = \begin{cases} 0 & , \quad \upsilon_{\mathbb{LF}_\xi} > \upsilon_{\mathbb{LF}_\varepsilon} \\ \left(1 - \frac{\upsilon_{\mathbb{LF}_\xi}}{\upsilon_{\mathbb{LF}_\varepsilon}}\right) * \mathfrak{z} * \mathbb{LF}_\varepsilon * \upsilon_{\mathbb{LF}_\varepsilon}, & \upsilon_{\mathbb{LF}_\xi} < \upsilon_{\mathbb{LF}_\varepsilon} \end{cases}$$

$$\mathbb{U}_{\mathbb{LF}_{\varepsilon_{\mathbb{s}}}} = \mathbb{U}_{\mathbb{LF}_T} + \mathbb{U}_{\mathbb{LF}_u}$$

$$\mathbb{U}_{\mathbb{LF}_T} = \begin{cases} 0 & , \quad \upsilon_{T_\xi} > \upsilon_{T_\varepsilon} \\ \left(1 - \frac{\upsilon_{\mathbb{LF}_{T_{\varepsilon+1}}}}{\upsilon_{\mathbb{LF}_T}}\right) * \mathfrak{u}_\varepsilon * \mathfrak{v}_{\mathbb{LF}} * \mathfrak{w} * L_{\varepsilon_{\mathbb{LF}\to T}} * \left(1 - \upsilon_{\varepsilon_{\mathbb{LF}\to T}}\right), & \upsilon_{T_\xi} < \upsilon_{T_\varepsilon} \end{cases} \quad \text{Eq. 32}$$

$$\mathbb{U}_{\mathbb{LF}_u} = \begin{cases} 0 & , \quad \upsilon_{\mathbb{LF}_\xi} > \upsilon_{\mathbb{LF}_\varepsilon} \\ \left(1 - \frac{\upsilon_{\mathbb{LF}_{\varepsilon+1}}}{\upsilon_{\mathbb{LF}_\varepsilon}}\right) * \mathfrak{z} * \mathbb{LF}_\varepsilon * \upsilon_{\mathbb{LF}_\varepsilon}, & \upsilon_{\mathbb{LF}_\xi} < \upsilon_{\mathbb{LF}_\varepsilon} \end{cases}$$

From the perspective of the unemployed, it is assumed that the main drive is to become employed as soon as possible. Therefore, re-skilling and up-skilling depends on the relative unemployment rate in similar fashion as with the students age cohorts. However, a success-rate factor is introduced to control for inhibiting financial, incentive, and socio-economic factors [$\mathfrak{z}$]. If the difference is small, few people will invest time, effort, and money in training since the increased probability to become employed is small. If the unemployment ratio is higher, no-one will up- or re-skill and simply allocate the labour supply to a task with lower unemployment. For re-skilling and up-skilling of the working age population, it is assumed that there are no capacity limitations due to the growing and broad availability of courses and programmes with public (e.g. post-secondary vocational education) and private (e.g. online certificates) organisations and this markets capability to respond to increasing demand (Frey & Osborne, 2015). Although both streams (i.e. employed and unemployed) of re-skilling and up-skilling are aimed at improving employability, there is a distinct difference. The employed [$\mathbb{R}_{\mathbb{LF}_T}$ and $\mathbb{U}_{\mathbb{LF}_T}$] are incentivised from the labour demand's perspective based on the unemployment rate per tasks, whereas the unemployed [$\mathbb{R}_{\mathbb{LF}_u}$ and $\mathbb{U}_{\mathbb{LF}_u}$] are incentivised from the labour force's perspective based on unemployment per socio-economic group (Eq. 31 and Eq. 32). For comprehensibility, the skill level to up-skill to is noted as $\varepsilon + 1$, the task to up-skill to is noted as $T_{\varepsilon+1}$, and the task to re-skill to is noted as T_{ξ} - as restricted by Table 1.

8.5 Education model synthesis

The education and training systems are vital to ensure that the labour force adopt to changing skills in the economy to realise the feasible productivity growth, welfare stability, and inequality minimisation. Three simplified education systems have been constructed based on the relevant factors; one concerning compulsory education up to the age of 15 ($\mathbb{CH}$ age cohort); one concerning secondary and tertiary education (concerning $\mathbb{ST}$ age cohort); and one for the labour force (concerning $\mathbb{WA}$ age cohorts). These sub-systems are combined into the overall education model which is closely related to the demographic model and labour market. The latter two are based on the labour market conditions and aimed at improving the economic position of the population member. This is a rational approach to determine the effect of re- and up-skilling on unemployment outcomes. Yet, as described, education and skill attainment are based on personal motivation, interests, and preferences. Therefore, the model is insensitive to these aspects of education but will be discussed in the reflections.

9 Technology model

Over time, multiple waves of automation technology have altered the way we work and reshaped the labour market (Arntz, Gregory, Zierahn, 2016; Frey & Osborne, 2017). Technology is increasingly capable of performing human activities and therefore replace labour in production (Frey & Osborne, 2017). The effect of various substituting technologies can be measured across a similar set of dependent variables and provide similar casual relations, yet the effect on the labour market is distinct (Graetz & Michaels, 2017; IFR, 2017). In other word, technologies affect the labour market in heterogeneous ways (Michaels & Graetz, 2015). Michaels and Graetz (2015) conclude that robotic substitution is skewed towards low-skilled employment. On the other hand, ICT appears to be polarising by mainly affecting middle skilled occupations and favouring high skilled employment (Frey & Osborne, 2017; Michaels & Graetz, 2015). However, it is uncertain how and what technological capabilities will be developed since technological progress is inherently difficult to predict (Frey & Osborne, 2017). Therefore, the present developments may not be representative for the future. Moreover, the adoption of technology and the substitution of labour depends mostly on the associated relative costs (Autor, 2015; Autor, Dorn, & Hanson, 2015; Autor, Levy, Murnane, 2003; Graetz & Michaels, 2017; Gregory, Salomons & Zierahn, 2016). Essentially, technology will only be adopted if it provides a (large enough) financial advantage (in a short enough amount of time). Based on the current literature, the expected technological and associated financial developments are operationalised for implementation in the technology sector in the model. Yet, this literature is limited; *'no study has yet quantified what recent technological progress is likely to mean for the future of employment.'* (Frey & Osborne, 2017, p. 255). Hence, this study is, per definition, a future exploration.

The extent to which input and task substitution are feasible depends on technological progress, relative costs, and the complexity of activities within the task types (routine, abstract, or manual). Actual implementation depends critically on economic, regulatory, and societal conditions (Arntz, Gregory, Zierahn, 2016; Brynjolfsson, Rock & Syverson, 2017). Financial feasibility is achieved if the gain in productivity offsets the additional costs involved with the new capital (Graetz & Michaels, 2017). Universally across technology, the reduction in price of technological capital is a (if not 'the') major factor that drives substitution (Autor, 2015; Autor, Dorn, & Hanson, 2015; Autor, Levy, Murnane, 2003; Graetz & Michaels, 2017; Gregory, Salomons & Zierahn, 2016). The reduction in price directly improves the relative factor price of capital over labour (i.e. given developments in wages). Therefore, '*Firms' technology choice is simple: adopt robots when profits from doing so exceed profits from using the labor-only technology by at least the fixed setup cost'* (Graetz & Michaels, 2017, p. 11). Especially the combination of reducing capital prices and rapidly improving capital quality has driven technology adoption over time (Graetz & Michaels, 2017; Michaels & Graetz, 2015; Sirkin, Zinser & Rose, 2015). As a result, the quality-adjusted price reduction exceeds the price level drop. This trend is expected to continue for robotics up to 2025 with an adjusted annual cost reduction of 2-8% and productivity growth of 5% for robotics (Sirkin, Zinser & Rose, 2015). Graetz and Michaels (2017) find an annual labour productivity growth of 0.37% for robots and a TFP that is *'roughly two thirds as large as the increase in labor productivity'* (p. 31). In comparison, IT is responsible for 0.6-1.0% labour productivity growth in total (Graetz & Michaels, 2017) or between 0.1% to 0.17% concerning specific technologies (Brynjolfsson, Rock & Syverson, 2017). The TFP reflects the actual effect of technological progress on economic outcomes (Brynjolfsson, Rock & Syverson, 2017). The difference (5% to 0.1-1.0%) can be explained by the method of measurement. The prior is a production level while the latter is a macro-level. However, implementation is somewhat delayed. According to the Boston Consulting Group (Sirkin, Zinser & Rose, 2015) there is a threshold difference between robotic production costs and labour production costs of 15% beyond which companies pursue automation.

The technological feasibility critically depends on the development of humanlike technological capabilities (Frey & Osborne, 2015; Graetz & Michaels, 2017). In relation to labour substitution and the TBTC and RRTC frameworks, this implies that feasibility is determined by whether the activities in the tasks can be captured in computer code and/or be physically performed by technology (Gregory, Salomons & Zierahn, 2016).

However, the increasing autonomous and self-learning capabilities of technology will extend beyond rule-based computer code (Frey & Osborne, 2015). Therefore, cognitive intense tasks are unlikely to remain the exclusive domain of humans. Moreover, the tangible and intangible domains are slowly becoming technologically integrated due to sensors and interconnectivity (De Backer, DeStefano, Menon & Ran Suh, 2018; Frey & Osborne, 2015). Therefore, it is slowly becoming possible for technology to automate adaptive intelligence-depended activities and substitute the associated labour input.

The various technologies are introduced, categorised into Information Technology (IT) and into Robotic Technology. Studies have different technological scopes (e.g. technological change, robotics, computers), use different definitions for the technologies (e.g. automating technology or ISO8373 compliant industrial robots) and, consequently, come to different estimations of the impact on labour (Frey & Osborne, 2015). The adopted definition, impact of both technology categories, and impact once technology become interconnected is defined.

9.1 Information technology (IT)

information technology *noun [U]* • *abbreviation* ***IT***

The study or use of systems (especially computers and telecommunications) for storing, retrieving, and sending information.

computer *noun [C]* •

An electronic device for storing and processing data, typically in binary form, according to instructions given to it in a variable program.
(Oxford University Press)

In contrast with robotics, IT technology is restricted in the tasks it can automate since three dimensional and complex physical tasks cannot be addressed (Graetz & Michaels, 2017). The introduction of IT changed labour through multiple channels and is often referred to as computerisation or digitalisation. First, within existing labour arrangements, IT is strongly complementary to abstract task-intensive occupations by providing more extensive and cost effective information and analysis resources (Autor, 2015). The result is that abstract tasks can be performed more productively by shifting labour resources from performing data analysis to data utilisation and application. Contrarily and simultaneously, IT substitutes the supportive occupations (often manual task intense) associated to such abstract task-intensive jobs (Autor, 2015). Manual tasks-intensive occupations barely utilise IT to perform their tasks and, thus, provide limited possibilities for IT to complement (Autor, 2015). In contrast, computerisation has resulted in a decline in routine intensive employment (Frey & Osborne, 2017). Hence, IT is polarising in nature by, mainly substituting middle skilled tasks and reducing the middle skilled labour hour share, while improving the position of high skilled employment (Michaels & Graetz, 2015). Second, IT facilitates globalisation by relieving location constraints in production processes (Autor, 2015). As a result, processes can be offshored to realise lower production costs due to lower labour factor costs. Therefore, physical routine jobs were offshored and thus not substituted for technology but for low wage labour elsewhere. In this respect IT has a dual polarising nature.

Even though IT has become an integral part of today's society, and is sometimes referred to as the third industrial revolution, computers and internet have (so far) had limited productivity effect (Brynjolfsson, Rock & Syverson, 2017). Conversely, the effects of IT on labour markets is widely noted and noticeable through increasing automation of information processing tasks in the service sector (Autor, Dorn, & Hanson, 2015, Frey & Osborne, 2017). This is catalysed by reducing prices for computing equipment and an accelerating pace of technological development (De Backer, DeStefano, Menon & Ran Suh, 2018; Frey & Osborne, 2017). Consequently, expediting the urge for adequate socio-economic policy (Frey & Osborne, 2017). Moreover, the conclusion on the limited productivity growth sparked by IT may be premature as the revolution is still ongoing and arguably the most significant technologies are still to come (IFR, 2017). The future of information technology is mainly embodied by various (sub-)forms of Artificial Intelligence (Frey & Osborne, 2017).

9.1.1 Artificial Intelligence

> ***big data*** *noun [U]* •
>
> *Extremely large data sets that may be analysed computationally to reveal patterns, trends, and associations, especially relating to human behaviour and interactions.*
>
> ***machine learning*** *noun [U]* • *abbreviation* ***ML***
>
> *The capacity of a computer to learn from experience, i.e. to modify its processing on the basis of newly acquired information.*
>
> ***artificial intelligence*** *noun [U]* • *abbreviation* ***AI***
>
> *The theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages. (Oxford University Press)*

Unlike the polarising nature of current IT, the new generation of IT (consisting of big data, ML, and other forms of AI) will become cognitively competitive with, and operationally superior to, humans (DeCanio, 2016; Frey & Osborne, 2017). This suggests that IT technology may have a negative impact on the high-skilled labour force. Especially the progress in AI will result in automation technology that will surpass human capabilities beyond routine tasks (Frey & Osborne, 2015; IFR, 2017). Consequently, cognitive tasks will become a shared domain of technology and humans. The advantages of new IT are flexibility, scalability, information processing capacity, rational unbiased processing, and continues uninterrupted operation (Frey & Osborne, 2017). This shifts the activities demanding labour input in abstract tasks and widens the scope of IT application and automation. Therefore, the high skilled labour augmenting nature of IT may shift in part to a substituting one (Frey & Osborne, 2017).

In this respect, the current substitution paradigms may fall short and the elasticity of substitution between AI and humans will increase (DeCanio, 2016). AI is distinctly different from earlier forms of computerisation in the capabilities it holds (Brynjolfsson, Rock & Syverson, 2017) – as mostly discussed and analysed by posterior analysis sited in this study. The problem with AI, and especially the currently most promising sub-form ML, is that the potential productivity advantages have not materialised yet (Brynjolfsson, Rock & Syverson, 2017). Moreover, it is uncertain when and to what extent productivity growth, augmentation, and substitution will materialise. Recent breakthroughs in AI, for instance in medical diagnostic imaging in cooperation with Google DeepMind[59], demonstrates how AI can outperform humans in abstract tasks (Brynjolfsson, Rock & Syverson, 2017; De Fauw et al., 2018). However, the development of such diagnostic AI-driven technology dates back at least three decades (see for instance the work of Szolovits, Patil, and Schwartz (1988) from 1988). Moreover, the principle of AI and the possibility it would be able to replicate human-level intelligence in all forms dates back to the 1950s (Müller & Bostrom, 2016). AI is not an outlier in this respect since other emergent technologies took similar periods before becoming widely adopted and measurable in productivity statistics (Brynjolfsson, Rock & Syverson, 2017). However, there is significant contrast between the technological potential we observe and the effects we measure. Especially the perspective of the labour force is bleak since wages have stagnated and productivity growth has halved over the past 2-3 decades, *'We thus appear to be facing a redux of the Solow (1987) Paradox: we see transformative new technologies everywhere but in the productivity statistics.'* (Brynjolfsson, Rock & Syverson, 2017, p. 1).

[59] The same platform and Google subordinate have also been able to outperform human cognitive capabilities in various games (Brynjolfsson, Rock & Syverson, 2017).

Problematically, the theoretical boost in productivity associated with technologies like AI is likely to remain theoretical for a significant period (Brynjolfsson, Rock & Syverson, 2017). According to Brynjolfsson, Rock, and Syverson (2017) this is for four reasons. Firstly, the technology may not live up to the expectations as it never matures and materialises up to an operationally or financially feasible level. Secondly, the limited productivity growth during the past wave of new technology (i.e. IT) may be due to mismeasurement since the effects materialise in other forms than productivity growth, i.e. utility, or leak via profit offshoring. Thirdly, the effects of new technologies are concentrated with a few beneficiaries and applications, thereby limiting dissipation, entrance of competitors, realisation of feasible productivity growth, and trickling down of the advantages to the labour force. This problem materialises in the form of increasing inequality (income-wise and profits share-wise between large and small firms) and market and wage setting power of the few beneficiaries. Lastly, and probably most relevant, is that it takes considerable time for the real impact of technology to materialise. Therefore, there is a period in which actors have a notion of the technology and its potential, but the technology needs more time and development resources until it is ready for economy-wide implementation and for the productivity growths to be noticeable. Currently, the economy with limited productivity growth yet significant technological progress (both tangible and intangible), is in such a state (Brynjolfsson, Rock & Syverson, 2017).

Yet, it is uncertain when and to what extent AI will accelerate productivity growth and substitute labour. Multiple studies attempt to bridge this gap in knowledge based on expert elicitation. Based on this expert input, operational high-level AI is expected to be realised in 2040-2050 with a 0.5 probability, and in 2075 with 0.9 probability (Frey & Osborne, 2015; Müller & Bostrom, 2016). From that moment, it is estimated that it will take less than three decades for Super Intelligence to be operational - although the development is likely to accelerate due to AI self-evolving (Müller & Bostrom, 2016). Another study concludes that within 45 years AI driven technology will be able to outperform humans in all (cognitive or intelligent) tasks (Grace, Salvatier, Dafoe, Zhang & Evans, 2018) (Figure 10). Hereafter, this pace of development is expected to result in full automation of labour in 122 years with a probability of 0.5. Although optimists (or pessimists from the perspective of the labour force) estimate that high-level Machine intelligence (HLMI) can be reached as early as 2029 according to Korinek and Stiglitz (2017). The large difference[60] between technological automatibility (i.e. when technology is capable of automating human activities or tasks) and actual substitution is in line with the observed paradox by Brynjolfsson, Rock, and Syverson (Brynjolfsson, Rock & Syverson, 2017) – although the expert studies do not provide such underlying mechanisms.

The problem with predicting the impact of technology is that productive trends are only significantly correlated over short time periods – not even with adjacent decades (Brynjolfsson, Rock & Syverson, 2017). Therefore, forecasting the future impact of technology by extrapolating the current trend would lead to unreliable conclusions. Moreover, some expert consultation studies are faced with systematic shortcoming that can prove to be problematic when assessing the future of IT technology (Armstrong, Sotala, & Ó hÉigeartaigh, 2014). Moreover, the four constraints identified by Brynjolfsson, Rock, and Syverson (2017) can continue to inhibit realisation of the technological automatibility estimates (i.e. actual substitution is lower than technological automatiblity). Yet, when exploring the impact of technology under uncertainty, i.e. the methodology employed in this study, will account for this uncertainty space and use it to determine the robustness of policies (e.g. re-skilling and up-skilling stimulation) and the effects on critical factors (i.e. unemployment). Especially the S-shaped growth variance (Figure 10) provides opportunities to simulate the model across a broad space of scenarios. In practical terms this implies that the estimates and the relative substitution growth behaviour are used as input in the model to determine the technological substitutability of labour. Hereafter, the model is simulated from the same initial point across the space of plausible AI developments.

[60] HLMI is expected between 20 and 107.5 years from now with median of 45 years (confidence interval 0.25 to 0.75), actual substitution is expected between 55 and 212.5 years from now with median of 122 years (confidence interval 0.25 to 0.75) (Grace, Salvatier, Dafoe, Zhang & Evans, 2018). Therefore, the difference between technological substitution and automatibility is approximately 2.71 to 2.75.

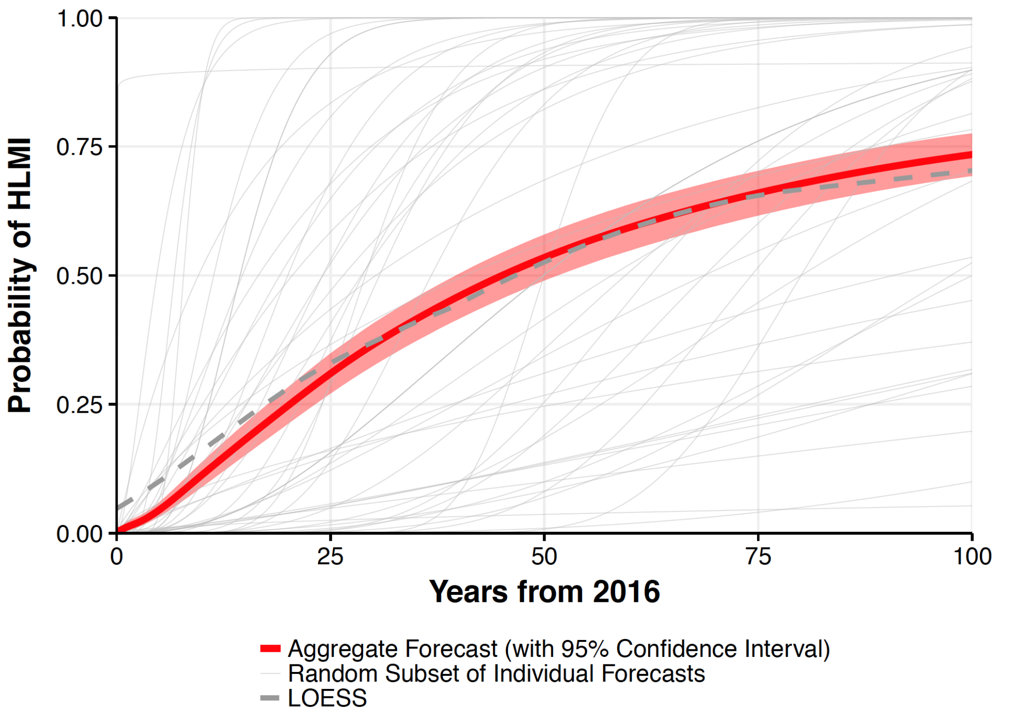


Figure 10 Aggregate probability of 'high-level machine intelligence[61]' arrival by future years (source: Grace, Salvatier, Dafoe, Zhang & Evans, 2018, p.1)

9.2 Robotic technology (RT)

> ***robot*** *noun [C]* •
>
> *1 A machine resembling a human being and able to replicate certain human movements and functions automatically.*
> *1.1 A machine capable of carrying out a complex series of actions automatically, especially one programmable by a computer.*
> *1.2 A person who behaves in a mechanical or unemotional manner.*
> *(Oxford University Press)*

The general utilisation of a robot is to automate physical human activities, either as an actual representation of a human or as machinery. Studies exploring the impact of technology use different definitions for the technology studied, which complicates comparison and creates ambiguity. The prior definition (above in the text box) implies that the robot resembles a human as a productive source, yet, a robot is associated with unemotional behaviour. Therefore, a robot is only a simplified system capable of performing physical human activities autonomously. It is not resembling an actual human being since it is insensitive to emotions; lacks cognition, intelligence, and reasoning; and does not have social capabilities and conscience. This distinction is relevant considering other technologies that can add such traits and expand the capabilities of robots beyond physical automation of routine tasks. The latter definition, as a machine, is consistent with the standardised definition of *robots and robotic devices* (ISO, 2012). Within this definition, there is a distinction between applications, i.e. industrial and service robots, and types of robotic technology[62] (IFR, 2017; ISO,

[61] ' *"High-level machine intelligence" (HLMI) is achieved when unaided machines can accomplish every task better and more cheaply than human workers*. […] The LOESS curve is a non-parametric regression on all data points.' (Grace, Salvatier, Dafoe, Zhang & Evans, 2018 p.2)
[62] The common definition between the applications is that of a multipurpose mechanical manipulator that has two or more axes of freedom, is reprogrammable, and performs tasks with a degree of autonomy based on a control system that senses and/or

2012). For completeness and comprehensibility, the terms robotic technology (RT) is used from here on forward encompassing all types of *robotic devices* and *robots* as defined in ISO documentation, i.e. all actuated mechanisms that automate physical human labour activities.

Following this definition, RT substitutes labour input since such systems do not require human intervention except for programming and maintenance. As a result, industrial robots have substituted labour across various industries (Graetz & Michaels, 2017). However, these substituted labour hours are, thus far, offset by spill-over effects elsewhere in the industry and economy due to productivity growth (Autor & Salomons, 2017; Graetz & Michaels, 2017; Gregory, Salomons & Zierahn, 2016). Consequently, the implementation of RT has had no significant implication for the overall labour share (Graetz & Michaels, 2017). Nevertheless, mainly low skilled occupations and task are substituted, shifting the labour demand to middle and high skilled labour (De Backer, DeStefano, Menon & Ran Suh, 2018; Michaels & Graetz, 2015). Hence, the effects of the spill-over effects accumulate in other socio-economic groups. In contrast, RT may augment labour by relieving humans from physical work (i.e. the human controls the physical labour that is performed by the device). The problem with these findings is that they stem from posterior analysis and may not be representative of future developments.

The future impact of robotics is tied to three developments. The first development concerns the integration, or confluence, of technologies into more flexible and adaptive robots, termed advanced robotics and mobile robotics (as used by Frey & Osborne (2017)). The majority of current generation RT is pre-programmed to perform a (set of) task(s) with limited sensory feedback or control (De Backer, DeStefano, Menon & Ran Suh, 2018). RT equipped with sensors and computational capabilities due to machine learning, or artificial intelligence will be able to self-correct and perform a wider range of tasks (De Backer, DeStefano, Menon & Ran Suh, 2018; Sirkin, Zinser & Rose, 2015). As a result, RT will gain sensorimotor capabilities and become physically flexible, reactive, and (situationally) adaptive. Consequently, automation will move from routine tasks to non-routine tasks (De Backer, DeStefano, Menon & Ran Suh, 2018; Frey & Osborne, 2017). Hence, consistent with the task definitions in TBTC and RRTC, RT will start to automate manual tasks, e.g. non-routine maintenance tasks (Frey & Osborne, 2017), whereas abstract tasks are not impacted since the technology only automates physical processes. In the contrary, RT is highly likely to complement high skilled labour and wages (De Backer, DeStefano, Menon & Ran Suh, 2018; Sirkin, Zinser & Rose, 2015). The result of the confluence of technologies is that current technological bottlenecks are resolved, creating a vastly wider array of tasks where labour can be substituted.

The second development is related to product and production quality and innovation. The flexible, adaptable, sensory, and performance capabilities of advanced RT enable day-round production at reduced production times and of higher quality (control), consistency, and reliability (De Backer, DeStefano, Menon & Ran Suh, 2018; Frey & Osborne, 2017). In addition, products themselves continuously change due to innovation and emergence. Furthermore, the development cycle is speeding up whereby products are becoming more customised, have shorter production runs, and need to be available faster (De Backer, DeStefano, Menon & Ran Suh, 2018). The confluence of technology will aid product and production innovation by facilitating such requirements. Yet, for many products and processes this technology is too expensive in comparison to labour intensive production. However, reducing costs will also trickle down to advanced RT, expanding the activities and tasks that can economically and competitively be automated (De Backer, DeStefano, Menon & Ran Suh, 2018).

Thirdly, and related to the prior development, the price of RT will continue to reduce while the productivity increases (De Backer, DeStefano, Menon & Ran Suh, 2018; Graetz & Michaels, 2017; Michaels & Graetz, 2015; Sirkin, Zinser & Rose, 2015). This expands the adoption of RT to SMEs (IFR, 2017; Sirkin, Zinser & Rose,

communicates with its environment (equipment or users). Robotic devices comply to the same definition but lack the autonomy or degrees of freedom (Organisation Internationale de Normalisation (ISO), 2012). Commonly, the ISO 8373 definition for industrial robots is used: *"An automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which may be either fixed in place or mobile for use in industrial automation applications."* (Graetz & Michaels, 2017, 009IFR). See International Federation of Robotics (2017) for an overview of definitions or https://www.iso.org/obp/ui/#iso:std:iso:8373:ed-2:v1:en for the detailed glossary and terminology.

2015) and more complex tasks (Frey & Osborne, 2017), across a larger set of industries than currently observed (De Backer, DeStefano, Menon & Ran Suh, 2018; Sirkin, Zinser & Rose, 2015). In this respect, technologically feasibility will (only) materialise when automation becomes financially feasible.

The Boston Consulting Group expects that the real impact of robots on labour is only about to unfold, resulting in accelerating robot adoption in the next decade(s) (Sirkin, Zinser & Rose, 2015). The share of tasks performed by RT will increase from currently approximately 10% to 25% across all manufacturing industries by 2025 and up to 40% in some industries (Sirkin, Zinser & Rose, 2015). In developing countries, RT provides an opportunity to leapfrog in technology, productivity, and product quality, resulting in an overall automated task share that could reach 50% by 2025 (Sirkin, Zinser & Rose, 2015). However, industries that have a longer and richer history of RT implementation demonstrate diminishing marginal returns and productivity gains when technological implementation matures (Graetz & Michaels, 2017; Michaels & Graetz, 2015). Moreover, the market saturation point for technology is around 60%, beyond which substitution is limited (Sirkin, Zinser & Rose, 2015). Therefore, the continues adoption of robotics and associated productivity growth may slow down after the forthcoming robotic transformation up to 2025 – expected by Sirkin, Zinser, and Rose of the Boston Consulting Group (2015). This results in a scenario of linear costs reductions and productivity growth for the next decade, where after both slow down to an equilibrium state.

9.3 When IT and RT meet

The predictions by the Boston Consulting Group concern advanced RT, not the whole array of RT, IT and confluence systems. The most influential publication concerning the future impact of technology is the work of Frey and Osborne (2017). However, there is limited additional literature concerning plausible future developments and, concurrently, the impact on labour of substituting production technologies (Frey & Osborne, 2017).

Frey and Osborne (2017) estimate that 47% of occupations are technically (including both IT and RT[63]) highly probable (>0.7) to be automated in the next decades, although the exact progress over time is uncertain. Another 19% of jobs have a medium probability (0.3-0.7) to be "computerised" (Frey & Osborne, 2017). This trend will start with routine task intense jobs and progress to manual task intense service occupations, i.e. '*The computerisation of production occupations simply suggests a continuation of a trend that has been observed over the past decades*' (p.265). Hereafter, persistent technological bottlenecks will slow down further substitution, first in perception and manipulation complex tasks, and continuously in tasks involving creative and social intelligence. In this respect, tasks involving creativity, human heuristics, emotion, social perceptiveness, social intelligence, and social interaction are the least probable to be substituted (Frey & Osborne, 2017). This brings us back to the initial definition of a robot. The inherent lack of social and emotional capabilities will be the last, if not lasting, hurdle for robotics to fully substitute humans. Following Frey and Osborne's (2017) results, this leads to the conclusion that mainly abstract tasks and some manual tasks will remain to be challenges for automation. In this respect, the future trend is expected to break with the past polarizing labour market trend, catalyse the current high-skill favouring trend, and highlight the importance of re-skilling and up-skilling towards a higher skilled creative and social intelligent labour force (Autor, 2015; Autor & Salomons, 2017; Frey & Osborne, 2017; Nedelkoska & Quintini, 2018).

Frey and Osborne's findings sparked a wide discussion on the future impact of technology and should be considered as the upper bound of substitution for two reasons (Arntz, Gregory, Zierahn, 2016). That is, only technological feasibility is considered and an occupation based approach is likely to result in overestimation of substitutability since it assumes that technology automates all activities within an occupation (Arntz, Gregory, Zierahn, 2016). It should be noted that Frey and Osborne (Frey & Osborne, 2017) adopt an adapted task-based model based on the TBTC framework. Yet, they aggregate and extrapolate a sample of task automatibility across the economy-wide composition of occupations in the US, resulting in a deviation from

[63] It is important to note that Frey and Osborne (Frey & Osborne, 2017) *'make no attempt to forecast future changes in the occupational composition of the labour market'* (p. 265).

the TBTC-framework in their results (which are occupation based). Other studies applying the same methodology reach country specific estimates of 35% and 59% and an estimated range of 45-60% for European countries (see Arntz, Gregory, Zierahn (2016) for the respective literature). Brynjolfsson, Rock, and Syverson (2017) cite studies that demonstrate similar substitution estimates, namely that even with current technology 45% of activities performed in US can be automated. Deloitte (2016) performed a similar study for the Netherlands and concluded that 42,3% of middle skilled and between 19,3% (bachelor) and 10,4% (master) of high skilled occupations is highly probable to be automated in upcoming decades. Consistent with the findings of Frey and Osborne (Frey & Osborne, 2015, 2017), mainly routine and shortly thereafter manual tasks intense occupations will be automated.

Arntz, Gregory, and Zierahn (2016) find that 6% to 12% of jobs are substitutable (probability >0.7) based on a task-based approach rather than an occupation based approach. Another difference between the studies is the dataset that is used, namely, O*NET data (Frey & Osborne, 2017) and *Survey of Adult Skills (PIAAC)* data (Arntz, Gregory, Zierahn, 2016). They argue that, given the current state of knowledge and substitution frameworks, a task-based approach is more reliable and will provide more realistic results (Arntz, Gregory, Zierahn, 2016; OECD, 2017c). This is especially the result of the fact that not occupations as a whole but activities within the occupations, i.e. tasks, are substituted. Moreover, the task based approach accounts for reallocation of labour within occupations (i.e. from automated tasks to remaining tasks), which leads to TFP productivity growth (Arntz, Gregory, Zierahn, 2016; Graetz & Michaels, 2017). This results in a difference between task automation and actual substitution of occupations[64]. Frey and Osborne (2017) do incorporate this development in their model but do not account for it in their results[65]. The automatibility estimates of Arntz, Gregory, and Zierahn (2016) per country are similar to Frey and Osborne's (2015, 2017), e.g. for the Netherlands 39-40%, but the substitution estimates are significantly lower, e.g. 10% for the Netherlands. Concequently, Arntz, Gregory, and Zierahn (2016) find similar percentages as Frey and Osborne at the task level, but because of the methodology, occupation substitution is significantly lower.

Nedelkoska and Quintini (2018) expand on the work of Frey and Osborne (2017) and Arntz, Gregory, and Zierahn (2016) with a wider set of analyses based on the *Survey of Adult Skills (PIAAC)*. The results suggest that 14% of occupation have a high risk to be automated (>0.7 probability) in the next decades and another 32% are likely to automated (0.5-0.7 probability) in the long run (Nedelkoska & Quintini, 2018). In terms of wages, a 1% increase in automatibility is consistent with a 0,43% lower wage. However, Nedelkoska and Quintini (2018) use the same approach as Frey and Osborne (2017) and do note that the results consider exogenous and feedback mechanisms to a limited degree. Hence, the limitation identified by Arntz, Gregory, and Zierahn (2016) apply. Nedelkoska and Quintini (2018) emphasise that their findings demonstrate that high skilled occupations may be relieved all-together and that substitution will mostly hit young adults and the labour force that receives or participates in little training. This especially deteriorates the labour market position of the already vulnerable low skilled labour force. Consistently, all three studies find that automations will substitute low and middle skilled labour and favour high skilled groups. The studies agree on the future trend of substitution, albeit with different impact depending on endogeneity of associated factors.

One striking conclusion that is made by, or can be concluded from, Frey and Osborne (2017), Arntz, Gregory, and Zierahn (2016), and Nedelkoska and Quintini (2018) is the shift in automation manifestation. The prior polarising trend of routine-task automation will continue at the current pace, but the majority of automatibility can be found in low-skilled and manual tasks. Frey and Osborne (2017) emphasise that technological bottlenecks will inhibit manual task automation at first but will expand quickly thereafter in a second wave of automation until new bottlenecks prevent further automation (which are likely to continue to exist). Arntz, Gregory, and Zierahn (2016) emphasise the decrease of automatibility with ISCED skill level, whereby mainly low skilled employment -thus employed in manual tasks- will become automatable. Lastly, Nedelkoska and Quintini (2018) state, *'There is no indication that the risk of automation brought about by AI*

[64] Based on Arntz, Gregory, and Zierahn (2016) calculations of the *'Automatibility by OECD Countries'…' based on the Survey of Adult Skills (PIAAC)',* see table 4 on p. 33 in respective literature.
[65] In comparison, Arntz, Gregory, and Zierahn (2016) provide a literature review of similar substitution estimates (13% and 15%).

and ML is particularly high for the medium skilled jobs, as observed in the polarisation literature based on the routine content of jobs.' (p. 53). In this respect, the current polarising trend and theories appear to fall short for future technological change including rigid and isolated labour markets which are inconsistent with such findings.

The limitations of the expert-based and extrapolating methodology are significant, since spill-over effects are ignored; price development, economic, legal, and societal hurdles are excluded; and the adaptability of the labour force via educational and labour supply is not considered (Arntz, Gregory, Zierahn, 2016)[66]. Other scholars stress that these factors will dictate the pace of automation (De Backer, DeStefano, Menon & Ran Suh, 2018). Moreover, even though technology may be developed at an accelerating pace, the adoption of technology and the realisation of productivity growth significantly depends on, and may be slowed down by, firms' ability to reorganise and change culture (Brynjolfsson, Rock & Syverson, 2017; OECD, 2015a). At the industry and sector level, this effect is amplified due to changes in cross-firm supply chains that demands reorganisation of the sector as a whole (Brynjolfsson, Rock & Syverson, 2017) - and similarly input and output from other sectors.

A key variable in the variation of substitution estimates between countries is the organisation of tasks, occupations, and sectors in an economy (Arntz, Gregory, Zierahn, 2016; Nedelkoska & Quintini, 2018). For example, robot density, tends to be concentrated in specific industrial sectors in economies[67] and not all industries (can) adopt robots (Brynjolfsson, Rock & Syverson, 2017; Sirkin, Zinser & Rose, 2015). Within the sectors, cost effectiveness and technological feasibility of process automation are the main inhibiters or catalysers (Sirkin, Zinser & Rose, 2015). This results in significant variation in automation estimates between countries (6-12% in case of Arntz, Gregory, and Zierahn (2016) and 6-33% in case of Nedelkoska and Quintini (2018))[68]. Modelling an economy according to sectors would severely complicate the model since it would require a separate production model for each sector; incorporate all inter-sectoral input and output flows; account for future reorganisation and dynamics of the sectoral structure; and include sector-specific labour markets, educated labour forces and labour forces exchangeability. In subsequent future research, this would be possible by subscripting the model according to the World Input-Output Database (WIOD) (see Timmer, Dietzenbacher, Los, Stehrer & Vries (2015) and as done with posterior statistical analysis by Graetz & Michaels (2017) and Autor & Salomons (2017)). However, the task-base structure incorporates the economic production composition at a more aggregate scale. Industries with high shares of employment in manufacturing sectors will correspond with high proportions of routine and manual task labour demand. In this respect, the model accounts for sectoral composition in an aggregated manner.

9.4 Technology model synthesis and relation to other models

The impact of IT on the labour market has been noticeable but the bulk of substituted labour and productivity growth is only about to materialise. RT has a more profound effect on labour demand, especially in manufacturing sector intense economies. Yet, the decisive moment is arriving when IT and RT system confluence to become able to reproduce and outperform humans at lower costs. This may sound somewhat science fictional. However, the automatibility is estimated to range from 35% to 60% with a median value of around 45% and probability of 70%-100%. The estimated time frames within which this development will take place range from approximately two decades to 45 years, within which first routine tasks are automated and manual tasks follow in a later stage. To put these figures into context, the recent level of substitution in the European union has been between 4.5-5.1% per decade[69] (Gregory, Salomons & Zierahn, 2016). As discussed, there are significantly more factors and mechanisms that influence the actual manifestation of labour substitution including globalising, financial, societal, legal, organisational, and

[66] See pages 21 to 24 of Arntz, Gregory, and Zierahn (2016) for a detailed evaluation of the shortcomings.
[67] E.g. *'Transport equipment, computers and electronics and chemical and mineral production and food and beverage production.'* (De Backer, DeStefano, Menon & Ran Suh, 2018, p. 14)
[68] Based on Arntz, Gregory, and Zierahn (2016) calculations of the *'Share of Workers with High Automatibility by OECD Countries'…' based on the Survey of Adult Skills (PIAAC)',* see figure 3 on p. 16 in respective literature.
[69] Based on 8.9 to 10.1 million substituted jobs from 180 million jobs over 11 years (Gregory, Salomons & Zierahn, 2016).

sectoral systems. This highlights that the current model is nested in a significantly larger and more complex system. In this respect, the effects studied in this research focus on the most critical factors identified in literature: labour adaptability (via labour supply reallocation and via re-skilling and up-skilling), spill-overs, and a task based approach).

The importance of the latter is highlighted by the tasks where most of the substitution will accrue. IT technology will continue to automate manual tasks whereas RT will continue to substitute routine labour input and eventually move towards manual tasks. Therefore, the current high-skill favouring trend will continue in the near future (since automation of abstract tasks is unlikely (Nedelkoska & Quintini, 2018) or is only possible in the long run, e.g. 90-120 years (Grace, Salvatier, Dafoe, Zhang & Evans, 2018; Müller & Bostrom, 2016)). Moreover, European economies are increasingly becoming knowledge-based in general and thus high-skill favouring (European Commission, 2015). In this sense, and as emphasised before, the adaptability of the labour force is essential to mitigate mass unemployment and realise the potential productivity growth.

The substitution of labour is generated (to represent the bottlenecks defined by Frey and Osborne (2017) and Nedelkoska and Quintini (2018)) using a delay structure and the parametric uncertainty ranges. This implies that the range of growth profiles is combined with the range of substitution estimates; the range of time frames wherein these estimates are reached; and the range of probabilities across the tasks (Table 5). This will generate an ensemble of futures of task specific technological development, i.e. the range of outcomes given the same initial conditions and sampling from the ranges of uncertain parameters. These simulations are combined with the uncertainty ranges of parameters in other sub-models (e.g. re-skilling and up-skilling rates across skill levels and age cohorts).

9.4.1 Limitations

Note, that there is difference between technological automatibility and materialisation thereof into technological substitution. Unfortunately, terminology (e.g. computerisation, automation, substitution) and implications are ambiguously and interchangeably used in the literature. The studies exploring the impact of AI clearly demarcate the difference between HLMI and actual automation (thus implying substitution). Frey & Osborne (2015, 2017), Nedelkoska and Quintini (2018), and similar studies describe whether an occupation can be automated and what this implies for the labour market. Yet, the conclusions from such studies are often treated as technological substitution and unemployment estimates. Given the definitions of the literature, the estimates are treated as technological automatibility estimates. The implementation of advanced technology (such as operational AI) in production processes and the materialisation of their productivity and substitution effects will take considerably longer (De Backer, DeStefano, Menon & Ran Suh, 2018; Grace, Salvatier, Dafoe, Zhang & Evans, 2018; Müller & Bostrom, 2016) under influence of a wide variety of factors defined, for instance, by Arntz, Gregory, and Zierahn (2016) and Brynjolfsson, Rock, and Syverson (2017). Unfortunately, modelling these factors extends beyond the scope of this research as they, similarly to the complex models of STEM education, would require separate sub-models – not unlikely the size of the model developed in this research. In this sense, the factors are treated as exogenous and are included as a black box that influences the realisation of technological automatibility into technological substitution. This black box is defined as a delay function with an uncertainty range of delay time (e.g. in case of AI it will take 2.71 times longer than HLMI[70] (Grace, Salvatier, Dafoe, Zhang & Evans, 2018)).

[70] HLMI is expected between 20 and 107.5 years from now with median of 45 years (confidence interval 0.25 to 0.75), actual substitution is expected between 55 and 212.5 years from now with median of 122 years (confidence interval 0.25 to 0.75) (Grace, Salvatier, Dafoe, Zhang & Evans, 2018). Therefore, the difference between technological substitution and automatibility is approximately 2.71 to 2.75 according to this study.

Table 2 Estimates of technological automatibility

Source	Technology $[\tau]$	Task $[T]$	Automation estimate[71] $[\Xi_\tau]$	Time frame $[\Delta t_\Xi]$	Probability range $[P_\tau]$	Substitution difference
Gregory, Salomons, and Zierahn (2016)	Technology	Overall	4.9-5.6%	11 Years (1999-2000)	1.0	-
Frey and Osborne (2017) (I) First wave of Automation Technology (II) Second wave of Automation Technology	Advanced RT and IT[72]	$\mathcal{M}$ $\mathcal{R}, \mathcal{R}_\mathcal{R}, \mathcal{R}_\mathcal{M}$ $\mathcal{A}, \mathcal{R}_\mathcal{A}$	(I) 47% & (II) 19% (I) 47% & (II) 19% 33%	(I) ± 20 & (II) ± 30 Years (I) ± 20 & (II) ± 30 Years 30+ Years	(I) 0.7-1.0 & (II) 0.3-0.7 (I) 0.7-1.0 & (II) 0.3-0.7 0-0.3	Not specified
Arntz, Gregory, and Zierahn (2016) [73]	Advanced RT and IT	$\mathcal{M}$ $\mathcal{R}, \mathcal{R}_\mathcal{R}, \mathcal{R}_\mathcal{M}$ $\mathcal{A}, \mathcal{R}_\mathcal{A}$	21-77% 4-17% 0-1.5%	± 20 Years ± 20 Years ± 20 Years	0.7-1.0 0.7-1.0 0.7-1.0	0.17-0.34 times Automation
Nedelkoska and Quintini (2018)[74] (I) High Probability (II) Medium Probability	Advanced RT and IT	$\mathcal{M}$ $\mathcal{R}, \mathcal{R}_\mathcal{R}, \mathcal{R}_\mathcal{M}$ $\mathcal{A}, \mathcal{R}_\mathcal{A}$	(I) 14% & (II) 32% (I) 14% & (II) 32% 0%	(I) ± 20 & (II) ± 30 Years (I) ± 20 & (II) ± 30 Years ± 20 Years	(I) 0.7-1.0 & (II) 0.5-0.7 (I) 0.59-0.94 & (II) 0.39-0.64 (I) 0.47-0.85 & (II) 0.27-0.55	Not specified
Grace, Salvatier, Dafoe, Zhang, and Evans (2018)	AI	$\mathcal{M}$ $\mathcal{R}, \mathcal{R}_\mathcal{R}, \mathcal{R}_\mathcal{M}$ $\mathcal{A}, \mathcal{R}_\mathcal{A}$	100% 100% 100%	± 45-90 Years ± 45-90 Years ± 45-90 Years	0.5-0.9 0.5-0.9 0.5-0.9	2.71 times Time Frame
Müller and Bostrom (2016)	AI	$\mathcal{M}$ $\mathcal{R}, \mathcal{R}_\mathcal{R}, \mathcal{R}_\mathcal{M}$ $\mathcal{A}, \mathcal{R}_\mathcal{A}$	100% 100% 100%	± 30-60 Years ± 30-60 Years ± 30-60 Years	0.5-0.9 0.5-0.9 0.5-0.9	Not specified
Deloitte (2016)	Technology	$\mathcal{M}$ $\mathcal{R}, \mathcal{R}_\mathcal{R}, \mathcal{R}_\mathcal{M}$ $\mathcal{A}, \mathcal{R}_\mathcal{A}$	42.3% 42.3% 10.4-19.3%	± 20 Years ± 20 Years ± 20 Years	0.7-1.0 0.7-1.0 0.7-1.0	Not specified

[71] In case of AI the automation estimates are set equal to HLMI.
[72] *'we focus on advances in fields related to Machine Learning (ML), including Data Mining, Machine Vision, Computational Statistics and other sub-fields of Artificial Intelligence (AI), in which efforts are explicitly dedicated to the development of algorithms that allow cognitive tasks to be automated. In addition, we examine the application of ML technologies in Mobile Robotics (MR), and thus the extent of computerisation in manual tasks.'* (Frey & Osborne, 2017, p. 258)
[73] Automation estimates based on ISCED skill level High Automatibility in Table 5 (Arntz, Gregory, Zierahn, 2016, p. 35) and Substitution difference based on Table 4 (Arntz, Gregory, Zierahn, 2016, p. 34). Due to the natural relation between skill levels and tasks, the shifts away from routinization can be explained. For the Netherlands, the estimates are as follows: $\mathcal{M}$ = 37%-51%, $\mathcal{R}, \mathcal{R}_\mathcal{M}$ = 7%, and $\mathcal{A}, \mathcal{R}_\mathcal{A}$ = 0%-1% and Δt_τ = 0.25 times
[74] Automation estimates based on Table 4.5 (Nedelkoska & Quintini, 2018, p. 46) corrected for OLS regression probability percent point deviation based on ISCED skill levels in Table 4.6 (Nedelkoska & Quintini, 2018, p. 54). For country specific estimates consult table 4.5 (Nedelkoska & Quintini, 2018, p. 46) and Figure 4.2 (Nedelkoska & Quintini, 2018, p. 49).

9.4.2 Productivity growth associated to technological advancement

Future total factor productivity is highly uncertain due to the uncertainty revolving around the development of the current technological frontier (OECD, 2015a). Nevertheless the *'average annual MFP growth in the OECD is anticipated to fall from 1.1% in the decade to 2030 to 1.0% to 2040 and 0.9% to 2050'* (OECD, 2015a p.27). Countries at the forefront of technology adoption, lower labour market mismatches (+0.2%), more trade (+0.33%), and more investment in basic research (+0.2%) will realise higher average growth rates (compared to a base of 2%)[75] (OECD, 2015a). Similar numbers are found for the Netherlands by the Netherlands Bureau of Economics (Figure 11). The data also clearly demonstrates a relation between TFP growth and the business cycle (i.e. parallel development of economic growth and TFP in 2001 and 2009 recessions). This link is incorporated in the model with a sensitivity factor. The relation between ICT productivity growth and the business cycle is weak and appears to be delayed. The associated TFP growth to RT and IT is estimated in the range of 0.1-0.17 percent point at the level of individual technologies, 0.25% for industrial robotics (out of a total TFP of 2% (Graetz & Michaels, 2017)), and 0.4%-0.67% for all current generation IT. Greats and Micheals (2017) highlight that, up to the moment of publication, there are no further estimates of productivity growth of robotics. Therefore, information is scarce.

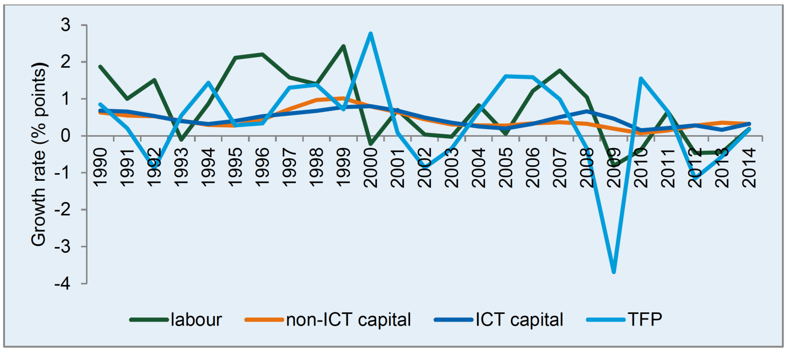


Figure 11 TFP development in the Netherlands, source: Elbourne & Grabska (2016)

Given the status of the influential factors and the expectation that they will not improve from the perspective of technological substitution (e.g. Arntz, Gregory, Zierahn (2016) and De Backer, DeStefano, Menon & Ran Suh (2018)), these rates are considered as representative for future technology driven productivity growth. In this respect, *'Robots' contribution could well continue for years to come'* (Graetz & Michaels, 2017, p. 5). Therefore, within a range of uncertainty, productivity growth can be defined given the current adoption rates versus the potential future rates (0.6%-1.0% Labour productivity and 0.4%-0.67% TFP for IT and RT[76]). The predictions of the OECD (2015a) provide a down sloping base line of productivity growth up to 2060 that does consider IT advancement, but it is unclear how and to what extent. An uncertainty range of deviation from the baseline is defined given the technology estimates (max 33,5% for IT at 2% TFP growth) that are proportion-wise realistic given the OECD estimates of factors (total of 36,5% at 2% TFP growth based on OECD (2015a)). This implies that a baseline scenario is created equal to the OECD prediction and corrected for the range of IT productivity growth (uncertainty range of 0.4%-0.67%). This resembles the macro-economic TFP growth that is independent of task-specific productivity growth. Therefore, each task has a (relative) task-specific technology dependent productivity growth in addition to the corrected baseline.

9.4.3 In relation to the system model

In relation to the other sub-models, task specific investment in technology $[I_{T_\tau}]$ and economic growth $[\Delta X > 0]$ will accelerate development. Vice versa, decelerating economic growth will reduce technological

[75] Compared to a base MFP of 2%, thus respectively lower skill mismatches (+10%), more trade (+16.5%), and more investment in basic research (+10%) in terms of MFP.
[76] The influence of RT is set equal to IT since the estimate of Greatz and Micheals (2017) only considers industrial robots and not the wider definition of RT (including service robots and robotic systems). This is because Industrial robots have been responsible for 0.25 percent point TFP growth and other technologies can realize 0.1% to 0.17% growth.

advancement and thus substitution. The absence of adequately skilled employees may inhibit the realisation of productivity growth since the technology cannot be implemented and operationalised (Acemoglu & Restrepo, 2018; IFR, 2017). Therefore, when the associated extended skill labour supplies reach demand, a shortage in adequately trained personnel will arise which will limit substitution and productivity growth [ΔA_T]. This problem is reinforced by a growing demand for extended skill labour in relation to technology development. Data on the exact relation between STEM labour demand and RT and IT implementation is scarce. The demand for STEM labour (thus including IT and other technology augmenting skills) is expected to grow in relation to how technology is changing labour markets (including digitalisation, advanced robotics, types of AI, and other technologies) (European Commission, 2015).

The estimates range from 5%-19% (Caprile, Palmén, Sanz & Dente, 2015) to 12,1%-18%[77] (European Commission, 2015) in European countries over 12 years up to 2025 that will mainly or nearly exclusively accrue in high skilled labour demand (European Commission, 2015). In the prior period from 2000 to 2013, STEM labour demand grew by 12% (Caprile, Palmén, Sanz & Dente, 2015). However, there is significant variation between countries in estimates to 2025, including contracting STEM markets (e.g. Netherlands -5.9% occupations), nearly stable markets (e.g. Sweden +0.1%), and significantly growing markets (majority of countries). Moreover, the issue of these estimates is that they are based on macro-economic projections with limited scenario and critical uncertainty exploration and therefore these methods are *'not suitable for analysing the combination of quantitative and qualitative effects of for example advanced forms of automation and digitalisation'* (European Commission, 2015, p. 50). In this sense, the model created in this study can enrich this shortcoming but the data should be used cautiously. The estimates are taken as the extremes of extended labour demand growth per country at the respective country specific estimate (EU wide market would imply 0.42% to 1.5% annual STEM labour demand growth). In relation to the extended skill labour force, routinisation manifests as an increase in extended skill labour demand relative to the substitution rate of routinised versus conventional task types.[78]

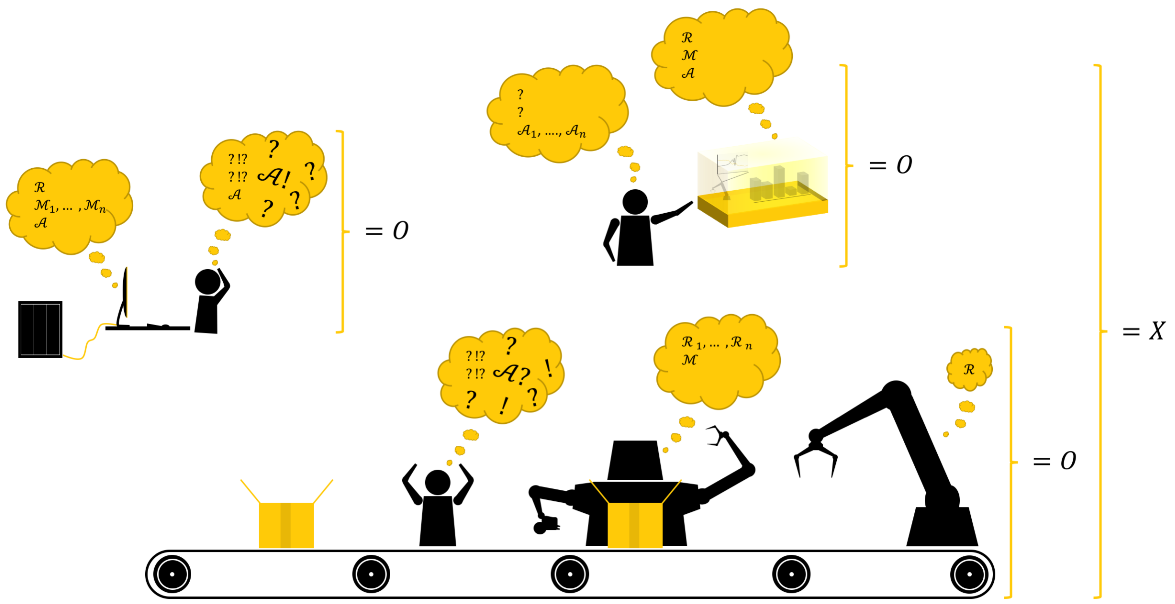


Figure 12 The future position of labour in production?

[77] The prior number concerns the EU wide growth in STEM occupations and the latter are multi- or trans-disciplinary occupations in the EU.
[78] In the model, the contraction of STEM labour demand across skill levels in the Netherlands as projected by the European Commission (2015) results in a relation between technological advancement and extended skill demand of 0.

10 Complex system model

In the prior sections, a model has been constructed based on five interrelated sub-models, namely, economic production, demographic, labour market, education, and technology. In this part, the sub-models are combined in to a conceptual model where after this model is operationalised as a SD model.

10.1 Conceptual model synthesis

The model and its sub-models have distinct interrelations, feedback mechanism, boundaries, and extension possibilities. To summarise (Figure 13), at the centre of the model is the labour market model that connects the economic and social sides of the technological change process. From top to bottom, the production model influences technological change via economic growth and innovation allocation. Simultaneously, the technology model determines the rate of labour substitution, technological productivity growth, and output price development which feedback to the production model. The latter, materialises the spill over effects associated with technological labour substitution. In relation with the labour market, the two models determine the labour input demanded per task and across tasks for production and to support technological change. Conversely, labour market shortages inhibit economic growth due to mismatches and inhibit technological change via shortages of adequately skilled labour input. Moreover, labour market outcomes in the form of income (via wages and employment) feedback to the production model.

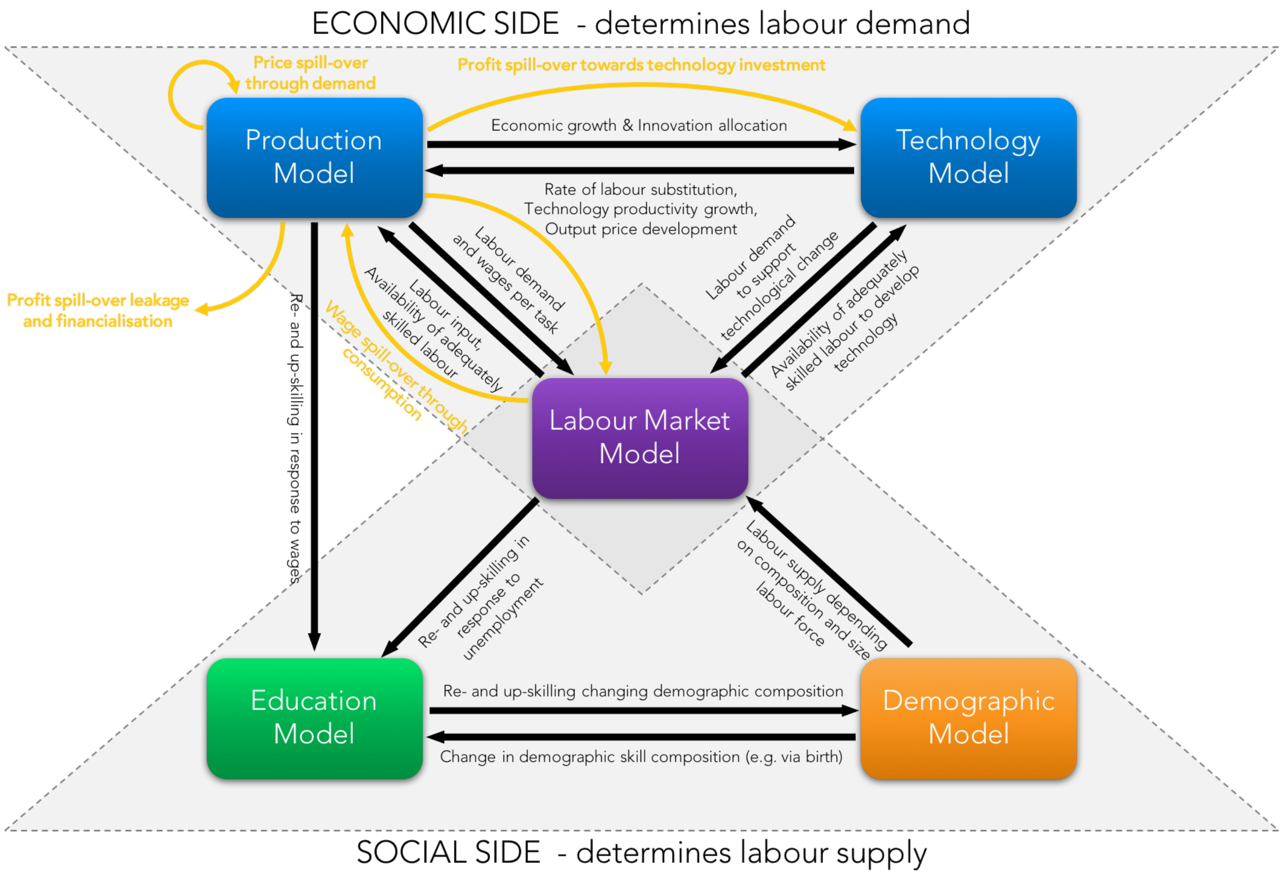


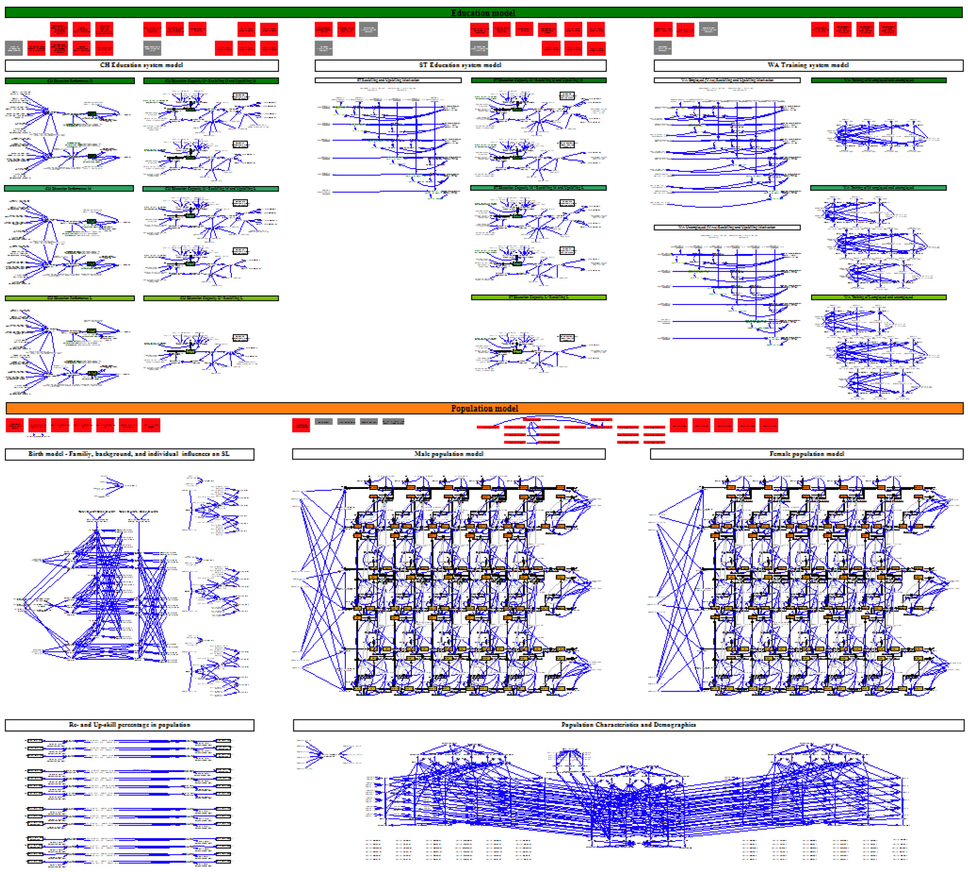
Figure 13 Conceptual model overview with feedback mechanisms

Within the labour market, labour demand and supply meet and determine the unemployment rate depending on the labour allocation per age cohort per skill level per tasks and if businesses prefer higher educated labour supply. Therefore, reallocation of labour supply is internalised in the labour market model.

On the supply side of the labour market, the relative unemployment rate and wage per task determine whether, and to what extent, labour is reallocated[79]. In relation to the labour market, demographic developments in the population model will change the composition and size of the labour force over time. In addition, re- and up-skilling under the influence of the relative unemployment rates drives further demographic reform. This introduces the last sub-model, namely the education model. Labour force members will opt for re- or up-skilling depending on the relative unemployment rates given their current skill level. In addition, employers are incentivised to re- and/or up-skill their employees to reduce relative labour supply shortages and mismatches.

10.2 System Dynamics implementation

The sub-models developed in Part I and summarised in the previous section (Figure 13) are operationalised using SD in Ventana Systems Vensim DSS. The model is developed in a modular fashion by separating the economic production, demographic, labour market, education, and technology sub-models and their components within. This approach facilitates comprehensibility, reusability and the development of the model, sub-models, components. A complete overview of the relation between the developed model in Part I and synonymous factors in the Vensim model are provided in Appendix II. This overview includes the data set, type of data, type in model, and sources. The operationalisation of the model required multiple simplifications to ensure consistency and conformity with the associated data (sources, types, ranges, and uncertainties), frameworks, and literature. A brief overview of the model is provided in Figure 14 SD model overview. The large red boxes in the model comprise uncertainties, the large grey boxes comprise policies, and the thin grey boxes are model property settings. The sub-models are individually discussed below and a complete overview of enlarged images can be found in Appendix III.



[79] When businesses prefer higher educated labour supply, the allocation process remains to be based on the average unemployment rate per task since the various skill level labour supplies still compete as before, only businesses are inclined to hire a higher educated individual.

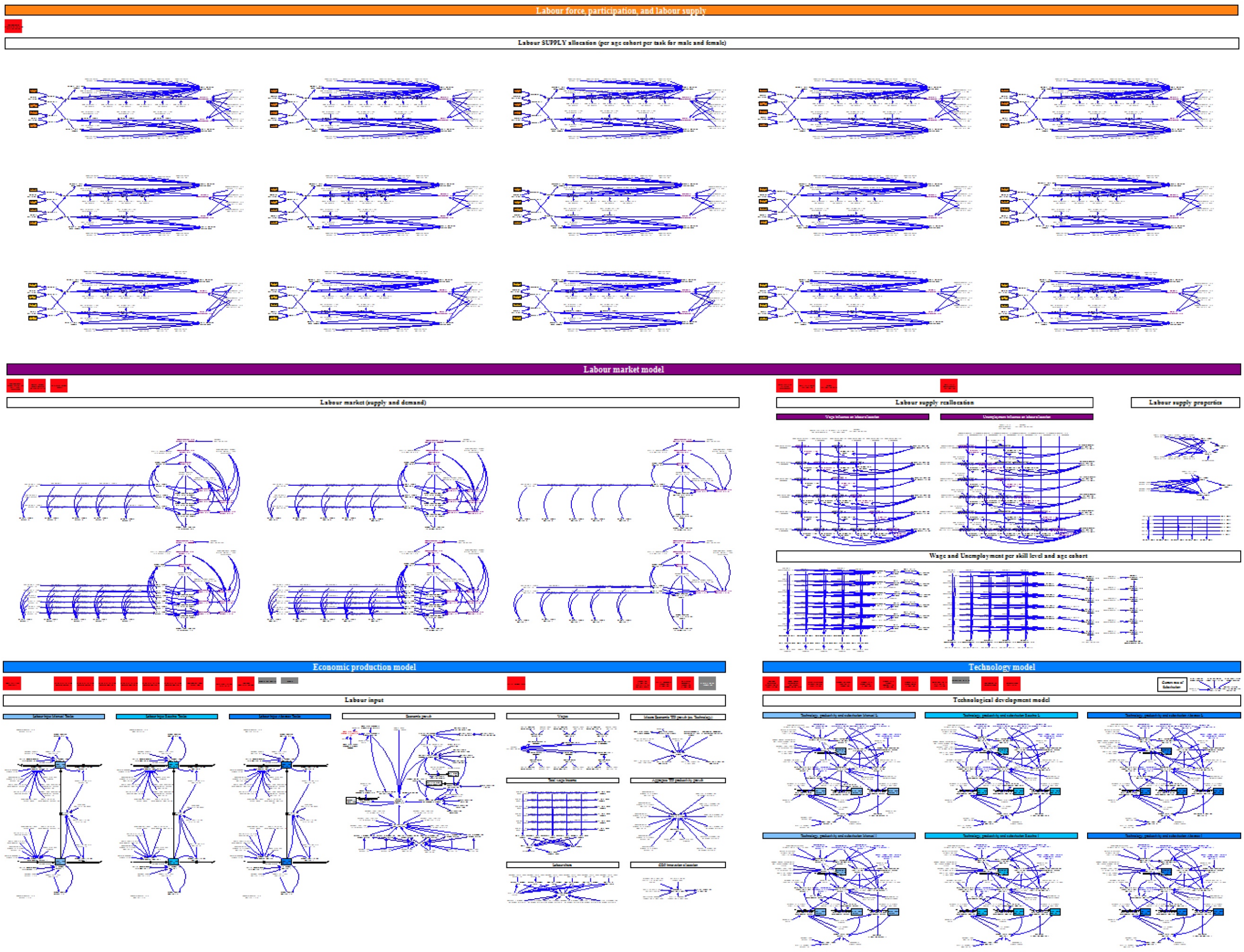


Figure 14 SD model overview

10.2.1 Production model

To operationalise the model, the production model is simplified to model the impact on labour input demand only while preserving the spill-over mechanisms. This is done to connect the technological substitution estimates with the model (i.e. match the technology model with the production model) and account for long term trends (i.e. productivity and economic growth). The economic outcomes can be generated with the production model, yet endogenising the sub-model and its factors in its entirety would complicate the model severely, add a significant quantity of associated data requirements, and complicate the connection between the technological substitution estimates and the other sub-models. The TBTC and RRTC economic models, upon which the production model is based, are used for posterior econometric analysis for which these problems do not exist. Moreover, the automatibility estimates do not account for economic growth due to their static nature. Furthermore, economic growth depends on significantly larger systems including, but not restricted to, capital and financial markets, interest rates, exchange rates, import and export, economic and technological competitive position, globalisation, government consumption, monetary and fiscal policy, sectoral composition, and exogenous factors/shocks. In this respect, predicting the aggregate macro-economic outcomes with the current production model would be oversimplified. From the perspective of boundary adequacy and representativeness of the model, these components would ultimately be initialised to generate outcomes that represent current projections (both from a verification and validation point of view). Therefore, the task structure, labour input, substitution, routinisation, and technology definitions in the production model are incorporated while economic growth is pushed into the model across an uncertainty range, while preserving the spill-over mechanisms.

The OECD expects future annual economic growth to settle around 1,9% from 2020 to 2060 (Figure 15)[80]. The estimate differs per country from 0,5% to 2,9% and the '*Forecast is based on an assessment of the economic climate in individual countries and the world economy, using a combination of model-based analyses and expert judgement*' (OECD, 2018). Two observations need to be made concerning the long-term projection. First, the economies are currently in the boom phase of the business cycle relative to the long-term projection. Which implies that economic growth is projected to decline in the next two years and recover and stabilise in the years after. Second, the historic trend demonstrates significant fluctuation in behaviour and significant variance in fluctuation patterns between countries and over time, e.g. the economic crisis in 2009 is clearly identifiable, but the impact differs between economies. The long-term projections lack such business cycle fluctuation. The absence of such variation is confirmed by the low and stabilising standard deviation in the lower yellow boxed graph. The consistently stable projection across countries over time from 2020 onwards is strikingly contrasting with the measured economic growth and behaviour patterns over the past 20+ years.

For this reason, the projections are used as a country-specific long-term baseline with a marginal error rate that is corrected to better represent economic growth and business cycle behaviour. Therefore, the base line is corrected for business cycle recessions, random short-term fluctuation, and probability for severe recessions in the run time of the model according to consistent patterns in the past (Table 3). It should be noted that prior economic developed cannot simply be projected into the future. For this reason, the model is run across an ensemble of plausible economic futures samples from the uncertainty space of the variables associated with the correction functions (i.e. as presented in Table 3). In other words, each configuration of the model, concerning the population, education, labour market, and technology is run across a set of sampled economic scenarios that resemble the fluctuating behaviour observed over the past 20 years given the OECD projected baseline economic growth of the country.

Table 3 Economic growth projection function

	Variable	Uncertainty range
Long term economic growth[81]	Base line error margin	-0.05 to 0.05
Business cycle recession[82]	Occurrence Duration Proportion of time in recession Amplitude	8 to 9.4 years[83] 3 to 3.64 quarters 0.18 to 0.21 -2.63 to -1.87% GDP per quarter
Business cycle fluctuation[84]	Occurrence Duration Amplitude	2 to 3 years ½ occurrence period 0.1 to 0.33% GDP per year
Severe recessions[85]	Occurrence Duration Proportion of time in recession Amplitude	0 to 1.14 times[86] 4 to 4.7 quarters 0.18 to 0.21 -4.89 to -6.31% GDP per quarter

This methodology may, at first sight, closely resemble an equilibrium approach in conventional economic modelling. However, the baseline is corrected for spill-over effects (and thus creating feedback-loops). Therefore, the generated economic growth rate is sensitive to endogenous developments that will dampen or stimulate economic growth compared to the baseline.

[80] The variation in *the mode* of the dataset can be attributed to coincidental equal values of two country specific projections.
[81] Assumption based on OECD (2018) dataset
[82] (Claessens, Ayhan Kose, & Terrones, 2009)
[83] (Claessens, Ayhan Kose & Terrones, 2009; Estrella & Mishkin, 1998)
[84] See Appendix IV
[85] (Claessens, Ayhan Kose, & Terrones, 2009)
[86] Based on "severe recessions" between 1960-2007 from Claessens, Ayhan Kose, and Terrones (2009), converted to 25 year span.

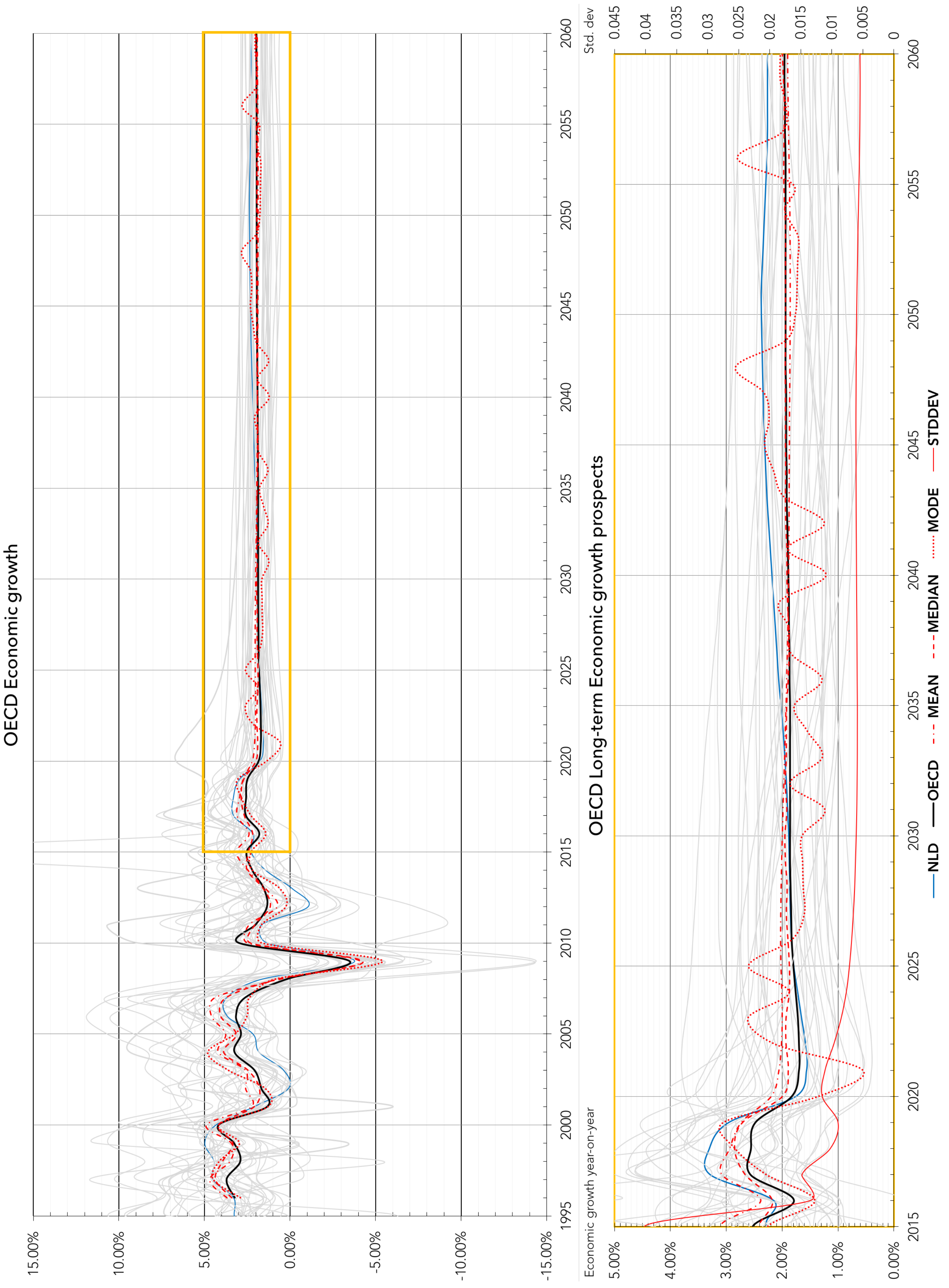


Figure 15 OECD Economic growth analysis and prospect based on OECD data (2018)

First, the macro-economic growth rate is corrected for relative total wage income dynamics (comprising all wages times the employed labour force across the tasks) under the assumption that the propensity to consume is constant. This implies that, the macro-economic growth rate may increase or decline compared to the baseline due to changes in demand depending on the unemployment rate and wage per tasks (given technological progress, substitution, productivity growth, and allocation). Second, at the tasks level, productivity growth that exceeds the projected technological productivity growth (see 9.4) will further reduce prices and create a task-specific demand effect in addition to the projected macro-economic growth rate. Since the economic growth baseline incorporates the projected productivity growth, the spill-over effect is based on the relative price development compared to continuation of the current levels of technological change. This implies, that technological advancement that exceeds the current pace will result in higher productivity growth, lower prices, and additional demand. Lastly, the profit spill-over effect is assumed to fully contribute to technological developed and leakage via financialisation, and thus, does not result in additional demand. To summarise, the (country specific) OECD economic growth projection is used as a baseline, which is corrected to represent the business cycle fluctuation and associated uncertainty, and incorporated in the feedback mechanisms associated with technological advancement (at the macro and task level). The model component that generates the macro-economic growth rate is provided in Figure 16, as is an example of the labour input component in Figure 17. A complete and enlarged overview can be found in Appendix III).

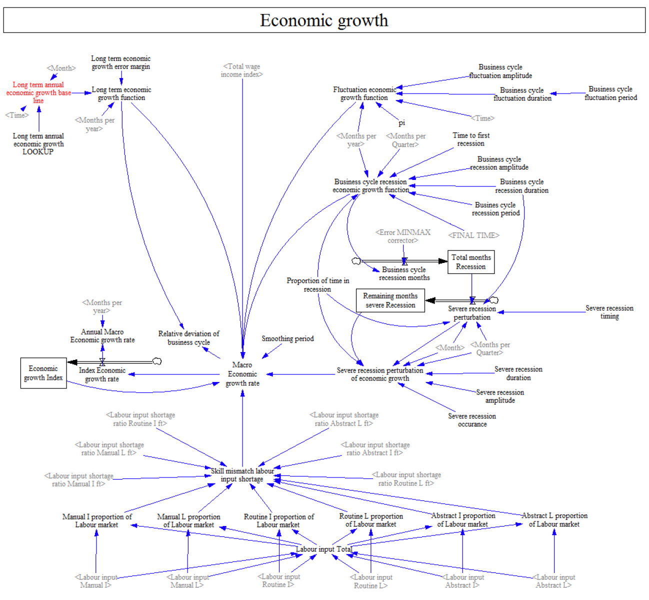


Figure 16 SD Model – Economic growth

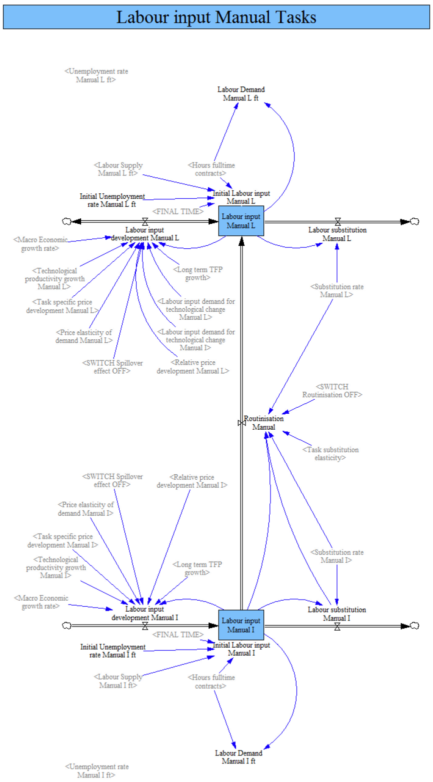


Figure 17 SD Model – Labour input

10.2.2 Demographic model

The demographic model implementation is identical to the described system (see 6). The SD sub model structure is divided in five main components: births, male population, female population, re- and up-skill percentages, and population characteristics. The latter two are included to monitor and specify outcomes of interest during simulation and have no further interrelation with the model. The prior three determine the demographic composition of the population via births, aging, and re- and up-skilling (in relation with the education model). The male population model component is presented in Figure 18 (complete overview including enlarged images can be found in Appendix III). Note that the female and male population model are identical with the exception that the skill level and size composition of young adult females (YA f in SD model) feedback to the births of new population members.

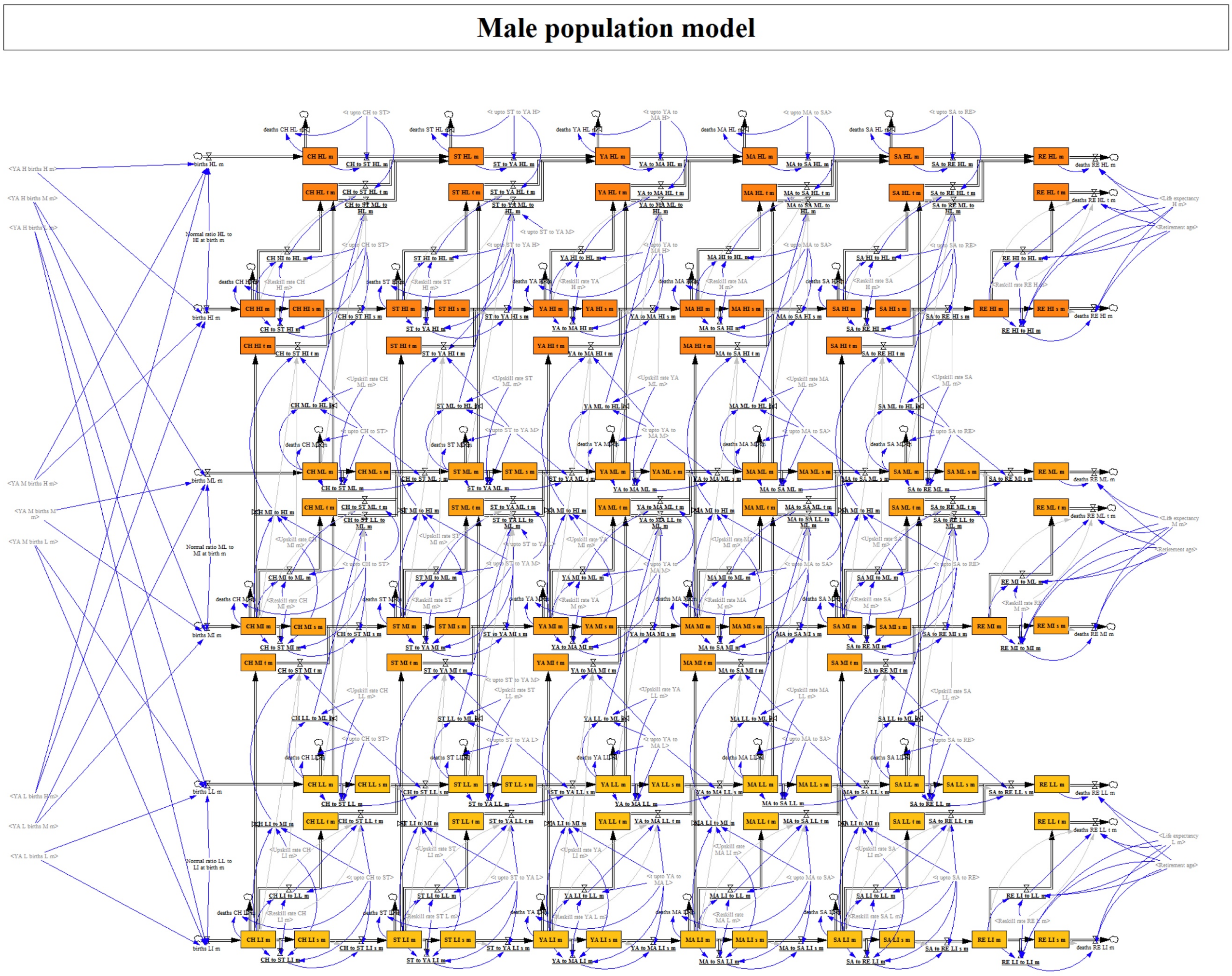


Figure 18 SD Model – Male population

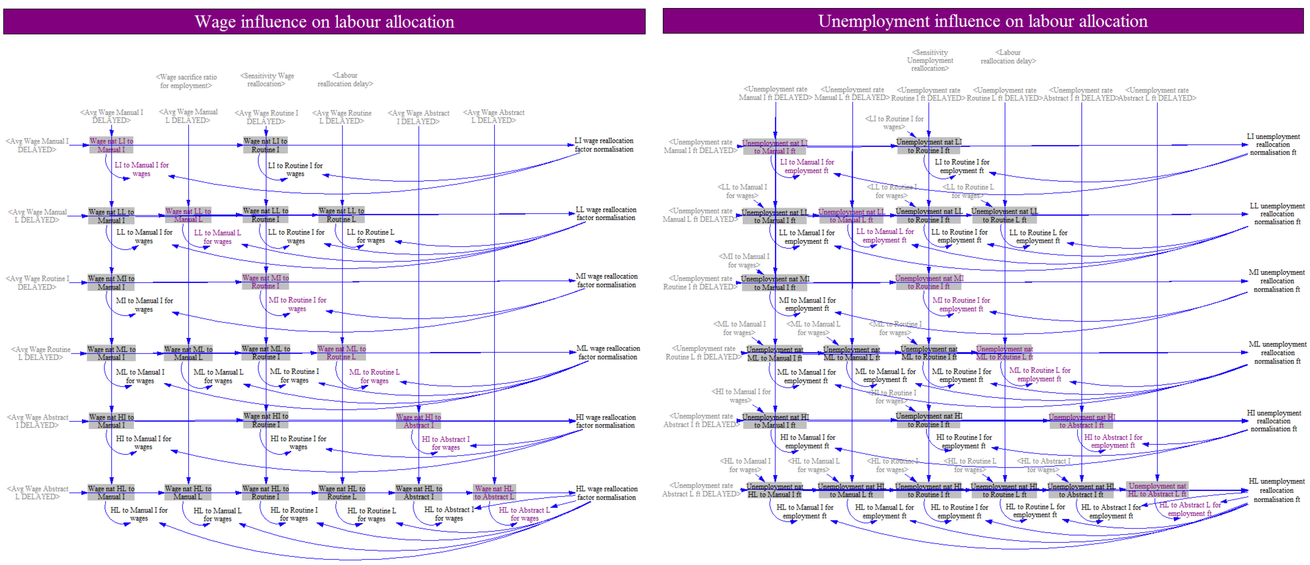


Figure 19 SD Model – Wage allocation (left) and Unemployment allocation (right)

10.2.3 Labour market model

The labour market model implementation is identical to the described system except for the division in full-time and part-time labour (see 7). Therefore, labour reallocation is based on the relative unemployment rates and wage of the tasks for which labour force members are qualified (Table 1). The division between full-time and part-time labour markets is excluded from the model since the technological substitution would be identical. More importantly, the TBTC and RRTC framework do not make the distinction between the two. In this respect, this approach is consistent with the frameworks and substantiated. Introducing both markets would also require interaction and flows of labour between the markets in consideration of reducing hours in existing full-time jobs (Borowczyk-Martins, 2017), involuntary part-time employment (Borowczyk-Martins & Lalé, 2017; Horemans, Marx, & Nolan, 2016; Valletta, Bengali, & Van der List, 2016) and increasing non-standard employment (NSE) (Schmid, 2010). However, this would extend beyond the scope of the model and this study. Therefore, for consistency with the model and frameworks, only one labour market is simulated. The labour market is divided in five main components: labour supply (with a sub-component for each labour force age cohort and skill level), the labour market per tasks, labour reallocation (including a sub-component for the relative wage and a sub-component for the relative unemployment), labour supply properties, and wage and unemployment outcomes. The latter two are included to monitor and specify outcomes of interest during simulation and have no further interrelation with the model. The sub-component for the relative wage and unemployment is presented in Figure 26, and an example of a task labour market in Figure 20 (a complete overview can be found in Appendix III).

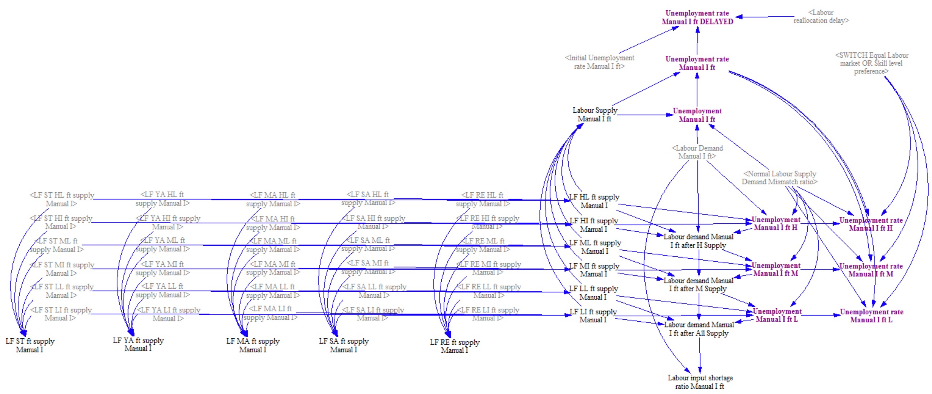


Figure 20 SD Model – Task Labour market

10.2.4 Education model

The education model implementation for children, students, and the working age population is consistent with the described systems (see 8). The education model is divided in three components (Children, Students, Working Age) with different sub-components to determine the rate of re- and up-skilling based on stimulation programs (for children), stimulation and young adult unemployment (for students), and stimulation and unemployment (for the working age labour force) (Figure 21, enlarged images can be found in Appendix III). In relation with the population model, the rate of re- and up-skilling is determined based on the labour market conditions and education stimulation.

10.2.5 Technology model

The technology model is developed to link the future substitution and productivity growth estimates with the production model. Substitution of input normally follows the relative price development of inputs given the substitution elasticity (see 5). However, these projections are not available. More importantly, this study is performed to determine the effect of adaptability and adaptability incentivisation for the future of work given the current automatibility estimates within the TBTC and RRTC framework. Therefore, the effects of adaptability are tested with the current estimates as the point of departure. Hence the model is structured accordingly. From an economic perspective, the model can be improved by incorporating the complete production functions once such price estimates and substitution elasticity estimates become available.

The technology model consists of a component per tasks to determine the rate of substitution, productivity growth, productivity spill-overs, wage development (wage development is located in the technology model and not in the labour market because of the spill-overs), labour share, and additional labour input to support the technology. Therefore, the automation estimate, time frame, probability range, and substitution time difference uncertainty ranges (Table 2) are combined to generate the substitution rate and productivity growth. In relation with the other sub-models, labour input shortages, economy wide and task specific innovation allocation, and macro-economic growth rate feedback to the substitution rate and productivity growth. The technology model components of one tasks is provided in Figure 22 (enlarged version can be found in Appendix III

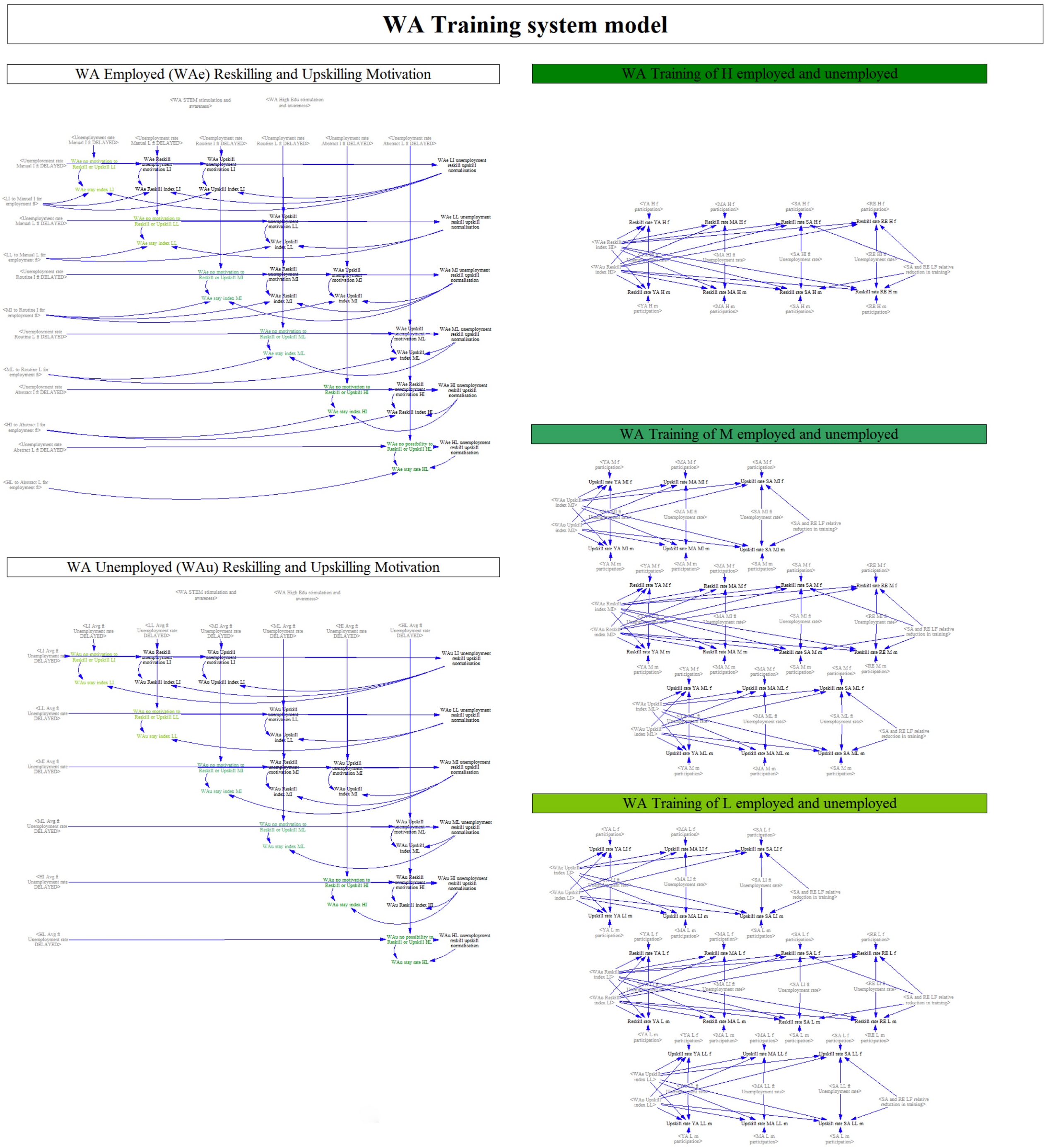


Figure 21 SD Model – Working wage education

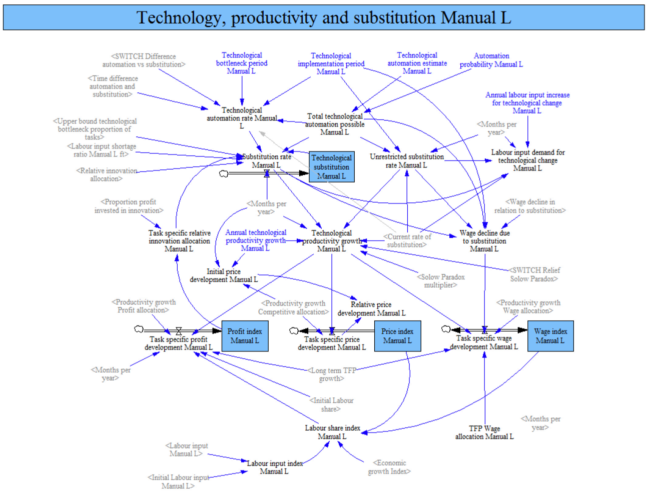


Figure 22 SD Model – Working wage education

10.3 Model properties

The model can be simulated for any country as long as the input data is available or adequately representative assumptions or uncertainty ranges can be defined. The model is initialised with four types of input, namely, settings (to ensure the model runs properly), initial values (constants and initial values of variables), policy variables (to evaluate levers to favourably alter outcomes), and uncertainties (variables of which the exact value is not ascertainable, not definable without an error margin, a distribution, or its effect on outcomes is of interest across a range of values). A complete overview of model input for the case study can be found in Appendix II. The settings, initial value corrections from the data sources, policy levers, and uncertainty space per sub-model are briefly introduced below.

10.3.1 Model settings

The Vensim SD model is run for the next 20 years (model settings: base date = 01-01-2018, Initial time = 0, and Final time = 240, Time step = 0.0625) using the Runge-Kutta 4 fixed integration method (RK4 fixed). An integration error check was performed for validation (see Sterman (2000)). The model returns one or multiple accuracy errors when the time step size is equal or larger than 0.125. Below 0.125, the model returned identical results for all time step configurations. The integration method did not influence the results across RK2 Fixed, RK2 Auto, RK4 Fixed, and RK4 Auto with the same time step setting. However, simulation times did differ significantly[87]. Therefore, a time step of 0.0625 and integration using RK 4 Fixed is adopted.

10.3.2 Initial values

The model is initialised using the latest available data from various sources to configure the model according to the current state of a country. Naturally, the model is a simplified and isolated representation of the actual real world system with distinct system boundaries. The initial values set the demographic, education system, labour market, economic, and technology conditions from which the future is explored. The initial values can be found in Appendix II. One correction in the initial values is made due to inconsistent data concerning the skill level proportions of children and students. The skill level proportions (i.e. the relative ratio of individuals per skill level per age cohort) of young adults is also used for children and students since the dataset contained unexplained deviation from the demographic skill level trend. This deviation is most

[87] With the same system running as a virtual machine with dedicated processing, RAM, and memory capacity. Times at RK2 Fixed (1.2 seconds), RK2 Auto (3.3 seconds), RK4 Fixed (1.7 seconds), and RK4 Auto (6.5 seconds).

probably the result of the definition of the highest achieved skill level, which is only measured above 25 years of age. The initial demographic configuration is provided in Appendix V (including the incorrect configuration and the disaggregate 5 year age cohort population relative to the age cohorts in the model) and in Figure 23.

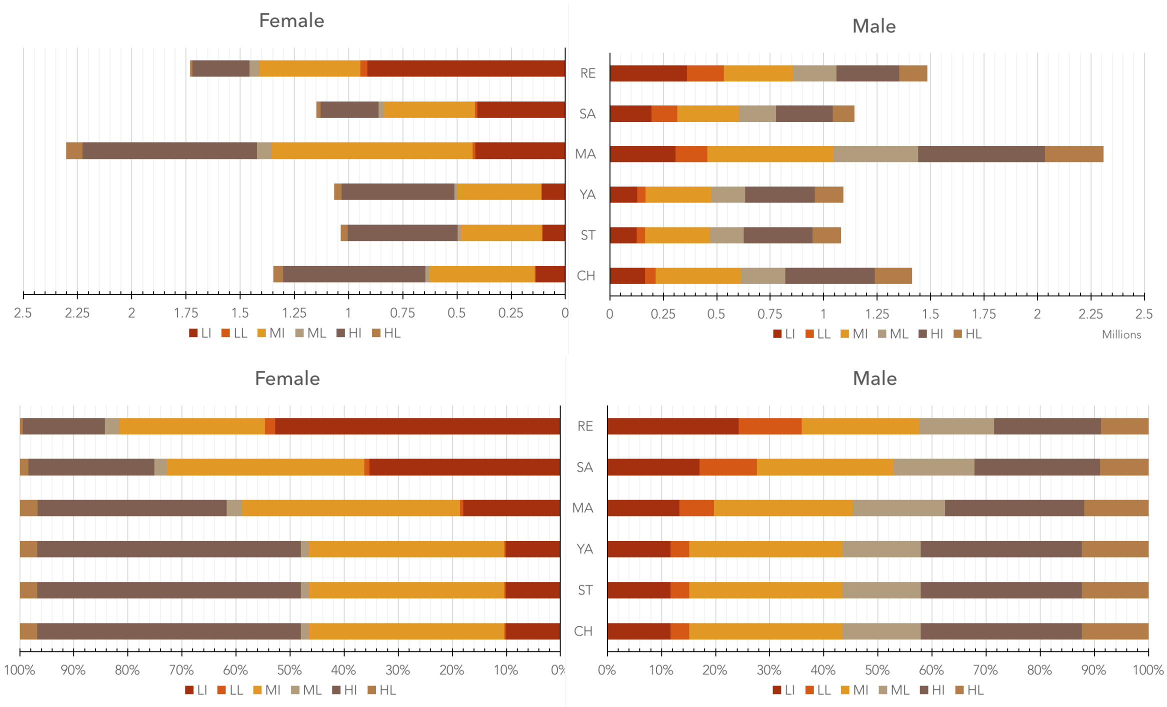


Figure 23 Corrected initial population

10.3.3 Policy variables

The policy space in the model is closely related to the sub-models and presented actors (i.e. the labour force, businesses, and the government). Three categories of policies can be identified in the model. The policy levers can be found in Appendix II.

Education policy to stimulate Re- and Up-skilling

Technological change is associated with changing skill requirements resulting in a need for re- and up-skilling of the labour force. This development is in the interest of all actors. Firstly, from the perspective of the labour force, re-skilling and up-skilling improves employability and wage potential and reduces wage and employment uncertainty. Secondly, from the perspective of businesses, inadequately trained personnel reduce productivity, inhibit production growth and innovation, and thus damages economic outcomes. Lastly, from the perspective of the government, the interests of all three actors needs to be balanced while satisfying budget constraints (including labour institutions, education resources, innovation stimulation, and economic policy). In the model, re- and up-skilling is determined by education programs for children and labour market conditions for students and the working age population. The prior develops parallel to demographic developments and is influenced by stimulation of education performance and STEM graduation via government intervention. The latter depends on the relative unemployment rates and sensitivity of the labour force to labour market conditions. The sensitivity is influenced by intervention of the government or businesses to incentivise re- and up-skilling of the employed and unemployed labour force.

Labour market flexibility and reallocation

The reallocation of labour supply to different tasks within occupations and across occupations in reaction to technological change is a critical feedback mechanism. It allows the labour force to adjust to technological change within the limited possibilities of reallocation (see Labour market model) and it allows businesses for more effective and productive allocation of production input. In the model, reallocation is influenced by the wage and unemployment sensitivity of the labour force and restricted by the willingness to sacrifice a relative proportion of wage in return for employment. The government can influence the sensitivity by incentivising the unemployed to seek employment elsewhere or increase the willingness to sacrifice income, e.g. via compensation or tax reforms.

Technological innovation stimulation

Stimulation of technological innovation – and thus indirectly stimulation of substitution – is in the interest of businesses but may accelerate technological unemployment development. This would suggest that stimulation improves productivity and economies growth in return for a higher level of unemployment. Yet, the labour force is expected to shrink under the influence of societal aging and may cause economic growth constraints in the upcoming decades (Peterson, 2017). Moreover, demographic skill development will change the composition of the labour force. When this development is skewed towards a higher skilled labour force, the effects of technological substitution in manual and routine tasks may be limited or even completely compensated for (while in return higher productivity and economic outcomes can be realised with technological innovation stimulation). In the model, business can allocate a higher share of GDP and task-specific profits to technological development, while governments can stimulate technological innovation.

10.3.4 Uncertainty space

Exploration of the future with a simplified and isolated representation of a highly complex and interrelated real world system ask for awareness of the limitations, boundaries, and uncertainties of the model. This does not render modelling and simulation exercises, as performed in this research, useless. On the contrary, exploration of the future provides the opportunity to gain an insight in the plausible situations we may face. This notion has been central during model development by stating research and model boundaries, limitations, corrections, and assumptions. Methodologically, this notion is extended to the simulation exercise with the use of uncertainty space exploration in the Exploratory Modelling and Analysis workbench (Kwakkel & Pruyt, 2013). This Python extension runs the SD model while sampling the uncertain parameters from the specified uncertainty ranges and creating an ensemble of scenarios – also termed futures. In other words, the model is simulated for the specified number of experiments with a different value for each uncertain parameter from the specified range. As an example, Figure 24 depicts a random selection of economic growth projections based on the parameter ranges from Table 3 with a run time of 240 months. The uncertain parameters and associated ranges are provided in Appendix II, and summarised as:

Production model	As presented in Table 3 to generate economic outcomes
Labour market model	Sensitivity to wage differences, Wage sacrifice ratio, and Sensitivity for unemployment
Population model	Birth rate
Education model	Student labour market awareness and sensitivity, Time before young adults' labour market positions are general knowledge among students, and Working age re- and up-skill sensitivity for employed and unemployed labour force members
Technology model	As presented in Table 2 to generate labour substitution estimates, Proportion of profit invested in innovation, Innovation allocation sensitivity to the business cycle, and Prior substituted labour

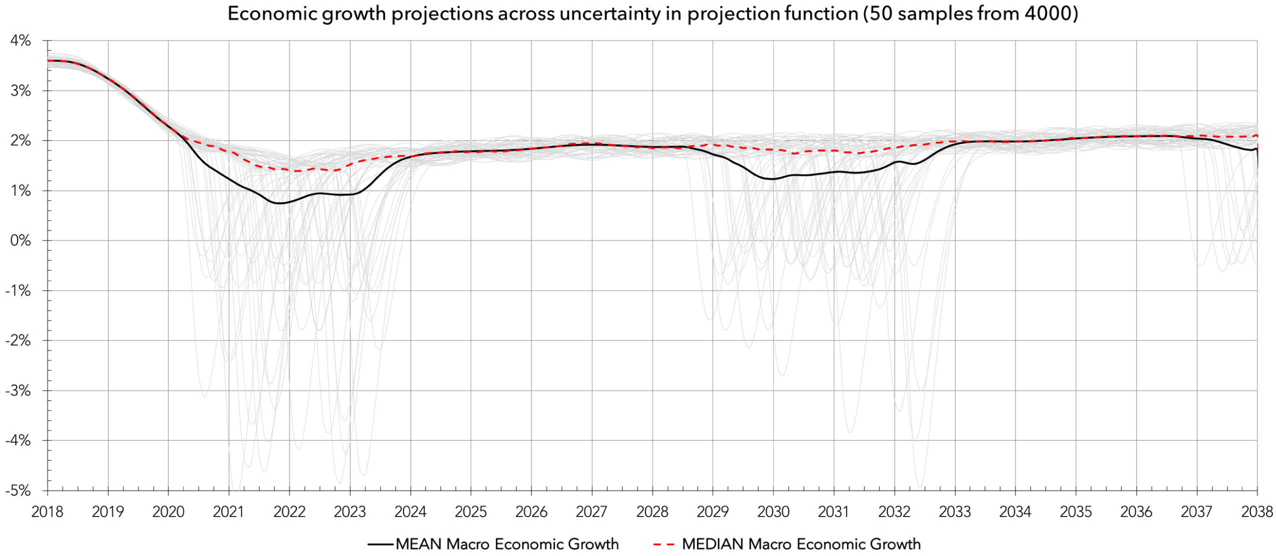


Figure 24 Sampled Economic growth based on OECD base line and projection function in Table 3

11 Model testing

System Dynamics modelling is not aimed at building the most correct representation of the real world but building a model that represent the real world to a degree that assists knowledge generation and decisions making to the best extent possible (Pruyt, 2013). In this sense, model verification and validation is aimed at model integrity and purposefulness instead of representativeness. The model developed in Part I and operationalised in the previous section, is tested to ensure validity of, and confidence in, the outcomes it generates.

11.1 Verification

Prior to model verification the model has been debugged to check for integration errors, equation consistency, simultaneous initials and equations, floating point errors, and replacement of discrete functions with continues alternatives. A unit check and model check provided no model or simulation errors or inconsistencies. Verification of the model is aimed at checking the operation, comprehensibility, and replicability of the model (Pruyt, 2013). This check has been performed by switching on the feedback mechanisms of related sub-models in sequence. The model was initiated with economic, population, labour market, and education data from the Netherlands[88].

11.1.1 Normalisation factor check

The model includes multiple normalisation equations to ensure value and scale consistency. The normalised factors associated with labour allocation; wages; children up-skilling and re-skilling indexes; student re-skilling and up-skilling indexes; and working age re-skilling and up-skilling indexes have been checked to sum to one. Hereafter, the actual labour allocation per skill level per age cohort have been checked for consistency by summing to the total amount of labour supply per skill level per age cohort. Note that normalisation of the birth ratio's is not included in the model since it is in the statistical input data. This implies that, when using a different dataset, it should be checked whether these rates are normalised across the combinations of gender and skill levels of the parents and children.

11.1.2 Population model check

The demographic model is based on a complicated stock-flow structure that includes aging, re-skilling, and up-skilling. Its integrity has been verified by switching all births and deaths off, which should result in a constant population that experiences societal aging over time. Both characteristics are present. Secondly, this check is repeated with re-skilling and up-skilling to ensure the demographic model continues to function. This is confirmed to be the case. Thirdly, the re-skilling and up-skilling structure relies on delay functions to simulate the flow of population members with aging consistency, i.e. every person is born and ages consistent with run time of the model. This check is performed by verifying if the scale of the flows is consistent with the associated stock and equations, and re- and up-skill ratios. Both are confirmed to function properly. It should be noted that the transition stocks, containing upskilled and reskilled individuals are equal to 0 at initiation since those individuals are included in the associated stock (where the individuals have upskilled or reskilled to) in statistical input data. Lastly, the proportion of births is verified to ensure consistency in the birth sub-model. This should imply that the younger age cohorts become increasingly high educated without re- and up-skilling. This is confirmed to be the case and is consistent with historic trends of the Netherlands[89].

[88] Details on this dataset are provided in Part II and in Appendix II.

[89] Note that the young adult age cohort is used since this is the earliest state from which the highest achieved skill level is recorded in statistics data. The model trends (greyscale) remain stable for the past 5 years where after the indexes accelerate and stabilize. This is the result of the delayed feedback mechanism of births and young adult composition. The actual historic trend demonstrates more fluctuation, most probably due to exogenous factors. However, more importantly, the relative index values and scale correspond to the prior trend, especially considering the timespan.

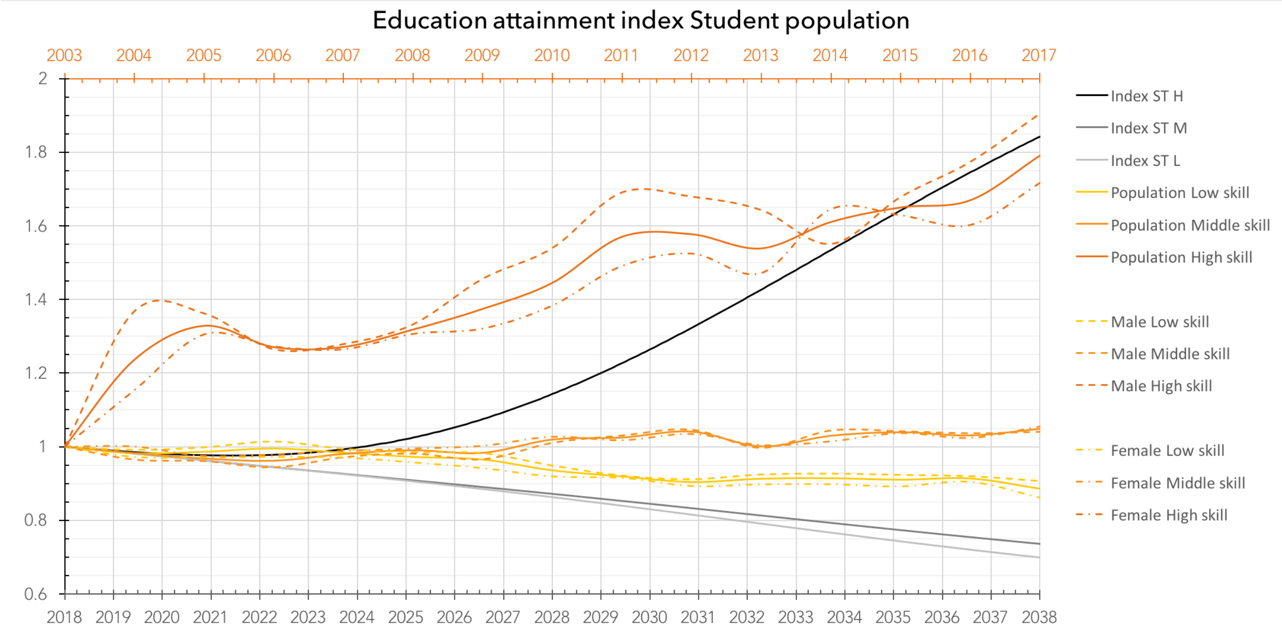


Figure 25 Demographic skill level development students

11.1.3 Labour market and initial unemployment stability check

The labour market model is built to ensure consistency between unemployment rates per age cohort per skill level and per task. At initiation of the model this should result in an unemployment rate per skill level that is consistent with the allocation to the natural task type and qualified tasks and their respective unemployment rates. Here after economic, labour market, education, and technology dynamics will result in shifts and reallocation. First, all associated feedback mechanisms have been switched off: re-skilling and up-skilling; labour and wage reallocation; and labour input development and labour substitution are set to current levels. This should imply that unemployment of tasks and their natural labour supply should develops in parallel. Moreover, this unemployment rate should develop in parallel to relative labour input demand versus natural labour supply changes under influence of demographic changes. Both are confirmed to function properly. Second, the labour reallocation feedbacks are switched on and tested at three sensitivities (0.1, 0.5, and 1.0). Compared to the test without reallocation, the unemployment rates should decline or increase depending on their relative value to each other and reallocation possibilities. This behaviour is confirmed. Thirdly, this test is repeated but with the student and working age education model active at three sensitivities (0.1, 0.5, and 1.0). The same behaviour should arise including a shift towards high skill levels when abstract unemployment is lower (since abstract tasks are the exclusive domain of the high skilled labour force). This behaviour is present (F).

11.1.4 Education model check

The process of re-skilling and up-skilling of students in reaction to the labour market has been confirmed to function as expected, i.e. students and the working age population will re- and up-skill when the unemployment rate of the associated skill level is lower and do this more when the sensitivity is increased. Within the education model, multiple checks are performed. First, for each of the children and student education capacity sub-models (per skill level) the capacity limitation has been verified to limit re-skilling and up-skilling. One adaption has been made in the model, namely, that the children and student education capacities grow (not declines) in correspondence with demographic shifts. In addition, a natural capacity expansion index is added to keep track of the additionally required capacity to enable for the demographics shifts (thus excluding re-skilling and up-skilling). The student education capacity growth (in reaction to children skill level development) can also be switched off, and will in that scenario prevent re-skilling and up-skilling outside the spare capacity that may be present. Not doing so would inhibit any re-skilling and up-skilling, effectively rendering the education model obsolete. Second, the delay in capacity growth has been verified by variation of the realisation time (should slowdown or accelerate capacity growth), the fixed period (should shift the capacity growth), and planning parameter (should increase or decrease capacity growth). All are confirmed.

11.1.5 Technology and production model check

The technology and production model are closely related due to the model implementation. First, the technology model is verified by checking if the productivity growth follows the substitution rate. This is confirmed. Second, the substitution growth is verified by variation of the implementation period (should slowdown or accelerate the curve), the bottleneck period (should shift the curve), and possible substitution (should increase or decrease the maximum value). All are confirmed. In relation with the production model, labour substitution behaviour should run parallel to the technological substitution rate given the delay due to exogenous factors. One test is performed without a delay and a second including the implementation delay. The labour input stock and labour substitution flow behaved as expected in both cases. Lastly, the aggregate TFP should sum to the baseline plus the weighted technological productivity growth given the relative proportions of the tasks in the economy. This is confirmed.

11.2 Validation

Model validation relies on multiple test that extend beyond the conventional representability approach in modelling (Pruyt, 2013). In this respect, it is important to note - especially for readers with a background in labour economics (and study the impact of technological change) - that validation does test the goodness of fit with historic data due to the system approach and future orientation. The latter, naturally, implies that a good fit with historic trends may not imply good representativeness of (plausible) future trends (Pruyt, 2013). The validation process is an iterative and integrated process during model development. These efforts include intermediate verification and validation (as presented in the previous section). To ensure the validity of the model multiple tests have been performed.

11.2.1 Model Structure

The structural (i.e. task based approach at macro-level) and equational (i.e. mathematical, dimensional, parametric) substantiation of the model has been provided in Part I to ensure the model's foundation stems from the current paradigms in associated literature. In this sense, structural validation has been performed. Some operationalisation improvements and simplifications have been made during the construction of the model and implementation in the SD software package (see 10.2). These simplifications correspond with the intended scope of the model and this research and thus do not degrade the structural validity of the model. Yet, the simplifications represent otherwise functioning feedback-loops that could alter dynamics and behaviour. Therefore, as will be discussed in the last sections of Part III of this document, the limitation and system boundaries provide opportunity for expansion. The most evident simplifications concern wage dynamics and rationalisation of labour allocation and education of students and the working age population. Literature emphasises that wages have not reacted to labour market developments under technological change as economic theory would dictate (Goos, Manning, & Salomons, 2011; Mishel, Shierholz & Schmitt, 2013). Moreover, wages have been insensitive to market developments in Europe due to institutional rigidities (Goos, Manning, & Salomons, 2011; Gregory, Salomons & Zierahn, 2016). The rationalisation of labour market decisions by labour force agents is based on the intended goal of the model (see 7.1) and is controllable via the sensitivity levers in the model. In this respect, Boundary adequacy, Structure Assessment, Dimensional consistency, and Parameter assessment have been performed (Forrester & Senge, 1979; Sterman, 2000).

11.2.2 Model Behaviour

During model development, each of the components of the five sub-models has been tested to perform with a wide range of configurations, initial values, and extreme values. The most evident weaknesses were found in the education capacity model for children and students and the technology models per task. The prior has been fixed by created a demographic growth rate that would otherwise inhibit re- and up-skilling. In the technology model, the technological productivity growth did not behave as expected under circumstance where the substitution rate was lower than the current rate of substitution or significantly higher. This is issue was caused due to relative weighing of the actual substitution rate versus unrestricted rate. This issue has been resolved. Therefore, extreme value testing was performed (Sterman, 2000).

The verification of the model included behavioural anomaly testing by switching of re- and up-skilling, reallocation, and substitution feedback loops in the model. For validation purposes, a separate behaviour anomaly test has been performed using EMA. The model was simulated without feedback mechanisms, including labour supply reallocation, and including reallocation and re- and up-skilling for each of the automatilibity estimates (excluding the AI estimates) in Table 2 with 50 simulations per feedback configuration (750 experiments). The results are provided in Appendix VI and demonstrate that switching off feedback loops does change outcomes drastically value-wise but not behaviour-wise. To be more specific, the outcomes are more extreme and can be clearly separated value-wise but the behavioural patterns are similar. A dichotomy in behaviour can be observed between dynamic unemployment and consistent minimal unemployment at the set minimal employment mismatch. The latter case implies that there is a consistent shortage of skilled labour supply or labour supply willing to sacrifice wage to be employed. The population model demonstrates identical outcomes, independent of feedback configuration. The outcomes per automatilibity estimate correspond to the uncertainty ranges in the simulation configuration – most evidently the technological substitution per task. The outcomes do provide deviating results but these can be explained by the mechanisms in the model relative to the uncertainty ranges of the estimates. In this respect behavioural anomaly testing has been performed and provides reason for confidence in model reliability (Sterman, 2000).

In addition, behaviour reproduction was performed for the population model (Sterman, 2000). Behaviour wise, the model corresponds to population estimates from the Dutch Central Bureau of Statistics (CBS) for total population size[90], births, children (CH), students (ST), Young Adults (YA), and Retirees (RE) (see Appendix VII) (Figure 53). Deviation in behaviour for the mature adult (MA), and senior adult (SA) can be explained by the aggregation of individual age cohort into larger groups (see 5-year age cohort demographics versus model structure age cohorts in Demographic configuration). Consequently, the model evens out the otherwise distinct demographic dynamics.

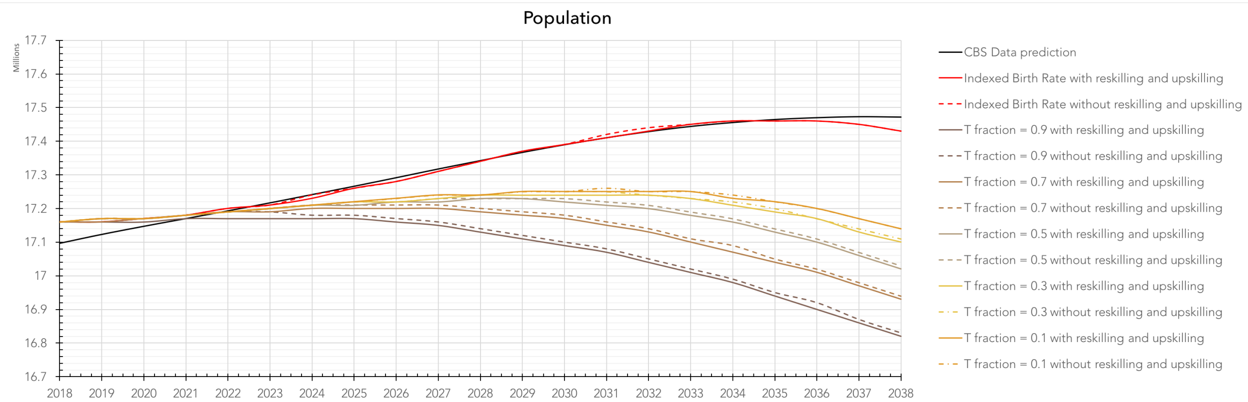


Figure 26 Model Population Behaviour validation: Total population

During model development, and in comparison with CBS data on future births, it was concluded that the fertility rate had to become dynamic over time since it is expected to grow. Therefore, a Lookup was added to the model based on an index of the fertility rate in CBS data over time (termed "Indexed Birth Rate" in Figure 53). Model-wise, the population structure required an additional re- and up-skilled population stock

[90] Note: the CBS estimate is corrected for immigration since the model does not consider immigration patterns.

per skill level and age cohort for integration consistency. As a result, a time fraction needed to be added to aid mathematically correct integration and population outcomes, which is set at 0.1.

Part II Case study of the Future impact of Robotics and AI on the Labour market in the Netherlands

The model developed in Part I is simulated for the Netherlands based on the current labour market composition for the next 20 years. The future scenarios (of technological development and uncertainties) are simulated to determine how the labour force natively (without intervention) will adapt to replaced labour inputs and loss of labour demand. This provides a range of plausible futures, i.e. how technology and labour could co-develop given the uncertainties faced. This base case is expanded upon by exploring the critical sensitivities that can mitigate unemployment. A profile of policies is established given these outcomes.

12 Model preparation and setup

Part I of this thesis operationalised a simulation model to study possible future labour substitution given technological change. The main outcome of interest is unemployment across socio-economic groups and the ability to adapt to changing labour market conditions via labour supply reallocation and re-skilling and up-skilling. Simultaneously, demographic dynamics continuously change the composition of the population and labour force on the labour supply side while, on the labour demand side, spill-over effects counterbalance labour substitution. In this part, RDM analysis is performed with the SD model using the EMA workbench and PRIM algorithm to determine plausible future unemployment scenarios for the Netherlands and identify policy levers.

12.1 Model configurations and scenarios for exploration and policy identification

The second and third step of the RDM framework are performed since the first step has been performed in Part I, i.e. the relevant system is conceptualised, uncertainties identified, and outcomes of interest specified (Kwakkel, Haasnoot, & Walker, 2016). Some further specification is performed concerning the outcomes of interest and data input for the Netherlands. Following RDM, the second step employs exploratory modelling of different model configurations to analyse the behaviour of the system given the uncertainties and in consideration of feedback limitations. This implies that four SD model configurations are used, namely:

I. **Without any form of feedback mechanism in relation to the labour market** - conforming to Frey and Osborne (2017) and Nedelkoska and Quintini (2018) in respect of occupation substitution
II. **Including labour reallocation** - conforming to Arntz, Gregory, and Zierahn (2016) and the semi-open labour market structure with dynamic skill-tasks relations as described by Acemoglu and Restrepo (2017, 2018), among others
III. **Including labour reallocation and re- and up-skilling** - conforming to the TBTC frameworks
IV. **Including labour reallocation, re- and up-skilling, routinisation, and spill-over effects** - conforming to the RRTC framework and implying that in additional to projected economic growth, spill-overs will further increase output demand (defined as the *productivity effect* by Acemoglu and Restrepo (2018) and *product demand effect* by Gregory, Salomons, and Zierahn (2016))

The SD model parameters to switch off the feedback mechanisms is provided in Appendix VIII. In addition, one model is used to determine the effect of increased productivity growth. This implies that future technological advancement is to diverge from the current trend of a stagnant productivity growth compared to the technological development pace, termed as *'a redux of the Solow (1987) Paradox'*[91] By Brynjolfsson, Rock, and Syverson (2017, p. 1). In the model this would shift the spill-over effects resulting in higher relative price decreases and thus task-specific demand growth, higher wage growth, stimulation of technological development through innovation investment from profits, but also less labour demand compared the macro-economic growth rate.

V. **Including labour reallocation, re- and up-skilling, routinisation, spill-over effects, and increased productivity growth** – conforming to plausible future conditions under which productivity growth exceeds the current levels due to technological advancement

In sense of scientific relevance, incorporating these dynamic mechanisms extends the current static expert projections to include the fundamental adjustments to technological change: *'the labor market impacts of*

[91] i.e. *'we see transformative new technologies everywhere but in the productivity statistics.'* (Brynjolfsson, Rock & Syverson, 2017, p. 1).

new technologies depend not only on where they hit but also on the adjustment in other parts of the economy'. (Acemoglu & Restrepo, 2017a, p. 1). The five model configurations are simulated across the future automatibility estimates in Table 2. However, country specific estimates are adopted for Arntz, Gregory, and Zierahn (2016) and Nedelkoska and Quintini (2018) since both sources specify such estimates for the Netherlands based on labour market and sectoral composition. This results in a set of seven input uncertainty scenarios, namely;

A. Gregory, Salomons, and Zierahn (2016)
B. Frey and Osborne (2017)
C. Arntz, Gregory, and Zierahn (2016)
D. Nedelkoska and Quintini (2018)
E. Grace, Salvatier, Dafoe, Zhang, and Evans (2018)
F. Müller and Bostrom (2016)
G. Deloitte (2016)

However, the AI automation estimates of Grace, Salvatier, Dafoe, Zhang, and Evans (2018) and Müller and Bostrom (2016) (E and F) are not used because they are not consistent with the TBTC and RRTC framework and/or methodology. This prevents accurate implementation and comparison since the estimates only activities in general. Therefore, estimates A, B, C, D, and G are used to ensure comparative and substantive consistency. The exploration (thus step 2) of the plausible future impact of technology on unemployment is divided in two tests. One test is performed to determine the effect of labour reallocation, re- and up-skilling, and spillovers and routinisation on unemployment. The second test is performed to simulate the plausible outcomes for the Netherlands.

The third step of RDM, scenario discovery, is performed to identify policy levers and the conditions under which they fail to prevent high unemployment rates. This analysis employs the PRIM algorithm to determine these conditions for the unemployment outcomes of interest. The algorithm generates a set of boxed uncertainty spaces (given the dimensions set by the uncertain parameters) which are characterized by coverage and density: *"Coverage is the fraction of all the cases that are of interest that fall within the box. Density is the fraction of cases within the box that are of interest."* (Kwakkel, Haasnoot, & Walker, 2016 p.169). Based on the ensemble of boxes, the most relevant is selected depending on the Coverage and Density characteristics. Within this box, the influence of the uncertain parameters is analyzed using quasi-p values to evaluate for statistical significance and comparative parameter relevance (Kwakkel, Haasnoot, & Walker, 2016, Bryant & Lempert, 2010). These outcomes assist behavior explanation and policy lever identification to determine labour force adaptability, policy lever sensitivity, and system properties relevant to unemployment caused by advanced RT and AI.

12.2 Outcomes of interest and policy levers

Briefly returning to the main research question, *To what extend is the labour force capable of adapting to labour substitution by advanced robotics and artificial intelligence, and can be incentivised to do so, to mitigate future unemployment?,* provides three outcome categories of interest: unemployment, adaptability, and adaptability incentivisation. First, unemployment is measurable per task, per skill level, and per age cohort for all combinations of skills and tasks in the labour market (Table 1). In relation with the substitution frameworks, we are interested in the unemployment rate per skill level. In addition, relative wage developments per skill level are of interest to study inequality dynamics associated with technological change.

Second, the effects of adaptability are first and foremost measured with the five model configurations. Within these configurations, the relative adaptability is determined by sensitivity factors across an uncertainty range. During exploratory modelling the sensitivities are treated as a Boolean, i.e. 0 to switch the feedback mechanisms off and 1 to switch it on. In economic terms, a sensitivity of 1.0 implies that the tasks are effectively perfect employment substitutes from the perspective of labour supply. During scenario discovery, the sensitivities are treated as uncertainty ranges from 0 to 1 to determine their effect on unemployment and potential as policy levers.

Lastly, the outcomes concerning the adaptability sensitivities from the exploratory step and scenario discovery are used for a new round of scenario discovery including policy levers. More specifically, the policy levers identified in Part I are tested across an uncertainty range to evaluate their statistical significance and comparative parameter relevance. This is possible by isolating the ensemble of futures to a limited set of futures of interest based on unemployment values and using the PRIM algorithm to search within this set. In relation to the main question, this set contains all futures with unemployment rates beyond a certain threshold (e.g. the current level of unemployment per skill level). In addition, labour market (labour supply per skill level, labour demand per task, labour allocation per skill level per task) and technological substitution (Total technological substitution per task) parameters are monitored during exploratory modelling.

13 Exploration and Policy Identification

The exploration of future labour markets under the influence of technological change is performed using the EMA workbench in Python in combination with the Vensim SD model configurations. The five model configurations are setup with the same initial, constant, setting, and lookup values but differ in the feedback mechanisms that are switched off or on. In the EMA workbench in Python, the uncertainty ranges are set depending on the uncertainty scenarios (A, B, C, D, and G) and the outcomes of interests are universal. This exploration using simulation serves two purposes.

First, the effects of labour force adaptability on unemployment are determined using Frey and Osborne's (2017) automatibility estimates (thus running uncertainty scenario B across model configurations I, II, III and IV). These original estimates are restricted to automatibility and do not account for demographic labour force shifts, labour supply reallocation at the task level, skill attainment, and spill-over effects. In other words, the automatibility estimates are static predictions of the demand side of the labour market (Frey & Osborne, 2017)[92]. In this respect, this experiment is aimed at contributing to our understanding of technological change by exploring the dynamics of supply and demand. Therefore, the current automatibility estimates are extended upon to include unemployment given the adaptability of the labour force. Hence, the first purpose of exploration is to make an attempt in bridging the current knowledge gaps, since, *'Given the gravity of the technological transformation we are undergoing, there is astonishingly little research effort in understanding the subsequent response through skill adjustment'* (Nedelkoska & Quintini, 2018, p. 36) and since the automatibility estimates do not account for the reallocation of labour across tasks which is critical to understand the impact of technological change (Acemoglu & Autor, 2012; Acemoglu & Restrepo, 2018).

Second, the plausible future impact of technology is explored using three tests. First, the difference between automatibility, substitution, and unemployment is tested given the labour force adaptability using Arntz, Gregory, and Zierahn's (2016), Nedelkoska and Quintini's (2018), and Deloitte's (2016) estimates for the Netherlands[93]. This creates a diverse set of uncertainty scenario's. Respectively, with high substitution rates of manual tasks; manual and routine tasks; and manual, routine and (relatively) abstract tasks (see Table 2). The three uncertainty scenarios are simulated across model configurations IV. Uncertainty ranges are used for reallocation, re- and up-skilling, and price elasticity of demand instead of Booleans (0 or 1). In addition, the current substitution rate obtained from Gregory, Salomons, and Zierahn (2016) is simulated to determine the plausible futures under continuation of the substitution status quo. Second, uncertainty scenario D is simulated using model configuration V to study the effect of spill-overs and abolishment of the currently observed Solow paradox. In other words, the effect of increasing productivity growth in the future is evaluated. Third, scenario D is simulated using model configuration IV to study the effect the difference between automatibility and substitution[94] in consideration of exogenous factors that inhibit technological advancement and implementation (as discussed in 9).

Hereafter, the outcomes of interest from the previous tests are analysed using PRIM to evaluate the conditions, and identify potential policy levers, under which unemployment will grow in relation with technological advacements in RT and IT. Therefore, the simulation outcomes above the current unemployment rates are analysed to determine which factors contribute to these outcomes and which policy levers are among those factors that can be influenced to reduce the unemployment rate. In addition, the required re- and up-skilling in the next 20 years is explored to ensure adequate labour force adaptiblity and minimize unemployment.

[92] 'We make no attempt to forecast future changes in the occupational composition of the labour market.' (Frey & Osborne, 2017, p.265)

[93] Note that Frey and Osborne's (2017) estimates are not used since they are specific to the US and Nedelkoska and Quintini (Nedelkoska & Quintini, 2018) provide a country specific update on Frey and Osborne using the same dataset and methodology.

[94] This requires one adaptation to model configurations IV and V, whereby 'SWITCH Difference automation vs substitution' is set to 1 instead of 0.

13.1 The effects of labour force adaptability on future outcomes

The results generated across the four models (1000 experiments per model with the script provided in Appendix X) demonstrate a consistent relation between unemployment and feedback mechanisms, albeit dependent on demographic developments. An overview across the skill levels is provided in Figure 28 for uncertainty B (Frey and Osborne (2017)). A detailed representation per skill level over time is provided in Appendix XI, and an example of such a representation is provided in Figure 27. The box-whisker plots (in Figure 28 and at the bottom of Figure 27) provide an overview of the plausible unemployment given the uncertainty projected over time at 5 year intervals per model (I, II, III, and IV). The boxes indicate the first, second, and third quartile of the outcomes given the standard deviation and outcome distribution, the dots indicate the mean value of the uncertainty range, and the whiskers encompass the whole range of outcomes (and thus the uncertainty range). It is important to note that the unemployment outcomes are only indicative since the test is performed to determine the effect of adaptability compared to current shortcomings of future automatibility estimates and methodologies. The results are polarised due to the use of Boolean values (i.e. the highest sensitivities are used to demonstrate the effect of adaptability and feedback mechanisms). The subsequent test will explore the actual plausible future of work for the Netherlands.

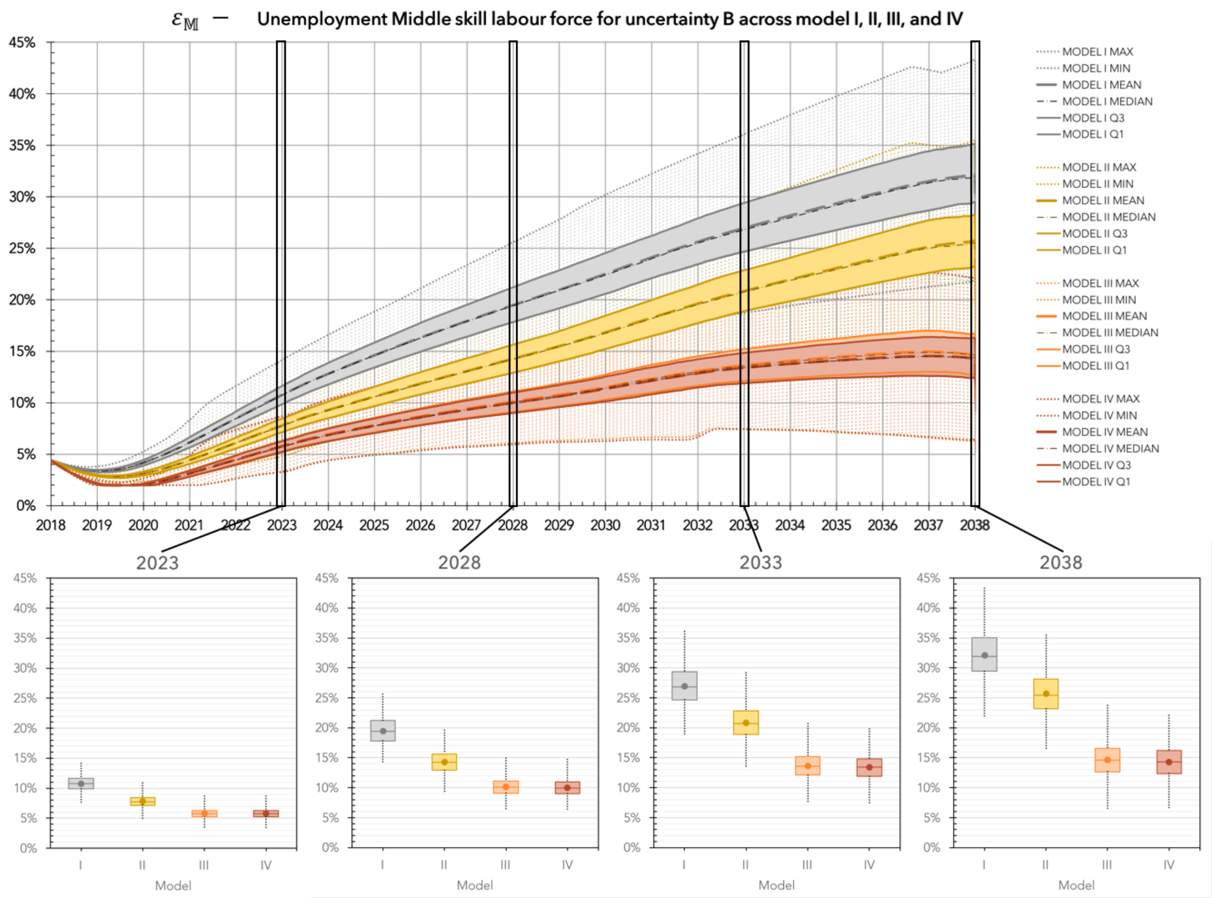


Figure 27 Unemployment projections $\varepsilon_{\mathbb{M}}$ for uncertainty B with and without adaptability and spill-over (models I, II, III, and IV)

From a systems perspective, multiple conclusions need to be drawn from the results concerning labour reallocation, re- and up-skilling, and spill-overs. Concerning reallocation, the difference between model I (i.e. isolated labour market) and II (i.e. reallocation across qualified tasks) is apparent for middle skilled ($\varepsilon_{\mathbb{M}}$ and $\xi_{\mathbb{M}}$) and low skilled unemployment ($\varepsilon_{\mathbb{L}}$ and $\xi_{\mathbb{L}}$). Respectively, accounting for reallocation results in lower unemployment and lower uncertainty ($\varepsilon_{\mathbb{M}}$ and $\xi_{\mathbb{M}}$) and higher unemployment and lower uncertainty ($\varepsilon_{\mathbb{L}}$ and $\xi_{\mathbb{L}}$). The results stem from the middle skilled labour force reallocating labour supply to low skilled tasks in reaction to the reduced labour demand. Initially in model I, the combination of demographic skill development and labour substitution of low skilled labour demand results in relatively low unemployment or even labour supply shortages. However, when middle skilled labour starts to reallocate supply (in model II), the low skilled labour force needs to compete with the middle skilled over the same tasks. In this respect, this demonstrates, and is consistent with, the current observations where higher skilled labour is forcing out low skilled labour (Autor & Salomons, 2017; Frey & Osborne, 2017)[95].

Concerning re- and up-skilling, the difference between model II and III is apparent across the skill levels, albeit with different behaviour. The ability to attain new skills in reaction to technological substitution reduces unemployment and uncertainty of the low and middle skilled. However, due to up-skilling, in reaction to the relatively low unemployment of the high skilled, more individuals climb the socio-economic ladder and increase the high skilled ($\varepsilon_{\mathbb{H}}$ and $\xi_{\mathbb{H}}$) labour force. Therefore, the high skilled labour supply increases and unemployment grows relative to model II. In this respect, the labour demand effects of technological change in routine and manual tasks are spread towards abstract tasks. In other words, the drastic increase in unemployment associated with future technologies is spread across skill levels. Furthermore, accounting for re- and up-skilling reduces the unemployment uncertainty range.

Concerning the spill-over effect (model IV), the outcomes do not demonstrate behaviour as expected based on the increased output demand (defined as the *productivity effect* by Acemoglu and Restrepo (2018) and *product demand effect* by Gregory, Salomons, and Zierahn (2016)). This would imply that unemployment reduces relative to model III across all skill levels. The outcomes (see boxes for model IV compared to III in Figure 28) only show minor reductions of the third quartile for low skilled ($\varepsilon_{\mathbb{L}}$ and $\xi_{\mathbb{L}}$) and high skilled ($\varepsilon_{\mathbb{H}}$ and $\xi_{\mathbb{H}}$) unemployment. The model deviates from the expected behaviour due to the continuation of the current levels of productivity growth. As a result, the relative increase of productivity growth above current levels is limited and therefore the spill-over effect (task specific and in addition to the projected macro-economic growth) is limited (in addition to the projected economic growth rate). This is not necessarily a weakness of the model but a logical consequence of relative limited productivity growth and therefore limited spill-over effects (additional test performed in subsequent section). The spill-over effect does reduce the uncertainty range of plausible future unemployment slightly compared to model III even though more uncertainty is introduced in the model.

Accounting for labour force adaptability drastically changes and reduces unemployment projections. In this respect, the outcomes are consistent with, and confirm, the premise of Arntz, Gregory, and Zierahn (2016) whom state that not accounting for adaptability results in overestimation of the impact of technological change (as is the case with Frey and Osborne (2017) according to Arntz, Gregory, and Zierahn (2016) and therefore Nedelkoska and Quintini's (2018) whom adopt the same methodology). From scientific relevance point of view, these outcomes demonstrate that the current methodologies can be enriched by accounting for dynamic behaviour associated with adaptability.

13.2 Exploration of future labour markets of the Netherlands under technological uncertainty

The plausible future impact of technology is explored using three tests: one with continuation of the current productivity growth (Solow paradox), one to explore the effect of increasing productivity growth, and one to determine the effect of the difference between automatibility and substitution under influence of exogenous factors (see 9). The difference between automatibility, substitution, and unemployment is tested given the labour force adaptability using Arntz, Gregory, and Zierahn's (2016) (C), Nedelkoska and Quintini's (2018) (D), and Deloitte's (2016) (G) estimates for the Netherlands. In addition, the current substitution rate obtained from Gregory, Salomons, and Zierahn (2016) (A) is simulated (Table 4). Two adaptations have been made to the data. First, Nedelkoska and Quintini's (2018) (D) estimates across two probability levels for the Netherlands have been recalculated into a corrected single estimate fitting the upper probability range and

[95] It should be noted that he model is simulated without a preference for higher skill levels for the same labour demand. This option can be switched on using "SWITCH Equal Labour market OR Skill level preference".

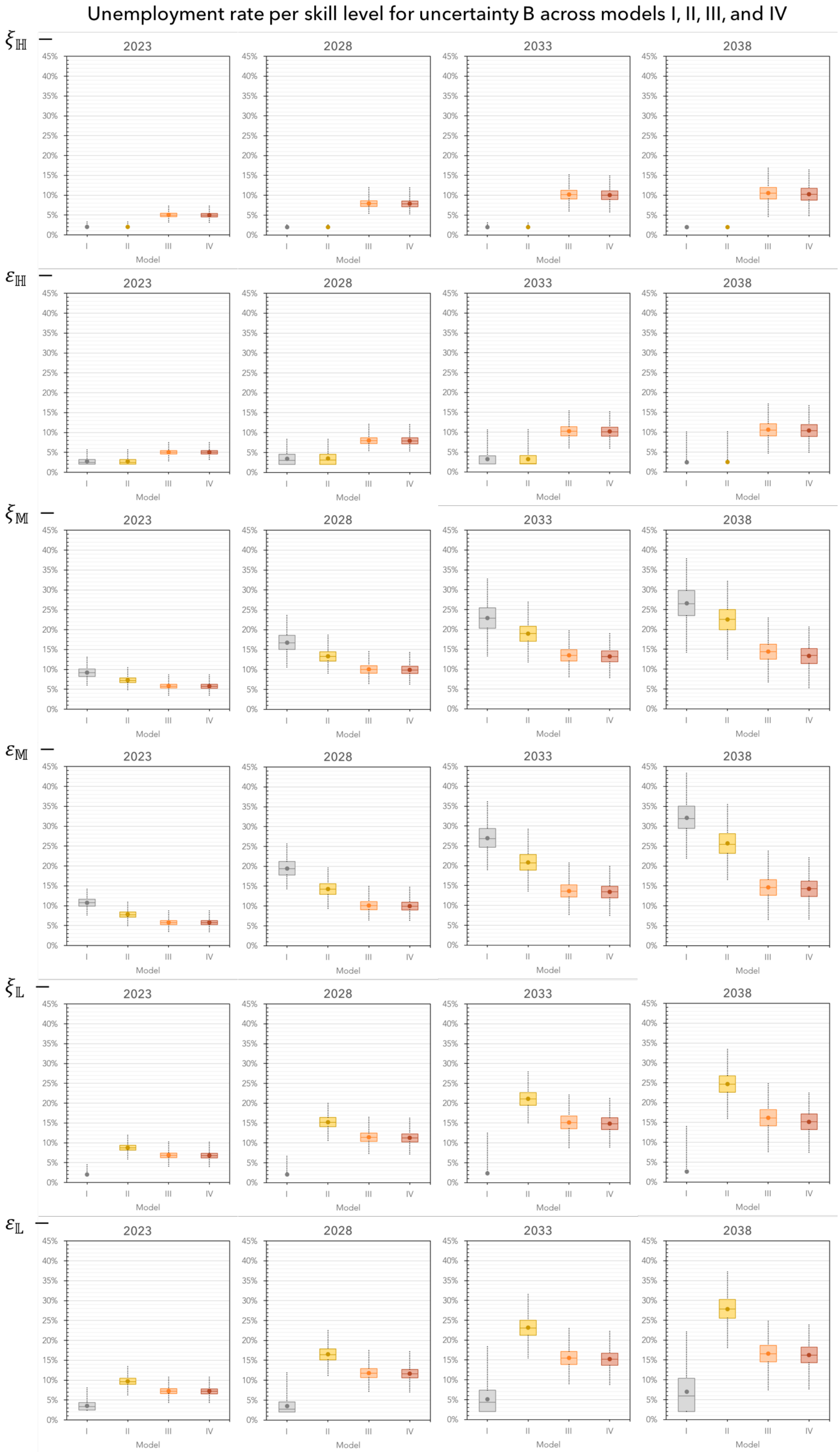


Figure 28 Unemployment projections for uncertainty B for all skill levels (Overview per 5 years)

time frame. Second, Gregory, Salomons, and Zierahn's (2016) (A) estimate has been corrected to continue at the current substitution rate for the entire time period of the simulation.

13.2.1 Future labour markets with Solow Paradox

The results generated across the four uncertainty ranges (1000 experiments per uncertainty using the scripts provided in Appendix XII) demonstrate different outcomes and behaviour. An overview across the skill levels is provided in Figure 29. Whereas, a detailed representation per skill level over time is provided in Appendix XIII. For each of the automatibility estimates the results are discussed.

Table 4 Estimates of technological automatibility for the Netherlands

Uncertainty	Task $[T]$	Automation Estimate for NL $[\Xi_\tau]$	Time frame $[\Delta t_\Xi]$	Probability range $[P_\tau]$
A. Gregory, Salomons, and Zierahn (2016)	Others	9.0-10.2%	20 Years	1.0
	$\mathcal{A}, \mathcal{R}_\mathcal{A}$	0.9-1.02%	20 Years	1.0
C. Arntz, Gregory, and Zierahn (2016)[96]	$\mathcal{M}, \mathcal{R}_\mathcal{M}$	37-51%	± 20 Years	0.7-1.0
	$\mathcal{R}, \mathcal{R}_\mathcal{R}$	7%	± 20 Years	0.7-1.0
	$\mathcal{A}, \mathcal{R}_\mathcal{A}$	0.1-1%	± 20 Years	0.7-1.0
D. Nedelkoska and Quintini (2018)[97]	$\mathcal{M}$	24.5%-42.2%	± 20 Years	0.7-1.0
	$\mathcal{R}, \mathcal{R}_\mathcal{R}, \mathcal{R}_\mathcal{M}$	28.9%-32.6%	± 20 Years	0.59-0.94
	$\mathcal{A}, \mathcal{R}_\mathcal{A}$	0.001-0.01%	± 20 Years	0.27-0.85
G. Deloitte (2016)[98]	$\mathcal{M}$	42.3%	± 20 Years	0.7-1.0
	$\mathcal{R}, \mathcal{R}_\mathcal{R}, \mathcal{R}_\mathcal{M}$	42.3%	± 20 Years	0.7-1.0
	$\mathcal{A}, \mathcal{R}_\mathcal{A}$	10.4-19.3%	± 20 Years	0.7-1.0

A. **Gregory, Salomons, and Zierahn (2016)**
The outcomes for A (Grey boxes in plots in Figure 29 and in Appendix XIII) demonstrate that continuation of the current rate of labour substitution is likely (75% of outcomes across the uncertainty range) to result in reducing unemployment across all skill levels up to 2028, albeit with the upper 25% of outcomes demonstrating small increases in unemployment. The unemployment rates for those later cases outside of the third quartile are, however, similar to current unemployment rates with a maximum ranging from 6,1% for the high skilled ($\varepsilon_\mathbb{H}$ and $\xi_\mathbb{H}$), and 6% for the middle skilled ($\varepsilon_\mathbb{M}$ and $\xi_\mathbb{M}$), and 6-8% for the low skilled ($\varepsilon_\mathbb{L}$ and $\xi_\mathbb{L}$). Yet, from 2028 to 2038 the unemployment rates are expected to decline and result in labour supply shortages across all skill levels for the upper quartile (i.e. the top 25% range of most adverse outcomes). These values occur at the same point in time of the recessions in the economic model and demonstrate temporary peaks during this period (Appendix XIII). Hence, these values are most likely the result of adverse economic conditions and not technology. Concerning the outcomes within the first to third quartile, unemployment is likely to develop in parallel with the business cycle and remain near the current levels up to 2028. Here after a consistent shortage of labour supply can be observed. These shortage projections are in line with the currently observed trends in relation to demographic and labour force developments due to societal aging (Bloom, Canning & Fink, 2001, 2008; Peterson, 2017). Note that the model does not include regional and intercontinental migration.

[96] Based on Table 5 in Arntz, Gregory, and Zierahn (2016, p. 34), for the single 7% estimate a 5% error margin is used and for the time frame a 10% up and down margin is used.
[97] Based on Figure 4.2 in Nedelkoska and Quintini (2018, p. 49), estimates corrected with 5% up and down to account for possible measurement error in graph interpretation and a 10% up and down margin is used for the time frame.
[98] For the single 42,2% estimate a 5% error margin is used and for the time frame a 10% up and down margin is used (Deloitte does not specify a concrete timeframe or timeline)

Unemployment rate per skill level across uncertainty A, C, D, and G

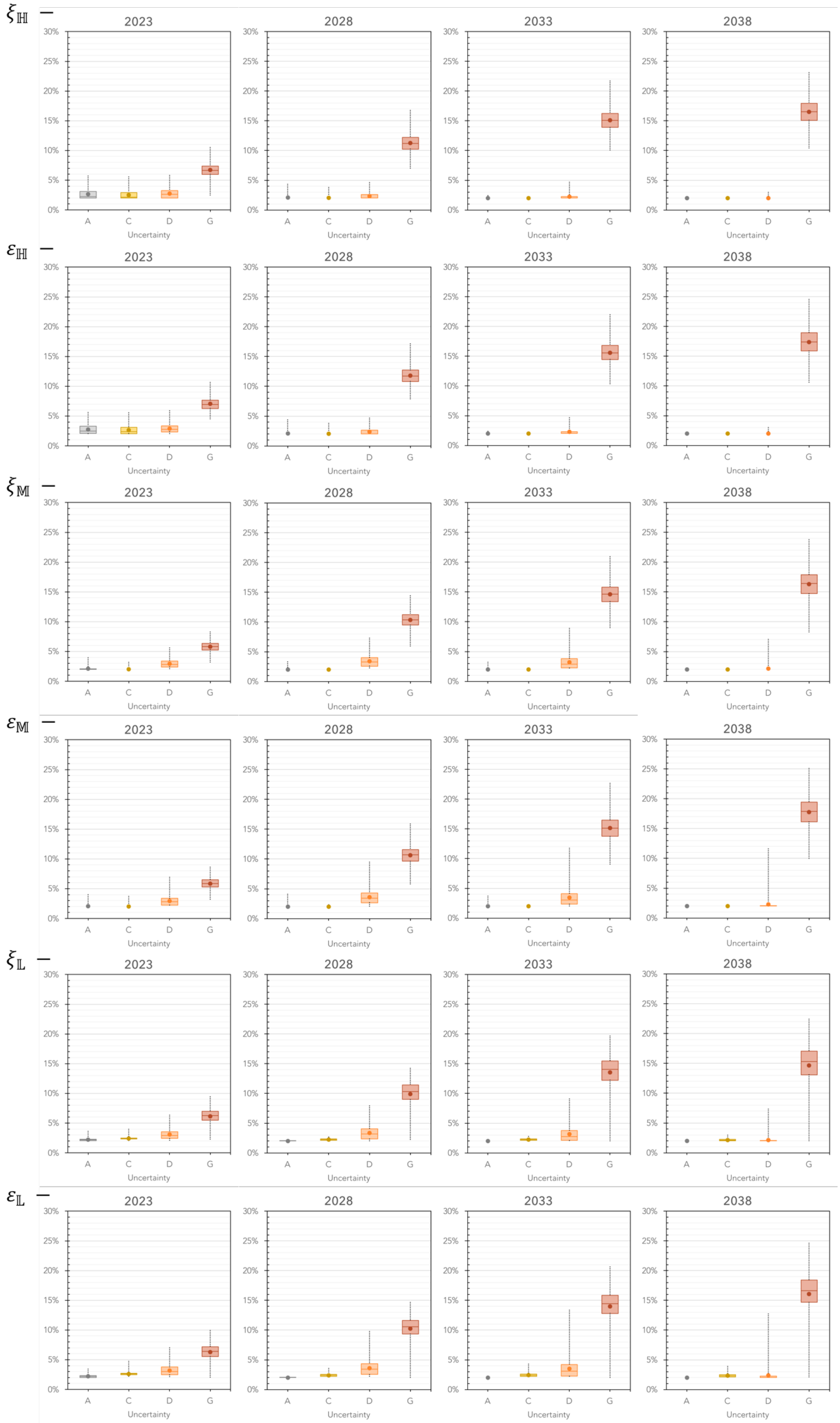


Figure 29 Unemployment projections for the Netherlands across uncertainties A, C, D, and G (Table 4) for all skill levels

C. **Arntz, Gregory, and Zierahn (2016)**

The outcomes for C (Yellow boxes in plots in Figure 29 and Appendix XIII) demonstrate a consistent decline in unemployment across the skill levels up to 2023 for all projections. Hereafter, a systematic shortage in labour supply can be observed. The contrast with automatibility estimate A stems from the lower automatibility estimate for routine tasks. The considerably higher automatibility of manual tasks is offset by reallocation to routine tasks and by declining low skilled labour force under demographic trends. Therefore, the drastic difference in projected outcomes compared to the other automatibility estimates can be explained by the contrasting manual task-skewed nature. Moreover, the automatibility estimate for routine tasks is below the current rate and, thus, reduces simultanoes pressure on labour supply reallocation. Hence, the results demonstrate that even if a significant share of a task type (Manual tasks $\mathcal{M}$, $\mathcal{R}_{\mathcal{M}}$ in this case) is substituted, reallocation and re- and up-skilling will be counterbalance this trend. Furthermore, the automatibility estimates are based on Arntz, Gregory, and Zierahn's (2016) ISCED categorised outcomes which may have caused inconsistency in the relation between skill levels and tasks in respect of the methodology employed in this study.

D. **Nedelkoska and Quintini (2018)**

The outcomes for D (Orange boxes in plots in Figure 29 and Appendix XIII) demonstrate relatively stable unemployment projections across the skill levels up to 2033 within the first to third quartile of the projections. The unemployment rate projections range from 2.1-3.1% (2023), 2.0-2.7% (2028), 2.0-2.2% (2033), and a consistent shortage of supply at 2.0% (2038) for the high skilled ($\varepsilon_{\mathbb{H}}$ and $\xi_{\mathbb{H}}$). For the middle skilled ($\varepsilon_{\mathbb{M}}$ and $\xi_{\mathbb{M}}$), the projections range from 2.2-3.4% (2023), 2.5-4.2% (2028), 2.1-4.1% (2033), and a consistent shortage of supply around 2.0-2.1% (2038). Lastly, the unemployment rates for the low skilled ($\varepsilon_{\mathbb{L}}$ and $\xi_{\mathbb{L}}$) range from 2.4-3.9% (2023), 2.3-4.3% (2028), 2.1-4.1% (2033), and 2.0-2.1% with a shortage of supply (2038).

However, in the upper quartile of most adverse conditions the uncertainty range demonstrates unemployment rates upto 6% (2023), 4.8% (2028), 4.9% (2033), and 3.0% (2038) for the high skilled; 5.8-7.0% (2023), 7.2-9.5% (2028), 9.0-12.0% (2033), and 7.0-10.8% (2038) for the middle skilled; and 6.2-7.1% (2023), 8.0-9.9% (2028), 9.1-13.2% (2033), and 7.3-12.9% (2038) for the low skilled. Across all skill levels, the extended skilled labour force ($\xi_{\mathbb{L}}$, $\xi_{\mathbb{M}}$, and $\xi_{\mathbb{H}}$) has a consistently 0.1% lower projected unemployment rate than the non-extended skill labour force within first to third quartile. For the fourth quartile projections of the middle and low extended skill labour force, respectively, have a 1.2-3% and 0.9-5.6% lower unemployment rate.

From 2033 to 2038, the same labour supply shortage trend as with automatibility estimate A can be observed for the projections within the first to third quartile. However, in the fourth quartile, the uncertainty range demonstrates continuation of the higher unemployment rates across the skill levels, albeit with a small decline. The results demonstrate that there is a significant difference between automatiblity, consequential substitution, and actual unemployment. Although 2 to 3 times as many tasks are automatable compared to the current rate (A), the first to third quartile unemployment rates remain within present unemployment rate margins across the skill levels, ranging from 2.0% to 4.3%.

G. **Deloitte (2016)**

The outcomes for G (Orange boxes in plots in Figure 29 and Appendix XIII) demonstrate consistently higher unemployment rates compared to A, C, and D - which is to be expected given the higher automatibility estimates (Table 4). The projections demonstrate a consist increase in the lower bound (lower whisker), the first to third quartile, and upper bound (top whisker) of unemployment. The unemployment rate of the high skilled labour force contrasts significantly with other automatibility estimates. Whereas with A, C, and D the high skilled labour force experiences a consistently lower and declining unemployment rate, the unemployment rate with G increases in parallel with the other skill levels. This difference in behaviour can be attributed to the relatively high automatibility of abstract in scenario G (i.e. 0-1.02% compared to 10.4-19.3%).

The unemployment rate projections for the high skilled ($\varepsilon_{\mathbb{H}}$ and $\xi_{\mathbb{H}}$) range from 6.0-7.7% (2023), 10.2-12.9% (2028), 13.9-16.8% (2033), and 15.0-19.0% (2038). For the middle skilled ($\varepsilon_{\mathbb{M}}$ and $\xi_{\mathbb{M}}$) the projections range from 5.1-6.5% (2023), 9.5-10.7% (2028), 13.3-16.5% (2033), and 14.8-19.5%

(2038) and for the low skilled ($\varepsilon_{\mathbb{L}}$ and $\xi_{\mathbb{L}}$) from 5.5-7.2% (2023), 9.0-11.7% (2028), 12.1-15.9% (2033), and 13.0-18.5% (2038) for the low skilled ($\varepsilon_{\mathbb{L}}$ and $\xi_{\mathbb{L}}$).
Interestingly, the automatibility of abstract tasks is 54-75% lower compared to the other task types, yet the unemployment rate is comparable. This dissonance can be explained by the demographic growth of the high skilled labour force share. Again, the results demonstrate that there is a significant difference between automatibility, consequential substitution, and actual unemployment.

13.2.2 Future labour markets without Solow Paradox

The simulation of automatibility uncertainty scenario B to determine the effect of adaptability and spill-overs (see 13.1) highlighted that the difference between model configuration III (without productivity spill-overs) and IV (with spill-overs) was minimal. This behaviour deviates from the expected behaviour due to the continuation of the current levels of productivity growth. As a result, the relative increase of productivity growth above current levels is limited and therefore the spill-over effect (task specific and in addition to the projected macro-economic growth) is limited. To demonstrate the effect of increasing productivity and therefore spill-overs, the simulation of uncertainty scenario G was repeated (1000 experiments with the script provide in Appendix XIV) with a task-specific productivity growth 1.5 to 2 times higher (i.e. 0.9-2.0% instead of 0.6-1.0%). The results (Figure 30 for a brief overview and Appendix XV for detailed results) demonstrate that the spill-over effects can offset substituted labour input. Therefore, the model is consistent with the *productivity effect* as defined by Acemoglu and Restrepo (2018) and *product demand effect* by Gregory, Salomons, and Zierahn (2016).

13.2.3 Accounting for the automatibility versus substitution difference

Using the most extreme scenario for the Netherlands, i.e. G, the effect of the plausible difference between technological automatibility and actual implementation, and thus substitution, is simulated (1000 experiments with the script provided in Appendix XVI). Outside of the scope of the model, Brynjolfsson, Rock, and Syverson (2017) and Arntz, Gregory, and Zierahn's (2016) identified a range of factors that influence the development and implementation of technology. In relation to the difference between automatilibity and substitution Brynjolfsson, Rock, and Syverson (2017) describe that, first, technology may not mature up to an operationally or financially feasible level. Second, technology may not become widely adopted due to (legal) limitations and firm size/power whereby technology is exclusively available to few a beneficiaries and applications, and thus limiting dissipation, entrance of competitors, and economy wide implementation. Third, the implementation of advanced technologies will require organisational, business-cultural, and structural changes within and between firms. As a result, cross-firm supply chains and sectors will need to undergo reorganisation to adapt to the changing production processes and products. In relation with the latter, technology itself changes products and production by speeding up the development cycle and scalability (De Backer, DeStefano, Menon & Ran Suh, 2018; Frey & Osborne, 2017). In a reflection of the expert judgment based estimates, Arntz, Gregory, and Zierahn's (2016) highlight that future data processing and storage (availability) limitations may inhibit wide spread implementation of advanced IT and RT systems. Moreover, ethical, legal, and legislative factors can prevent the implementation of technology (e.g self-driving cars or drones). Unfortunately, modelling these factors extends beyond the scope of this research as they, similarly to the complex education models, would require separate sub-models that are not unlikely the size of the model developed in this research. In this sense, the factors are treated as exogenous and are included as a black box via a factor that creates a difference between automatibility and substitution (i.e. the endogenous feedback mechanisms are operational).

To simulate uncertainty scenario D, this factor was set to range between 1 (automatibility and substitution are equal) to 2.903[99] (therefore the automatibility is equal to the range in Table 4 times 1 divided by a value from the range 1 to 2.903). The latter number is set to ensure the substitution rate does not drop below the current levels (from uncertainty scenario A). The results (Figure 31 and Appendix XVII) demonstrate that 75% (up to third quartile) of the outcomes show a declining or stable unemployment rate. Analysis using PRIM (Appendix XVIII) indicates that upper quartile outcomes occur when the substitution difference factor is 1.0-

[99] Since 42.3% times 0.7 probability divided by the maximum current rate of 10.2 and probability 1 of A results in 2.903.

1.7 for $\xi_{\mathbb{H}}$; 1.0-1.6 for $\varepsilon_{\mathbb{H}}$; and 1.0-1.5 for $\xi_{\mathbb{M}}$, $\varepsilon_{\mathbb{M}}$, $\xi_{\mathbb{L}}$, $\varepsilon_{\mathbb{L}}$. This, in practical terms, implies that when substitution of $\mathcal{M}$, $\mathcal{R}$, $\mathcal{R}_{\mathcal{R}}$, $\mathcal{R}_{\mathcal{M}}$ exceeds 28.2% (D estimate is 42.%) and substitution of $\mathcal{A}$, $\mathcal{R}_{\mathcal{A}}$ exceeds 11.4% (D estimate is 10.4-19.3%), unemployment may drastically increase. Respectively, these number equate to an annual substitution rate of 1.41% and 0.57% (compared to the current maximum of 0.51% and 0.051% in scenario A). Yet, it is unlikely that this pace of substitution is realistic given the current evidence concerning the exogenous factors. In future research, the model can be expanded with a separate technology sector to embed these factor in the model and study their effects in detail for the extreme scenarios (substitution difference factor value of 1.0-1.7) rather than using the current implementation.

In relation with the automatibility estimates and findings for scenario C (Yellow boxes in plots in Figure 29 and Appendix XIII), it is concluded that especially substitution of abstract tasks and the loss of high-skilled labour demand will result in unemployment trickling down because re- and up-skilling to improve employability is no longer a viable strategy and labour supply re-allocation increases competition over routine and manual tasks. However, the high automatibility of abstract tasks in estimate D is in sharp contrast with the empirical and theoretical findings of Frey and Osborne (2017), Nedelkoska and Quintini (2018), Arntz, Gregory, and Zierahn (2016). The first argue that only after the next two decades and if the expected technological bottleneck concerning social, communicative, and creative (see 3.1) aspects of abstract tasks are resolved, then abstract task will become automatable. The second specifically emphasise that substitution of abstract tasks and high skilled (cognitive) labour is highly unlikely. Moreover, Arntz, Gregory, and Zierahn (2016) expect that at maximum 1.5% of high skilled labour is automatable in the next 20 years across OECD countries. In addition, Arntz, Gregory, and Zierahn (2016) specifically emphasise that the current automatibility estimates of all three are likely to be overestimations,

> *'However, even for the less restrictive task-based approach, there are good reasons to be cautious when interpreting the results. Firstly, the approach still reflects technological capabilities based on experts' assessments rather than the actual utilisation of such technologies, which might lead an overestimation of job automatibility. Secondly, even when new technologies are increasingly used, the effect this has on employment prospects depends on whether workplaces adjust to a new division of labour or not. Workers might adjust by increasingly performing tasks that are complemented by the new technologies. Thirdly, the approach considers only existing jobs.'* (Arntz, Gregory, & Zierahn, 2016, p. 21)

From this point of departure, and in consideration that the SD model does account for these dynamics, this hypothesis can partially be confirmed. Labour force adjustment through reallocation and re- and up-skilling reduces unemployment drastically. Moreover, spill-over effects associated with technological advancement will counteract the loss of labour input demand. Therefore, the methodology applied in this study accounts for these factors that result in overestimation. The results from the three tests in 13.2 indicate that unemployment will only increase drastically under extreme conditions, i.e. when substitution is 3-fold the current rate (which is improbable due to external factors) and/or a significant portion of abstract tasks is substituted (which conflicts with empirical and theoretical evidence). From the outcomes of 13.1 (concerning adaptability) it can be concluded that unemployment will only increase drastically under conditions where adaptability is non-existent (which conflicts with empirical and theoretical evidence). In respect of the research question, '*What are the labour market implications of technological advancement in the next 20 years?*', it is concluded that unemployment is will remain at current levels or reduce to labour input shortages (within the boundaries of the model).

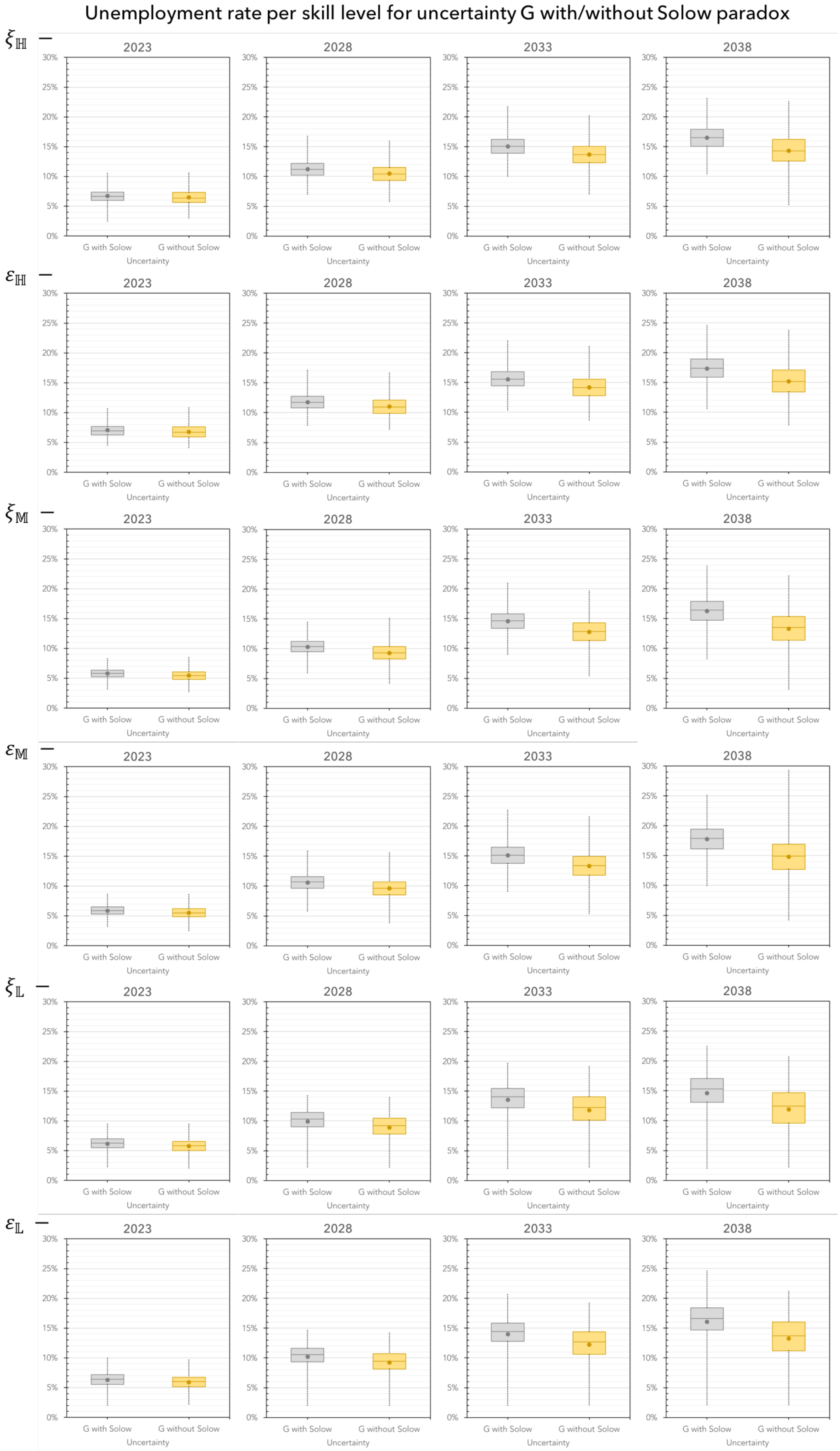


Figure 30 Unemployment projections for the Netherlands for uncertainties G with and without continuation of the Solow paradox (Table 4) for all skill levels

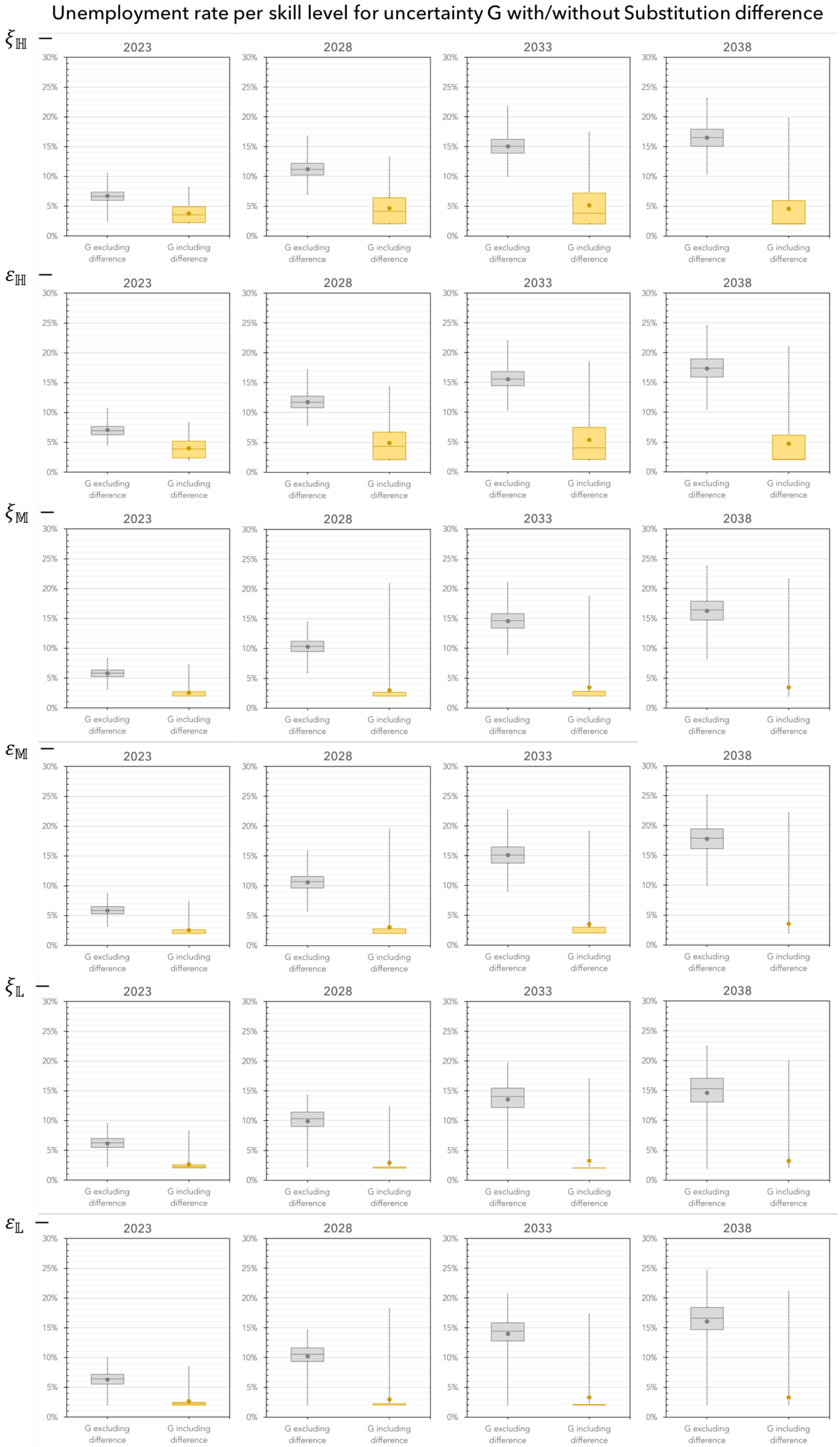


Figure 31 Unemployment projections for the Netherlands for uncertainties G with and without time difference between automatibility and substitution

13.3 Policy identification with PRIM

The exploratory outcomes from 13.2 demonstrate that unemployment is unlikely to increase beyond current levels in the Netherlands, except for uncertainty scenario G and the upper quartile of D. As stated in the previous sections, the high automatibility of abstract tasks projected by Deloitte (2016) (G), conflicts with the scientific consensus. Yet, for exploratory purposes, uncertainty scenario G provided a suitable range of outcomes to determine the effect of productivity growth spill-overs and the difference between substitution and automatibility. The outcomes of the other estimates are not suitable for this purpose due to the projected distribution and shortages (i.e. because of which the effects would not be present in the outcomes). In contrast, policy identification is performed based on the estimates that correspond to the current scientific consensus, TBTC paradigm, and real world representatives. Hence, within the TBTC and RRTC framework, the outcomes of uncertainty C and D, respectively demonstrate a consistent decline in unemployment and relatively stable unemployment rate. However, the upper quartile outcomes of uncertainty D imply that growing unemployment can occur. These upper outcomes are studied to determine whether policy levers exists (within the current model operationalisation) that could prevent future growth of unemployment. Moreover, analysing these outcomes facilitates comparison with the findings of Frey and Osborne (2017), Nedelkoska and Quintini (2018), and Arntz, Gregory, and Zierahn (2016).

PRIM is used with the outcomes of estimate D from the exploration simulation (Figure 29) to determine the conditions under which technological advancement results in growing unemployment and identify policy levers that can be used under such condition. PRIM creates boxes of projections of interest that are characterised by *coverage* and *density* (Kwakkel, Haasnoot, & Walker, 2016). After running the PRIM algorithm, the boxes with a coverage and density rate above 0.8 are selected and analysed. Within these boxes, PRIM defines the relative influence of the uncertain parameters based on quasi-p values. The values express the statistical significance and comparative relevance (Bryant & Lempert, 2010; Kwakkel, Haasnoot, & Walker, 2016). The lower the quasi-p values of an uncertain parameter within a box, the more relevant and statistically significant it is. Note, as described in 2.2, that use of RDM and PRIM deviates from the conventional application of the four steps for development and evaluation of alterative policies and strategies. Therefore, in line with the goals and research question of this thesis, the effects of adaptability have been identified. PRIM is employed in this analysis to determine the potential and need for incentivising policies.

The results of the PRIM analysis are provided in Appendix XIX (including script). For the high skilled labour force, 98% outcomes are equal or below the current unemployment rate (current average across age cohorts of 3.1% for $\varepsilon_{\mathbb{H}}$ and 3.0% for $\xi_{\mathbb{H}}$) with a maximum future unemployment rate of 3.9% for $\varepsilon_{\mathbb{H}}$ and $\xi_{\mathbb{H}}$. Moreover, PRIM cannot return a consistent enough set of boxes to meet the threshold criteria. In other words, the upper outlying projections do not have consistent input factor to which the outliers can be contributed. Furthemore, given the consistency, these results would not provide fruitful levers since the unemployment rate is not projected to increase compared to the current levels. For the middle skilled (initial unemployment 4.4% for $\varepsilon_{\mathbb{M}}$ and 4.0% for $\xi_{\mathbb{M}}$), the projections above the current unemployment rates (87 of 1000 for $\varepsilon_{\mathbb{M}}$ and 95 of 1000 for $\xi_{\mathbb{M}}$) do not contain boxes with a density and coverage above 0.8. Therefore, the projections are diverse and cannot be attributed to a consistent combination of factors. The only influential factor and potential policy lever that was identified, was the re- and up-skill sensitivity for $\varepsilon_{\mathbb{M}}$. This suggests a lack of re-skilling contributes to the higher unemployment rate of these outliers. It should be noted that 95% of the projections for $\varepsilon_{\mathbb{M}}$ result in an unemployment rate of 5.0% or lower (98% of outcomes below 6.0% and maximum of 8.4%) and 4.5% for $\xi_{\mathbb{M}}$ (98% of outcomes below 5.0% and maximum of 6.4%). For the low skilled labour force, the same problem as with the high skilled projections was present. Therefore, 98-99% of the outcomes (22 of 1000 for $\varepsilon_{\mathbb{L}}$ and 8 of 1000 for $\xi_{\mathbb{L}}$) are equal or below the current unemployment rate (current average across age cohorts of 6.2% for $\varepsilon_{\mathbb{H}}$ and 5.7% for $\xi_{\mathbb{H}}$). Even though the upper quartile whiskers (Figure 29) for the low skilled labour force suggest the possibility of unemployment growth, these outcomes are highly unlikely. Moreover, within the upper quartile projections and projections of unemployment growth (compared to the current unemployment rates) most outcomes are close to the third quartile boundary with some extreme outliers. The current unemployment rates of lower skilled are considerably higher than the other skill levels. Unfortunately, the outcomes above the highest unemployment rate of the other skill levels (4.4% of $\varepsilon_{\mathbb{M}}$) do not provide consistent policy levers for the future to reduce the low skilled unemployment rate within the scope of the model.

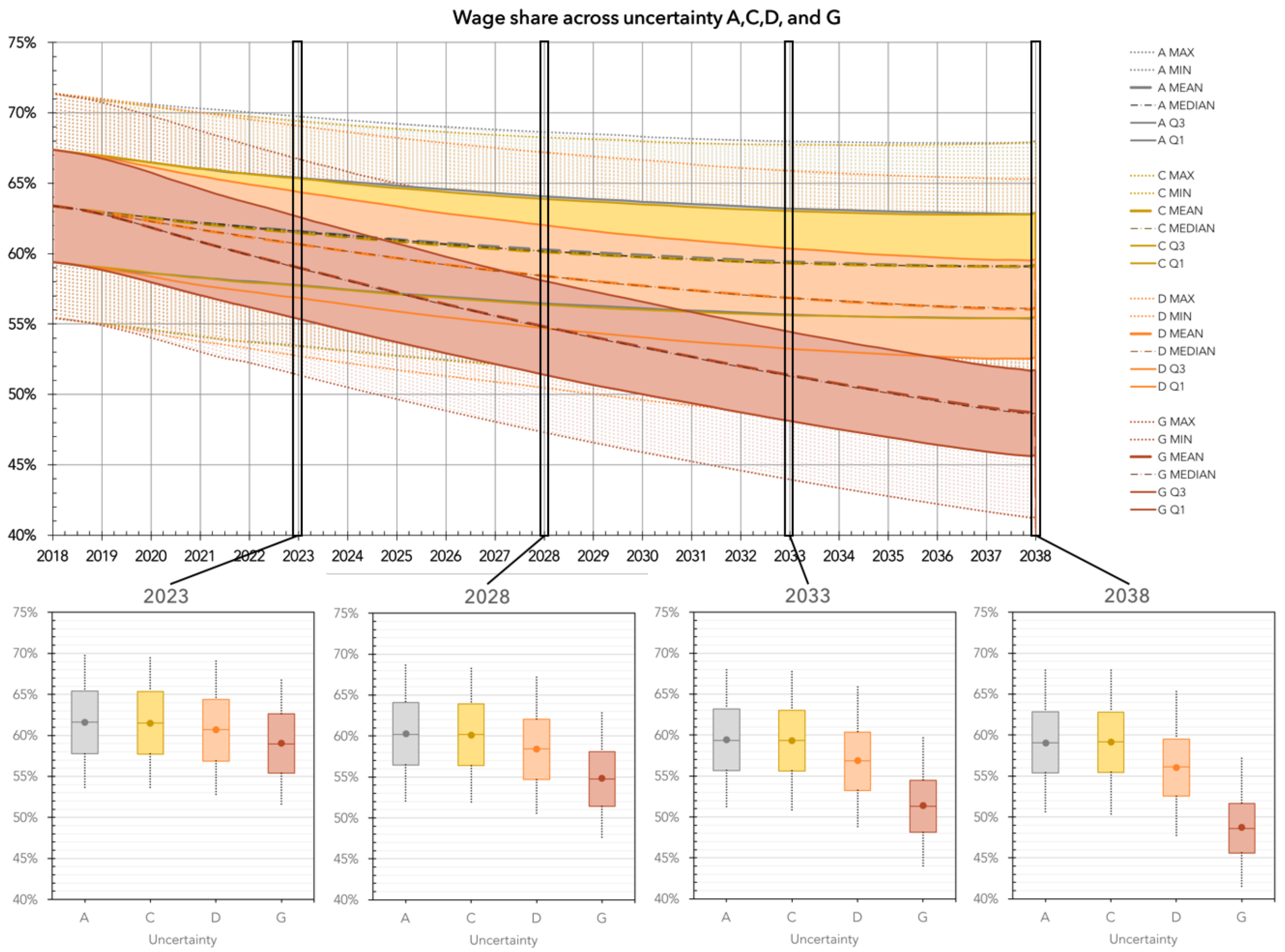
To conclude, the upper quartile projections and projections of unemployment growth across all skill levels are the result of a diverse combination of factors, that together create the adverse conditions for the labour force. These outcomes do not provide consistent opportunities for policy intervention, mostly because the projections predict unemployment rates that remain close to the current levels because of which policy intervention is unlikely to be necessary within the scope of this study. The projections of unemployment growth only occur under extreme conditions (>2%) and the growth is generally limited to 1 to 2 percent point and maxima of 2 to 4 percent point. In this respect, the sub-research question '*Which policy levers are available to mitigate the projected future unemployment trends and maximise economic and living standard growth brought about by advanced robotics and artificial intelligence?',* leads to the conclusion that policy intervention in reaction to advanced RT and IT is unlikely to be required concerning unemployment. Yet, the results from 13.1 concerning the effect of adaptability do highlight that adequate re- and up-skilling will reduce the future unemployment rate. Visually representing the total re- and up-skilling outcomes of estimate D from the exploration simulation in Appendix XX reveals that a considerable share of the labour force will need to be trained when substitution materialises at the pace of the automatibility estimates (which are 2- to 3-fold the current levels, see Table 4). Concerning reskilling, 1.1-1.2% of the high skilled labour force ($\varepsilon_{\mathbb{H}}$) will need to be reskilled (to $\xi_{\mathbb{H}}$) in the next 10-20 years; 1.0-1.3% of the middle skilled labour force ($\varepsilon_{\mathbb{M}}$) will need to be reskilled (to $\xi_{\mathbb{M}}$) in the next 20 years; and 0.5-1.0% of the low skilled labour force ($\varepsilon_{\mathbb{L}}$) will need to be reskilled (to $\xi_{\mathbb{L}}$) in the next 20 years. Concerning upskilling, 6.4-8.3% of $\xi_{\mathbb{M}}$; 7.7-9.0% of $\varepsilon_{\mathbb{M}}$; 1.4-2.4% of $\xi_{\mathbb{L}}$; and 1.9-3.5% of $\varepsilon_{\mathbb{L}}$ will need to be up-skilled in the next 20 years. The lower percentage of up-skilling of the low skilled labour force is partially due to the demographic trend whereby younger generations in the labour force are higher educated and lower educated older generations retire. Therefore, to revisit the sub-question, policy intervention should focus on improving the employability of vulnerable groups in the future, i.e. the middle skilled, through stimulation and incentivising skill attainment.

13.4 Synthesis of simulation results

The unemployment outcomes for the Netherlands under automatibility estimates A, C, D, and G demonstrate a diverse set of outcomes. Most notable are the shortage in labour supply in scenario A and C and the low unemployment rates of D up to the third quartile relative to the automatibility of labour input. Based on the exploratory projections across automatibility estimate G and the upper quartile of D, the conclusion is drawn that excessive unemployment will only occur in the extreme cases that substitution materialises at a similar pace as technological automatibility. Therefore, unemployment is unlikely to drastically increase in the next twenty years. The analysis of the conditions under which unemployment will increase (within the scientific consensus concerning abstract task) reveal that the upper outliers are scarce (>2%) and cannot be attributed to a single factor or potential policy intervention. These findings are consistent with the notion that the current future estimates (based on expert judgement, static task compositions, and not exclusion of adaptability) are likely to overestimate the impact of technological change on labour (Arntz, Gregory, and Zierahn (2016).

The scope and aim of this study concerned unemployment and moving from static analysis of the plausible future of work to dynamic simulation based on the TBTC and RRTC framework of technological change. Hence, the model has been developed to study plausible future unemployed resulting from technological advancement. Closely related to the concerns of future unemployment, are concerns for growing inequality and a reducing wage share (see 5.2 and 7.1). Over the past three decades, the wage share has consistently declined at an annual 0.3% percent point rate (OECD, 2015b). One on hand, the position of labour deteriorates, while on the other, technological productivity growth mainly attributed to profits. As a result, inequality grows as income form capital accrues mainly with the higher wage income groups (as discussed in 5.2). The current rate at which IT and RT are increasingly capable of substituting labour sparks debates whether the balance between wage-share and profit-share is becoming ever-in favour of capital owners (Autor & Salomons, 2017).

An analysis of the development of the wage share in association with the substitution process in the model, suggest that the concern over growing inequality are justified (Figure 32). The wage share continues to decline across all unemployment scenarios (A, C, D, and G). However, from approximately 2033 onward the wage share appears to stabilise for scenarios A, C, and D. The scatter plot at the bottom demonstrates that the wage share systematically declines across all initial wage shares (an initial uncertainty range is used since multiple definitions exists, see Cho, Hwang, & Schreyer (2017)) and uncertainty scenarios. If the current substitution and productivity rate continues in the future (A), the wage share will on average annually decline with 0.34%. This is consistent with the recent trend of 0.3%. In case of scenario C, the same decline can be expected (0.34%). If technological advancement accelerates, the wage share will decline faster with an annual rate of 0.58% (D) and up to 1.16% (G). The latter only occurs in the extreme case of scenarios G (which are not consistent with the scientific consensus concerning abstract task automatibility). To conclude, inequality will grow across all uncertainty scenarios. Hence, the negative economic and societal implications associated with inequality growth will continue to be a challenge that needs to be resolved. In contrast, in labour economic literature of the future of work, an emphasis is placed on plausible unemployment outcomes because of technological advancement. In this respect, and in consideration of the unemployment outcomes, this study suggest that unemployment will not be a major concern. Instead, the growing decline of the wage share implies that wage owners do not share in future economic growth and the plausible welfare effect of technological advancement. Therefore, a shift of focus towards inequality in relation with the future effect of technological advancement of RT and IT is required in future research.



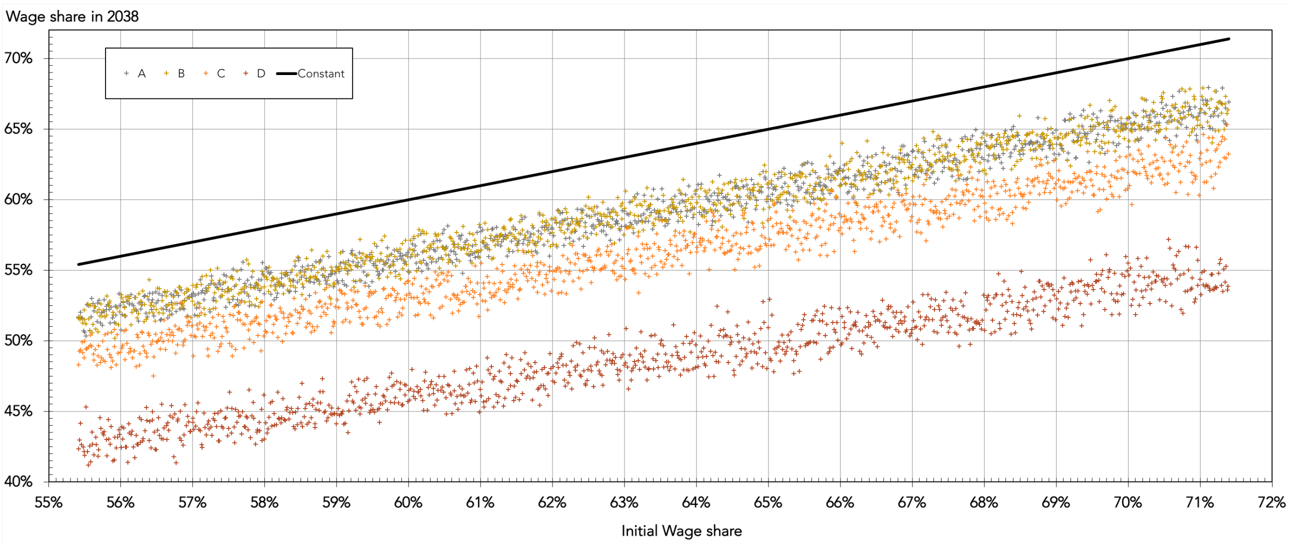


Figure 32 Wage share projections for uncertainty A, C, D, and G (model IV)

Part III Synthesis of Findings

The results generated for the Netherlands are reflected upon from a theoretical and empirical perspective. The implications of technological progress are placed in a broader international and societal/social context. To conclude, the research question is revisited, reflected upon, and the methodology and outcomes are discussed.

14 Findings & Conclusions

Technological advancement is situated at the centre of economic growth and reshapes how we work, what kind of work we do, and who has work. Concerning the latter, there is growing fear that future technological advancement will deteriorate the position of the working class because IT and RT are becoming increasingly capable of performing human labour input in production tasks. Therefore, the potential impact of robotics and artificial intelligence is at the centre of the academic and societal debate about labour and the future of work. An important factor contributing to this debate is the uncertainty involved with predicting the future capabilities of technology and the impact it may have on work and society. Advancements in IT and RT will result in technological assimilation and extension of the range of tasks technology can perform. As a result, the current polarisation paradigm and routine biased explanation will fall short to describe future substitution due to expanding technological capabilities. That is, the combination of sensorimotor, adaptive, flexible, and mobile RT with cognitively capable AI will extend the range of automatable tasks from routine to manual tasks - and abstract tasks in the long run. Moreover, continuous price reduction of such technology will make capital increasingly competitive with labour and substitution increasingly financially feasible over the next two to three decades.

In consideration of this context, the future effect of advanced IT and RT on labour substitution, unemployment, and labour force adaptability has been studied using dynamic simulation following the RDM framework. The technological change and labour substitution framework literature (TBTC and RRTC) was synthesized with a systems approach to conceptualise and operationalise a future oriented model. This model has been implemented in SD, simulated using EMA, and analysed using PRIM to determine the range of plausible futures and potential for policy intervention. The main findings contribute to answer the main question,

> *To what extend is the labour force capable of adapting to labour substitution by advanced robotics and artificial intelligence, and can be incentivised to do so, to mitigate future unemployment?*

This study shows that, although labour may become increasingly substitutable by technology, labour force adaptability via labour supply reallocation and skill attainment will be able to successfully counteract the loss of employability in all but the extreme cases. Moreover, spill-over effects that arise because of productivity growth associated with technological change will further counterbalance the substituted labour demand. Continuation of the current substation rate and technological advancement pace is likely to constrain future economic outcomes due to labour supply shortages rather than growing unemployment. Moreover, simulation across a variety of future scenarios illustrate that acceleration of unemployment is unlikely, except when the substitution rate 3- to 4-folds in the next 20 years (from current maximum annual rate of 0.51% of labour hour demand, or approximately 10% in 20 years (Gregory, Salomons, & Zierahn, 2016)). Although technological automatibility (i.e. the ability of technology to automate and replace human labour input in tasks) may develop at this pace, the implementation of technology and the substitution of labour takes considerably longer due to financial, technological, competitive, legal, social, sectoral, and structural factors. Therefore, the outcomes demonstrate that sufficient labour force adaptability should be able offset labour substitution. Yet, the adaptability of the labour force under these conditions does require that approximately 1.0% of the low, middle, and high skilled labour force needs to be reskilled to work with future technology and approximately 2.3% of the low skilled and 7.9% of the middle skilled labour force needs to be upskilled in the next 20 years in the Netherlands. Furthermore, the outcomes for the Netherlands suggest that only in adverse conditions where labour input in abstract tasks is substituted in addition to manual and routine tasks, that unemployment will significantly rise above current levels (i.e. a combination of 2- to 3-fold of manual and routine task input substitution at 1.41% annually and abstract task input substitution of 0.57% annually) since adaptation via re-and up skilling does not improve employability. However, the literature highlights that it highly improbable that the abstract tasks that employ the high skilled labour force will be automatable due to the social, communicative, creative, intuition, and inductive reasoning aspects of these tasks (as found by Arntz, Gregory, and Zierahn (2016), Frey and Osborne (2017), Nedelkoska and Quintini (2018)). As a result, the total substituted labour input of abstract tasks is expected to be at around 1-1.5% over the next 20 years. Hence, this combination of manual, routine, and abstract task labour input substitution conflicts with the current scientific consensus. Therefore, it is concluded that the future unemployment rate is likely to be equal or below the current skill level-specific unemployment rates. In addition, the labour force is likely to able to adapt to changing employability and labour markets to mitigate potential unemployment growth in relation with future technological advancements.

These findings are consistent with the current literature and empirical evidence even though the methodology employed in this study deviates from the existing body of work. In this respect, this study contributes to the academic field in an attempt to resolve the shortcomings of current expert judgement based *a priori* studies that examine plausible future job losses associated with technological advancement. Therefore, this study advances on these expert-based future labour market projections by embedding demographic dynamics, labour supply reallocation across tasks, re- and up-skilling, and spill-over effects. The model and this study are, as far as the literature available at the time of writing, the first attempt to operationalise the TBTC and RRTC framework to dynamically model and simulate future outcomes including these dynamics. This naturally implies that the model can benefit from improvement within the frameworks and extensions that reach beyond the TBTC and RRTC frameworks to incorporate sectors, markets, and factors. Therefore, the results should be considered within these aggregation limitations as well as the inherent space for improvement of representativeness and accuracy of a first and exploratory attempt. As a result, the adaptability of the labour force may be overestimated due to unobserved barriers (which are discussed in the discussion). Moreover, the model still relies on data from studies that employ expert judgments to study the future of work.

From a policy perspective, the exploratory outcomes highlight that re- and up-skilling improves the employability of the labour force and consistently reduces unemployment across the uncertainty space. Moreover, the outcomes suggest that these mechanisms naturally occur through employees that seek better employment possibilities and employers that seek possibilities to resolve mismatches. However, to ensure these mechanisms function, governments and businesses have a shared responsibility and interest in adequately equipping the labour force though education. Hence, education and advancement of education systems is a shared effort and responsibility that needs continuous attention. Even more so since, the lack of education possibilities will prevent the labour force from adapting, as a result, increasing unemployment and inequality. In respect of both inequality and policy making, the outcomes highlight that growing unemployment as result of technological advancement is highly unlikely, even when treating substitution as being equal to automatibility. In contrast, the outcomes concerning the wage share point to a continues decline of the position of the labour force in respect of economic growth and growing inequality. The outcomes point to a continuation of the current trend of a reduction of the labour share of 0.3% annually or acceleration to 0.58% (or higher in extreme scenarios). Hence, inequality should be at the centre of the policy debate given the societal implications associated with inequality. In respect of this study and its fundamental academic underpinnings, future attention should therefore shift to integrally studying inequality as a result of technological advancement.

Robots and Artificial Intelligence, the new economic motor or downfall of the working class?

To conclude, and return to the title of this thesis, IT and RT will not be the downfall of the working class in terms of employment and will only become the economic motor if the Solow paradox currently associated with the technologies ceases to exist. Yet, the question that needs to be raised for future research, is whether the working class will share in the economic outcomes that technology may bring.

15 Discussion

The complex systems model was developed to simulate future unemployment projections given the identified uncertainties. The model is, as far as described in available literature, the first simulation model of the TBTC and RRTC frameworks to study future impact of technological change and the first attempt to incorporate dynamics and feedback mechanisms in comparison to the a priori automatibility studies. Therefore, scope boundaries were set, and simplifications and assumptions made during model development and operationalisation. The quantitative nature of the model and analysis is insensitive to qualitative factors. Hence, the outcomes of the model need to be reflected upon from a more holistic social and societal perspective. The European Commission and European Group on Ethics in Science and New Technologies (EGE) are currently working on a policy perspective and evaluation of the future of work in consideration of the changes we face. This study and the results will be reflected upon from an ethical and societal perspective. Furthermore, the literature and process of technological change and globalisation are closely related. For that reason, this perspective is reflected upon.

15.1 Globalisation and offshoring

Parallel to the development of production technology, globalisation has shifted and relocated former labour through offshoring (Autor, 2015; Goos, Manning, & Salomons, 2011; Graetz & Michaels, 2017; Mishel, Shierholz & Schmitt, 2013). Initially globalisation was thought to completely reallocate manufacturing. However, later evidence revealed that tasks within the processes where offshored – as with substitution by technology (0112GMS). Hence, the observed loss of routine, production, and/or middle-skilled jobs was associated with both developments (Autor, 2013). Consequently, the simultaneous emergence of automation and globalisation complicated measurement and separation of the effects (Autor, 2013; Autor, Dorn, & Hanson, 2015; Goos, Manning, & Salomons, 2011; Graetz & Michaels, 2017). The complication with this co-emergence is that globalisation was partly made possible by technological development (DeCanio, 2016; Goos, Manning, & Salomons, 2009). Moreover, from a financial perspective, the motivation to offshore or automate the production process appears to be identical and target the same tasks. Namely, to reduce production costs by substituting routine task labour for either technology or low-wage labour abroad – catalysed by falling trade costs (Autor, Dorn, & Hanson, 2015).

Although co-emergent, the effect of globalisation and automation are distinct, industry dependent, and occupation specific[100] (Autor, Dorn, & Hanson, 2015, Goos, Manning, & Salomons, 2009). In the US, industries facing competition from low-wage labour imports experienced significant declines in labour demand for manufacturing and non-college employment. Therefore, globalisation altered the overall labour market composition and factor productivity of the tasks that remain (Autor, Dorn, & Hanson, 2015). On the other hand, technological substitution resulted in job polarisation and shifting occupational compositions but not a net decline in overall employment (Autor, Dorn, & Hanson, 2015). In Europe, the negative effect of globalisation on employment appears to have been limited compared to technological substitution (Goos, Manning, & Salomons, 2009, Goos, Manning, & Salomons, 2011). Altogether, globalisation results in a loss of jobs (mainly in low skill manufacturing) while technological substitution results in a shift in the labour composition. However, like technological change over the past decades, offshoring result in inequality growth and has been in favour of the high skilled labour force (Hummels, Jørgensen, Munch, & Xiang, 2014).

Contrarily to historic developments, the current progress in robotics enables manufacturers to re-shore parts of production back to the country of origin (IFR, 2017). The relative costs reduction and increase in productivity of robotic equipment can spark a new spill-over effect, termed reshoring (IFR, 2017). This implies that the increase in productivity and reduction of costs provides economically competitive

[100] See Goos, Manning, & Salomons (2009) for methodology and results on separating the impact of globalization and technological progress on an occupation-specific level.

production in high-wage countries. As a result, reshoring reclaims lost labour hours and restores the economic spill-over effects. In similar fashion, companies that already invested in substituting technology appear to be less likely to offshore parts of production at a later stage (IFR, 2017). The current evidence indicates that the lower price of robotics has slowed down off-shoring, but no re-shoring has occurred (De Backer, DeStefano, Menon & Ran Suh, 2018). Interestingly, China is currently the largest buyer of robotic equipment and will become a major technology manufacturer (Graetz & Michaels, 2017; Frey & Osborne, 2015; IFR, 2017). This trend extends to other developing countries (De Backer, DeStefano, Menon & Ran Suh, 2018; Graetz & Michaels, 2017; Sirkin, Zinser & Rose, 2015). The adoption of robotics allows developing countries to leap frog in technology, quality, and competitiveness especially due to lower operational costs (Sirkin, Zinser & Rose, 2015). Therefore, the question that arises is if eventually robots (and other technology) will reinitiate a globalisation trend due to capital cost offshoring - instead of prior labour costs offshoring. This implies production is (re-) located in (/to) countries with lower production costs due to higher capital factor productivity and thus undermining the re-shoring claims.

15.2 Societal and Social context

The methodology, framework, and model employed in this study relate to labour as a two-sided means to an end. On the one hand, labour input is a resource for production and is treated as a service in return for financial compensation. On the other hand, labour provides an income to households to pay for expenses and satisfy utility through consumption and saving. This economic perspective is embedded in the model through relative unemployment-based labour allocation and re- and up-skilling. The literature and results in this study demonstrate that technological advancements will change the tasks we perform, the employment opportunities we have, the competition and uncertainty we face, and inequality we may encounter. Each of these aspects influences individuals, households, communities, demographic groups, and society beyond employment and income.

From an ethical perspective, the implications of technological advancements are diverse. In this study, technological substitution of labour is treated from a labour economic narrative. However, the changes in the task composition and task themselves will change work from a value-based narrative. Firstly, the process of labour substitution implies that labour is replaced by capital which would suggest an impending loss of income and social security. This raises ethical questions whether societies will find such outcomes acceptable as it may violate humanitarian, social, and moral standards in society. Secondly, society may prefer activities and decision making to be performed by humans for social or ethical reasons. Both developments could imply that technological change is impaired as social forces prevent the implementation of technology (as also argued by Arntz, Gregory, and Zierahn (2016)). Conversely, this also implies that, implementation of technology by businesses and legislation concerning technology by governments, thus, comes with a social an ethical responsibility.

The work we do and the tasks we perform extend to a personal level of motivation, self-fulfilment, personal development, (societal) engagement, and contribution to our (social) environment. Therefore, our work is part of our social role and identity and extends beyond a financial means to an end. In sharp contrast, the model assumes that labour supply allocation and employment are a rational process whereby labour force members perform tasks according to the changing composition of labour opportunities available. However, these changes may imply that labour force members are forced to be employed and perform tasks that are dissonant with their intrinsic personal incentives. As a result, people may feel disengaged from the social and societal environment and the meaning they seek in their work. In relation with the model, this implies that, even though unemployment may be low and wages satisfactory, yet, the actual welfare and wellbeing growth we experience may be limited or impeded. Moreover, growing inequality deteriorates this position since it inhibits individuals from pursuing work that brings them value and satisfies those personal elements of work. Therefore, growing inequality (as projected by the results in this study) not only deteriorates the financial position of the labour force and the ability of households to safeguard the affordability of fundamental needs, living standards, and ability to accumulate wealth and financial independence.

Lastly, the model, and associated literature, treat re- and up-skilling as a vital mechanism to counteract the loss of labour demand due to technological advancement. From a labour economic narrative, the results confirm the criticality of skill attainment to adjust to changing labour demand. Yet, the model implementation is restricted to a rational process. However, people pursue education and training, not necessarily because of financial and employability motives, but because of intrinsic interest and personal development. Moreover, the process of skill attainment is a multi-actor problem that involves the labour force, employers, and governments to ensure education systems are equipped to provide adequate and relevant skills given how technology changes the demand for skills. This also implies, that business and government have an economic, financial, and social obligation to contribute to the capabilities of the labour force, rather than a rational narrative where labour force members engage in skill attainment to improve their employability (and economic and professional success in life). In combination with the notion that not all labour force members will be able to re- and up- skill (IFR, 2017), future research should focus on these multi-actor and social aspects of education to ensure (financial) accessibility of skill attainment and inclusive, decent, and equal work opportunities.

These concurrent developments with technical advancement deteriorate the position of the working class beyond unemployment. The findings using a dynamic simulation model in this study and the findings of Arntz, Gregory, and Zierahn (2016) and Nedelkoska and Quintini (2018) suggest that unemployment in reaction to future technological change will be limited – albeit in consideration of the limitations of the model. Therefore, future research and modelling should focus more on an integrated approach that considers the co-development of unemployment, inequality aspects, and deteriorating positions of labour force groups rather than restricting research into future unemployment. This suggests, that future modelling should focus on expanding the system boundaries to include a more representative labour market of contract types, labour hours, and wage formation. Moreover, from a policy perspective, expansion of the model to include these aspects will also enable more holistic policy analysis.

15.3 Method and model limitations and future work

Throughout the development of the model, adaptations have been made to ensure consistency with the TBTC and RRTC frameworks and methodology, future automatibility estimates and methodology, and to ensure consistent scope boundaries. This approach followed from the identified scientific gap concerning future estimates of unemployment in relation with technological advancement of IT and RT. These estimates are based on expert judgements on the automatibility and automation probability of tasks which are projected across the current occupational composition using the TBTC framework. Therefore, the estimates do not account for reallocation, re- and up-skilling, spill-overs, and changing task compositions. Yet, these factors have consistently been identified as critical mechanisms that change the materialisation of technological advancement and its impact. From this point of departure, a dynamics simulation model was developed to account for these effects and determine their implications in relation with the static estimates. Hence, the effect of adaptability was simulated across technological advancement estimates. In addition, these outcomes have been analysed to identify policy levers.

The simplifications equate to an isolated and simplified representation of the real-world system that is consistent with TBTC and RRTC framework but expands on the economy(etr)ic production function models. These expansions include a demographic model to simulate a changing labour force composition; a labour market model to account for labour supply reallocation across tasks; an education to include re- and up-skilling in reaction to unemployment; and technology model (in combination with the production model) to account for spill-over effects. During development of these sub-models scope boundaries have been set and simplifications have been made. These decisions, potential implications, and improvements and expansions are discussed for each sub-model and graphically summarised in Figure 33.

15.3.1 Demographic Model

The demographic model is structured into age cohorts and skill levels, respectively, based on the international definition for the work force (and associated statistics to ensure consistent input data) and the skill level composition of the TBTC and RRTC frameworks. The age cohorts encompass are pragmatically divided to represent different phases in life and associated societal or demographic roles. The result, is a structure of six age cohorts across six skill levels that ensure accurate representation of demographic dynamics during mathematical integration of the population flows. The current age cohort structure aggregates the population of multiple ages into single cohorts (see Appendix V). However, the representativeness of the demographic model can be improved using subscripting in the SD model. Subscripting can be used to slice each age cohort into 1-year 'sub'-cohorts without the need to create a stock-flow structure for each 1 year cohort. The narrower age cohorts will more accurately represent the real-world demographic composition of the population at initialisation. Moreover, the integration process of aging will more accurately represent real-world demographic projections (Appendix VII). Yet, it should be noted that this improvement requires year-based initial population data per sex per skill level. It would also require expansion of the demographic model with a returning flow for each population stock. On one hand, Expansion of the model based on this subscripting will ensure that the demographic composition does not deviate from the project trend. On the other hand, it is unlikely that the unemployment outcomes per skill level would be significantly different, albeit they may be slightly different per age cohort per skill level.

The birth component in the model is based on the current statistical correlations between parents' skill level and their children's highest achieved skill level for all combinations of parent, parent couples, and child. This information is available in multiple forms for the Netherlands via the Central Bureau of Statistics database and associated publications (Appendix II). The result is a detailed and accurate birth model. Yet, the required data input may not be available for other countries. Therefore, from a reusability perspective, the model can be improved with a birth model components that is based on universally available dataset across countries. The education factors in the OECD PISA database (see 8.2) provide a systematic set of indicators that could be used for this purpose. The family background [$\mathfrak{F}$] and individual ability factors [$\mathfrak{A}$] in the database[101] provide a comprehensive starting point. This would enable simulation for different countries and comparison of the outcomes.

The demographic model is isolated from interaction with the models' environment. Therefore, migration was not included in the model. However, migration will continuously change the demographic and labour force composition. Therefore, for better representativeness, the model needs to be expanded to include refugee and employment/economic migration. Migration is related to the model through multiple mechanisms. Firstly, migration changes the demographic composition of the population and labour force across age cohorts and skill levels. In addition, migration influences births due to changes in the young adult population. Second, (economic) migration is incentivised by better living conditions and employability (as well as environmental, political and social factors). Therefore, the relative unemployment rate and wage level between countries will influence migration patterns. Thirdly, the skill level and skill attainment capabilities of migrants is likely to be different due to differences in education system quality during childhood, skill attainment, and language barriers. Fourthly, the skill set is likely to be different due to differences in occupational compositions and labour practises in the country of origin. Therefore, labour adaptability is likely to be lower and requires attention to ensure economic integration and equal opportunities. Incorporating migration in the model requires an incoming immigration and outgoing emigration flow for each population stock. The quantity of the incoming and outgoing population can be forced into the model based on projected data or generated based on a separate migration sub-model. In both cases, the data should include skill level and age cohort specific quantifications. In relation with labour force adaptability, the model can be simulated under the assumption of unchanged reallocation and re- and up-skilling sensitives or a correction in these factors can be made depending on empirical evidence in relation with migration. Including migration in the model is likely to change unemployment outcomes due to population growth, shifts in the labour force across skill levels, and changes in labour supply across tasks.

[101] http://www.oecd.org/pisa/data/

Therefore, future expansion of the model with an embedded migration model will improve representativeness and accuracy.

15.3.2 Labour Market Model

The labour market model is based on the task division of the TBTC and RRTC frameworks and is expanded to include the new skills associated with technological change. The relation between skills and tasks is not consistent across models and studies within the frameworks. The cognitive capabilities required for abstract tasks inhibit middle and low skilled individuals from performing occupations that consists mainly out of abstract tasks (see 7.2). Therefore, the high skilled labour force has a comparative advantage over the other skill levels. The semi-open labour market was adopted based on the current state of models and empirical evidence. The mechanisms of labour reallocation are based on rational motivations to improve employability and maximise wages given the willingness to sacrifice income in return for employment. The tasks based structure of labour input demand and skill level supply simplify the labour market, because of which two points need to be discussed.

Skills are assumed to be universal. Therefore, there are no barriers to reallocate labour to different tasks outside of the supply allocation possibilities per skill level (Table 1). In contrast, in the real-world, education, skills, and human capital can be universal or domain, occupation, firm, and sector specific. Hence, reallocation of labour supply to different tasks within the same occupational category, production process, and/or sector in reaction to substitution is likely to be unrestricted. However, there are barriers in the real world that prevent individuals from reallocating labour across domains, occupations, firms, and sectors due to specific skill or human capital requirement (e.g. a doctor cannot suddenly perform the tasks of an electrician while, vice versa, the electrician will legally not be allowed to perform medical tasks). In this respect, the task-based labour market can be improved by accounting for the sectoral composition (Autor & Salomons, 2017); Graetz & Michaels, 2017) (using the World Input-Output Database (WIOD) Timmer, Dietzenbacher, Los, Stehrer & Vries (2015)), occupational categorisation (using the International Assessment of Adult Competencies (PIAAC) and ILO International Standard Classification of jobs (ISCO) as done by Arntz, Gregory, and Zierahn (2016) and Nedelkoska and Quintini (2018) among others[102]), labour force compatibility within and between sectors, and (legal) limitations. This would require a significantly enlarged and more complicated model but would improve representativeness significantly. However, this would require reliable data of labour demand and supply per task and per skill levels across the sectoral composition and inter-sectoral dynamics and compatibility. Moreover, given the uncertainty associated with future technological change the added value of this detail level is questionable.

The model was developed to study the effect of future technological change on unemployment. The model can be adapted and expanded to study wage inequality in more detail. This would require an income model component that incorporates labour market institutions, wage bargaining and formation processes, and income from capital across tasks and skill levels. In relation with the current model, this component would connect to the spill-over effects in the technological model via the allocation ratios and feedback into the model via consumption and saving (following the propensity to consume and save). In addition, this component can be improved by incorporating age cohort and wage dependent propensities and expenditure behaviour. An income model with wage formation and capital income will improve the current wage spill-over effect and facilitate simulation of wealth, inequality, and wage dynamics.

15.3.3 Education Model

The three education systems (i.e. children, students, and labour force) in the model are simplified to simulate the effects of skill attainment. Therefore, the education systems themselves are not part of the model. Including these systems in the model is beyond the current scope and would not change the outcomes in their current scope and form. However, future policy research to determine the costs, robustness, and effectiveness of education policy strategies to improve labour force adaptability through re- and up-skilling would require an expansion of the current black box method to include separate education

[102] Including Goos, Manning, and Salomons (2009, 2011, 2014) and Gregory, Salomons, and Zierahn (2016)

models for the three systems across the skill levels. Meanwhile, the expected developments and required changes in skills require education systems to be adjusted and offer programs to attain those skills (IFR, 2017). In this respect, expansion of the model with an education model will improve policy and resource strategy analysis. For children's education, the OECD PISA database and studies (e.g. OECD (2017a), Hanushek and Woessmann (2010, 2016)) provide a starting point for a model that accounts for education system, resource, institutional, and cultural/background heterogeneity. The STEM stimulation SD models (BHEF, 2010; BHEF, 2013; Newton, Richey, Mojtahedzadeh, 2009; Wells, Sanchez & Attridge, 2007) provide an existing operationalisation that can be implemented, expanded, and connected to the model. For students and the labour force, a similar education model can be build based on further research.

Consistency with the PIAAC data will ensure compatibility and consistency with the labour market model and other studies (e.g. Arntz, Gregory, and Zierahn (2016) and OECD publications). This would also allow for the implementation of a financial component including government, firm, and labour force investment in skill attainment. In the context of current developments, companies carry responsibility over their employees to provide relevant skill training and human capital development (especially since it essential to ensure realisation of productivity growth (Crook, Todd, Combs, Woehr, & Ketchen, 2011)). Conflictingly, current trend among business demonstrates declining investment in employee training and knowledge-intensive capital and development. Besides companies, responsibility also lies with government and the employees themselves. By extending the education model with an expenditure sub-model covering investments in re-skilling and up-skilling by government, companies, and employees, it might be possible to measure the effects of shifting responsibilities, investment, and policies. From a policy and multi-actor perspective this can enrich the model and outcomes and move from an exploratory phase into a policy analysis phase.

15.3.4 Production and Technology Model

The technology and production model in their current form are closely related and have been simplified to ensure consistency. The models have been developed to implement the TBTC and RRTC frameworks and automatibility estimates concerning future technological advancement into a dynamic model. From an academic perspective, this study advances on the current expert-based future labour market projections in relation with technological change. Moreover, it resolves five shortcomings of the current estimates and methodology, namely, accounting for production adjustment via reallocation of labour supply (Arntz, Gregory, & Zierahn, 2016); accounting for task composition dynamics (Arntz, Gregory, & Zierahn, 2016); including the potential effect of adequately skilled labour force shortages in association with the development and implementation of technology (Arntz, Gregory, & Zierahn, 2016); implementing spill-over effects associated with technological advancement (Acemoglu & Restrepo, 2018; Gregory, Salomons, & Zierahn, 2016); and incorporating skill attainment (Acemoglu & Restrepo, 2018; Autor, 2015; Nedelkoska & Quintini, 2018; OECD, 2017b; IFR, 2017). Unfortunately, one aspect has not been incorporated in the model, namely, consistent with the estimate studies and TBTC and RRTC framework the current model uses *'technological capabilities based on experts' assessments rather than the actual utilisation of such technologies.'* (Arntz, Gregory, & Zierahn, 2016, p. 21). Moreover, the model uses a substitution difference factor as a dummy for multiple factors that influence implementation and substitution of labour.

Therefore, in association with the production model and wage formation in the labour market, the model can be improved by incorporating the actual production functions in combination with a wage formation model component and technology (price) model component. Firstly, this would eliminate the need for the current economic growth component – albeit this improved model should consider exogenous economic factors[103]. Secondly and more importantly, this will ensure more realistic substitution behaviour based on relative price developments and associated feedback mechanism (Arntz, Gregory, & Zierahn, 2016). Relative factors price dynamics, upon which substitution is normally based, are not incorporated in the methodology of Arntz, Gregory, and Zierahn (2016), Nedelkoska and Quintini (2018), and Frey and Osborne (2017) nor in the model developed in this study. In relation with the suggested expansion of the labour market model to

[103] Including, but not restricted to, capital and financial markets, interest rates, exchange rates, import and export, economic and technological competitive position, globalisation, government consumption, monetary and fiscal policy, sectoral composition, and exogenous factors/shocks.

include wage bargaining and formation, this will ensure accurate representation of the actual substitution process. The technology model needs be expanded to incorporate the process of technology development, prices, and availability.

Brynjolfsson, Rock, and Syverson (2017) and Arntz, Gregory, and Zierahn's (2016) identified a range of factors that influence the development and implementation of technology. In relation to the difference between automatibility and substitution Brynjolfsson, Rock, and Syverson (2017) describe multiple factors in addition to factors that influence productivity growth of future technology (described in 9.1). First, technology may not mature up to an operationally or financially feasible level. Second, technology may not become widely adopted due to (legal) limitations and firm size/power whereby technology is exclusively available to few a beneficiaries and applications, and thus limiting dissipation, entrance of competitors, and economy wide implementation. Third, the implementation of advanced technologies will require organisational, business-cultural, and structural changes within and between firms. As a result, cross-firm supply chains and sectors will need to undergo reorganisation to adapt to the changing production processes and products. In relation with the latter, technology itself changes products and production by speeding up the development cycle and scalability (De Backer, DeStefano, Menon & Ran Suh, 2018; Frey & Osborne, 2017). In a reflection of the expert judgment based estimates, Arntz, Gregory, and Zierahn's (2016) highlight that future data processing and storage (availability) limitations may inhibit wide spread implementation of advanced IT and RT systems. Moreover, ethical, legal, and legislative factors can prevent the implementation of technology (e.g self-driving cars or drones).

Therefore, future model expansion should be focused on creating a technology model that incorporates the technology development process, price development, patents and availability, resource shortages, and supply chains. The most complicated aspect in modelling, as with wage formation, is the social aspects that influence the implementation of technology, the preferences of society, and interactions between actors. Agent based modelling may provide a solution to model these processes. In relation with the current model, the technology model expansion can be implemented as separate components that dictates the rate of substitution based on the relative price compared to the wage component.

15.3.5 Model reusability and simulation for other case studies

The developed model can be used to simulate and explore the plausible impact of technology across countries. This does require country specific data. The case study for the Netherlands was based on demographic data from the CBS database (CBS, 2017a, 2017b, 2018a-2018g); economic growth projection of the OECD database (OECD, 2018); country specific business cycle properties (Claessens, Ayhan Kose & Terrones, 2009); country specific wage share data (Cho, Hwang, & Schreyer, 2017); PISA education performance data (OECD, 2015c); universal data from technical advancement and labour economics studies (see Appendix II); and (country specific) automatibility estimates (see Table 2 and Table 4). Adopting the model for other countries will require four data changes. Firstly, the demographic data needs to be sourced, which is most probably available at the national statistics institute or an international database. However, the data should have the adequate and consistent age cohort and skill level disaggregation and categorisation (this was part of the reason to adopt standardised divisions). Note, that special attention needs to be paid to the births model inputs, as suggested above. Secondly, the economic growth projection needs to be updated with the respective country specific sample from the OECD database. Thirdly, the age share needs to be updated. Fourthly, the automatibility estimates need to be changed to the country specific estimates (notes at the bottom of Table 2 provide the relevant pages, tables, and figures in the sources). This will require some manual effort since some of the data is only provided in graphs. Updating the PISA education data is not necessary unless this specific aspect of the model is studies. Therefore, once the data is collected, the model can readily be simulated for other countries.

Subscripting can be used to simulate multiple countries simultaneously. The model is isolated from its environment in its current form. Future expansion of the model can open interactions between countries to allow for migration, import and export, relative economic performance and costs, globalisation, and technology development. However, it is advised to only move to this interactive state after the model is improved with migration flows, production functions, wage formation, and technology sector.

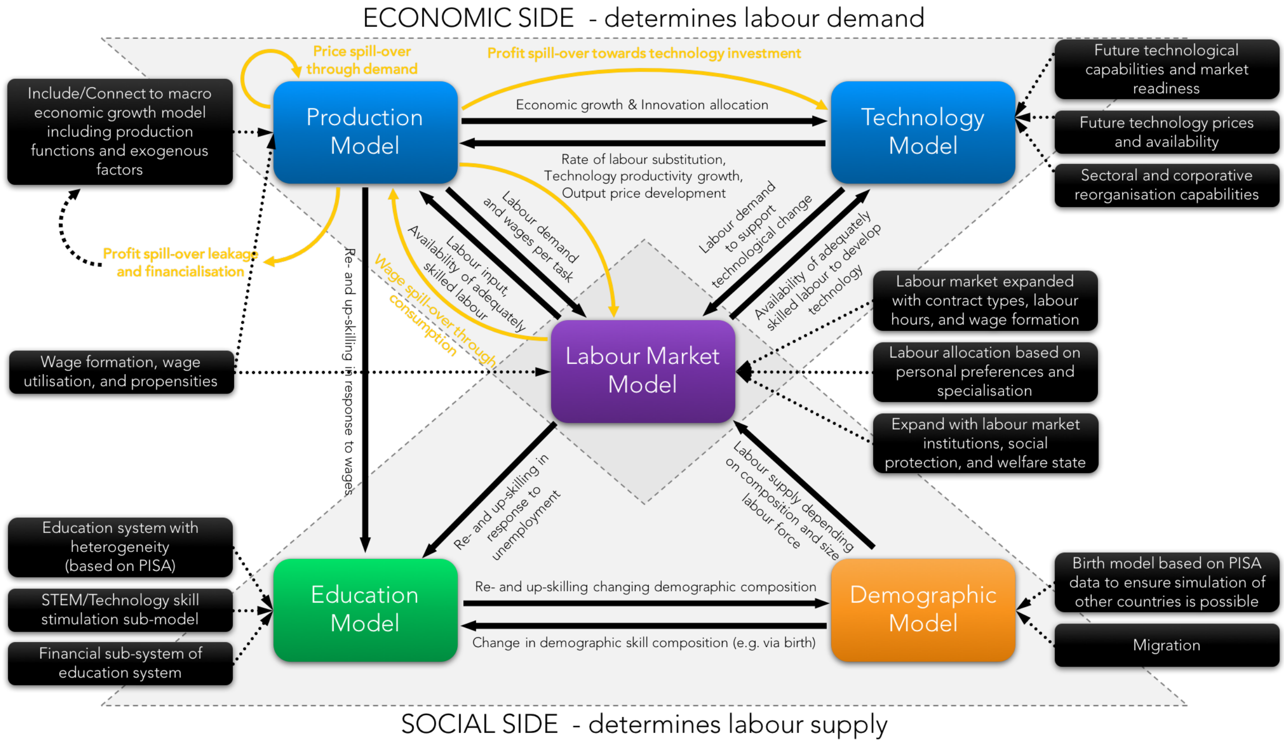


Figure 33 Expanded conceptual model with black boxes and relevant exogenous factors

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Appendices

I Education factors

Educational achievement is mostly influenced by the individual and family background [$\mathfrak{F}$] and the institutional structure of the school system [$\mathfrak{I}$], as well as the qualitative factors in the schools' resources [$\mathfrak{R}$], although to a somewhat lesser extend (Hanushek & Woessmann, 2016, Woessmann, 2016, Wößmann, 2003). Together these vectors are capable of accounting for 87% of variation at the country level (Hanushek & Woessmann, 2016). First, within the schools' resources (also referred to as school input) class size (i.e. students per class or students per teacher) and financial input (i.e. educational expenditure per student) have a limited effect on schooling, whereas qualitative factors do not (e.g. quality teachers) (Hanushek & Woessmann, 2016, Woessmann, 2016). In this respect, *'evidence that differences in teacher quality and instruction time do matter suggests that what matters is not so much the amount of inputs that school systems are endowed with, but rather how they use them*' (Hanushek & Woessmann, 2016 p. 168). In other words, additional financial resources do not result in a significant increase in performance, of which US expenditure versus performance is most evident (Woessmann, 2016). Better allocation of the resources and focused investment for factor improvement will yield more significant improvements (Woessmann, 2016, OECD, 2017a). Second, the individual and family background factors are incorporated in the population model as motivated before. Third, the institutional structure of the school systems introduces multiple relevant factors. However, education system changes are slow (Bybee, 2010) and the factors are hard to quantify (e.g. level of autonomy) (Woessmann, 2016). Therefore, these factors are not implemented as they are assumed to be constant properties of the education system. An overview of the factors that cover 83-87% of performance variation, according to Woessmann (Woessmann, 2016) and Hanushek and Woessmann (Hanushek & Woessmann, 2016), is provided in Table 5. The OECD PISA assessments database[104] contains a significantly larger set of criteria and variables. In this respect, the factor implementation is a simplification.

Table 5 Education factors (based on Hanushek & Woessmann, 2016 and Woessmann, 2016)

Vector	Factor	
$\mathfrak{R}$[105]	Shortage of (adequate) instruction material: Not at all or Strongly	$\mathfrak{i}$
	Instruction time: Minutes per week	$\mathfrak{t}$
	Teachers education: % Tertiary degree pedagogy in staff	$\mathfrak{s}$
$\mathfrak{I}$[106]	Choice: private operation or government funding	$\mathfrak{c}$
	External exit exam: Yes or NO	$\mathfrak{e}$
	Assessments used to decide about students' retention/promotion: Yes or NO	$\mathfrak{a}$
	Monitoring of teacher lessons: Internal, External, or NO	$\mathfrak{l}$
	Autonomy in management: Yes or NO	$\mathfrak{m}$
	Autonomy in hiring teachers: Yes or NO	$\mathfrak{h}$

Following Hanushek and Woessmann (2016), please consider Hanushek and Woessmann (2010) and Woesmann (2016) for a detailed evaluation of the institutional and resource factors and Hanushek, Piopiunik, and Wiederhold (2014) for the effect of teachers on the skill attainment of students.

The set of factors is not identical to the assessment analyses in the referenced literature since factors with no significant or inconsistent influence are excluded. The class-size factor has been omitted from the set but

[104] Available via http://pisadataexplorer.oecd.org/ide/idepisa/dataset.aspx

[105] Note that the factors "Class-size" and "Educational expenditure per student" has been omitted due to their limited effect. Moreover, the proportion of Fully certified teachers is omitted since nearly all OECD countries have a 100% certified level except for Chile and Mexico (See criteria *'Index proportion of all teachers fully certified'* in OECD PISA database at http://pisadataexplorer.oecd.org/ide/idepisa/dataset.aspx

[106] Note that the factors "Monitoring of teacher lessons by principal", "Monitoring of teacher lessons by external inspectors", "Assessments used to compare school to district/national performance", and "Assessments used to group students" have been omitted due to limited effect. Moreover, the autonomy in management factor includes "Autonomy in formulating budget"," Autonomy in establishing starting salaries", and "Autonomy in determining course content".

is not completely excluded from the model. In many countries, there is a legal maximum class-size rule (Woessmann, 2016). Moreover, school facilities will have a limited physical or resource capacity (e.g. classroom size, number of classrooms, teachers available) resulting in a maximum capacity in students per classroom and maximum total number students at each skill levels. Hence, a rule based factor is introduced for the total schooling capacity [$\mathfrak{C}_{\varepsilon}$] at each skill level and maximum (legal) capacity per classroom [$\mathfrak{C}_{c}$]. The effect of the latter is distinct since the students are equally distributed across classes up to the maximum. One student over the maximum and a new additional class needs to be formed (Woessmann, 2016)[107].

[107] *'Say that the maximum class size is 40, and that a certain grade has 120 students divided into three classes of 40 students each. If the grade rises to 121 students, the group is then divided into four classes - three of 30 students and one of 31 students. In this way, the rules give rise to discontinuous jumps in average class sizes whenever the enrollment in a grade in a school passes multiples of the maximum class size.'* (Woessmann, 2016, p.20)

II Model Thesaurus and Dataset

Thesaurus

Symbol	Name	Model Parameter
X	Overall production	
O	Occupation	Not included
T	Task	See specific tasks
$\mathcal{R}$	Routine tasks	Routine I
$\mathcal{A}$	Abstract tasks	Abstract I
$\mathcal{M}$	Manual tasks	Manual I
$\mathcal{R}_{\mathcal{R}}$	Routinised routine tasks	Routine L
$\mathcal{R}_{\mathcal{A}}$	Routinised abstract tasks	Abstract L
$\mathcal{R}_{\mathcal{M}}$	Routinised manual tasks	Manual L
$\mathscr{a}$	Share of routine tasks	Not needed
$\mathscr{b}$	Share of abstract tasks	Not needed
$\mathscr{c}$	Share of manual tasks	Not needed
L_T	Task specific labour input	Labour input {Task name}
K_T	Task specific capital input	Not included
W_T	Labour costs	Average wage {Task name}
Π_T	Capital costs	Not included
β	Labour input share	Not needed
α	Capital input share	Not needed
ε	Normal skill level	LI, MI, HI
ξ_τ	Extended skill level (skill- and technology-specific)	LL, ML, HL
η_T	Input elasticity of substitution	Not included
η_X	Task elasticity of substitution	Task substitution elasticity
τ_T	Task specific technology	Not directly included
P_T	Production price	Not directly included
p_{so}	Competitive allocation towards product price	Productivity growth competitive allocation
ϕ_{so}	Profitability allocation towards the profit mark-up	Productivity growth profit allocation
W_{so}	Wage allocation	Productivity growth wage allocation, and TFP wage allocation {Task name}
ϱ	Competitive allocation share	Productivity growth competitive allocation
ϖ	Profitability allocation share	Productivity growth profit allocation
ω	Wage allocation share	Productivity growth wage allocation, and TFP wage allocation {Task name}
p_t	Product price	Price index {Task name}

Symbol	Name	Model Parameter
ψ_{T_t}	Task specific profit	Profit index {Task name}
ϕ_c	conventional profit mark-up	Not included
A_T	Task specific Total Factor Productivity (TFP)	Technological productivity growth {Task name}, and Long term TFP growth combined
D_t	Profit not used for productivity growth	Not directly included
ι_T	Innovation investment share of profit	Proportion of profit invested in innovation
ν_T	Dividend share of profit	Not directly included (=1-Proportion of profit invested in innovation)
ε	Skill level	See each skill level
$\varepsilon_{\mathbb{L}}$	Low skill (level 1 and 2 of ISCED 2011)	LI
$\varepsilon_{\mathbb{M}}$	Middle skill (level 3, 4 and 5 of ISCED 2011)	MI
$\varepsilon_{\mathbb{H}}$	High skill (level 6, 7 and 8 of ISCED 2011)	HI
$\xi_{\mathbb{L}}$	Low extended skill	LL
$\xi_{\mathbb{M}}$	Middle extended skill	ML
$\xi_{\mathbb{H}}$	High extended skill	HL
$\mathbb{s}$	Sex	See each sex
♂	Male population	m
♀	Female population	f
$\mathbb{AC}$	Age cohort	See each age cohort
$\mathbb{CH}$	Childeren (age 0-15)	CH
$\mathbb{ST}$	Students (age 15-25)	ST
$\mathbb{YA}$	Young Adults (age 25-35)	YA
$\mathbb{MA}$	Mature Adults (age 35-55)	MA
$\mathbb{SA}$	Senior Adults (55-65)	SA
$\mathbb{RE}$	Retirees (65-Life expectancy)	RE
$\Delta t_{\mathbb{AC}_\varepsilon}$	Skill level specific age cohort periods	t upto {age cohort} to {age cohort}
$t_{\mathbb{RE}}$	Retirement age	Retirement age
$t_{\dagger_\varepsilon}$	Life expectancy per skill level	Life expectancy {skill level} {sex}
$\mathbb{R}$	Re-skilling	{Age cohort} {skill level} to {skill level} {sex}
$\mathbb{U}$	Up-skilling	{Age cohort} {skill level} to {skill level} {sex}
$\mathbb{c}_{\varepsilon_{\mathbb{YA}♀}\varepsilon_{\mathbb{YA}♂}}$	Young Adult couple ratio	Parents YA {skill level} {sex}to {skill level} {sex}
$\mathbb{e}_{\varepsilon_{\mathbb{YA}\,\mathbb{s}}\varepsilon_{\mathbb{CH}\,\mathbb{s}}}$	Parent – Child skill level relation ratio	YA {skill level} {sex} birth {skill level} {sex}
$\mathbb{d}_{\mathbb{YA}_{\mathbb{CH}\,\mathbb{s}}}$	Relative dominance ratio	Based on: Correlation strength YA SL {sex} on CH SL {sex}
$\mathbb{b}_\varepsilon$	Skill level specific birth rate	Avg birth per {skill level} f
$\mathbb{g}$	Ratio female and male childeren	Ratio female to male at birth
$\mathbb{a}_\xi$	normal rate of extended skill	Normale ratio {skill level} to {skill level} at birth {sex}
L_{ε_T}	Task specific labour demand $(L_{\varepsilon_{\mathcal{R}}}, L_{\varepsilon_{\mathcal{A}}}, L_{\varepsilon_{\mathcal{M}}}, L_{\xi_{\mathcal{R}}}, L_{\xi_{\mathcal{A}}}, L_{\xi_{\mathcal{M}}})$	
L_ε	Skill specific labour supply $(L_{\varepsilon_{\mathbb{L}}}, L_{\varepsilon_{\mathbb{M}}}, L_{\varepsilon_{\mathbb{H}}}, L_{\xi_{\mathbb{L}}}, L_{\xi_{\mathbb{M}}}, L_{\xi_{\mathbb{H}}})$	
$\mathbb{WA}_\varepsilon$	Working age population	WA

Symbol	Name	Model Parameter
$\mathbb{LF}_{\varepsilon_\mathbb{s}}$	Labour force	LF
$\mathbb{p}$	Part-time contract	Not included
$\mathbb{f}$	Full-time contract	Not needed
ς	Full-time ratio	Not included
$\rho_{\mathbb{WA}_{\varepsilon_\mathbb{s}}}$	Participation rate	{age cohort} {skill level} {sex} participation
$h_\mathbb{p}$	Part-time contract hours	Not included
$h_\mathbb{f}$	Full-time contract hours	Hours fulltime contracts
$L_{\varepsilon_{\mathbb{LF}\to T}}$	Task specific labour supply	LF{skill level} ft supply {Task name}
$L_{\varepsilon_{T\,D}}$	Total task-specific labour demand	Labour demand {Task name} ft
$L_{\varepsilon_{TS}}$	Total task-specific labour supply	Labour supply {Task name} ft
N	Natural task type	Not directly included
Q	Qualified task type	Not directly included
υ	Unemployment rate	Unemployment rate {Task name} ft
ϑ	Acceptable ratio of lost wage	Wage sacrifice ratio for employment
η_υ	Reallocation sensitivity	Sensitivity Unemployment reallocation
η_W	Utility elasticity of wages	Sensitivity Wage reallocation
$u_{\mathbb{LF}_{\varepsilon_\mathbb{s}}}$	Unemployment	{Age cohort} {skill level} ft Unemployment rate
I_T	Investment	Not included
I_{T_L}	Labour training investment	Not included
I_{T_τ}	Technology innovation investment	Not included
ϵ_T	Employment investment share of profit	Not included
G_{L_ε}	Government investment into education of the labour force	Not included
G_{T_τ}	Government investment in technological innovation	Not included
G_U	Unemployment benefits	Not included
c_{L_ε}	Labour force consumption of educational and training	Not included
$\mathfrak{T}$	Children’s education performance	CH Edu performance Overall {skill level}
$\mathfrak{x}$	Capacity planning constant	CH Edu capacity planning
$\Delta t_\mathfrak{C}$	Time to realise capacity growth	Time to realise CH Edu capacity expansion
$\mathbb{r}$	Re-skill rate	Reskill rate {age cohort} {skill level} {sex}
$\mathbb{u}$	Up-skill rate	Upskill rate {age cohort} {skill level} {sex}
$\mathfrak{y}$	Labour market prospect sensitivity factor	ST Labour market awareness and sensitivity, WAu reskill and upskill sensitivity, WAe reskill and upskill sensitivity
$\mathfrak{u}_\varepsilon$	Skill level specific training factor	Socioeconomic influence education and training {skill level}
$\mathfrak{v}_\mathbb{LF}$	Age cohort specific training factor	SA and RE LF relative reducation in training
$\mathfrak{w}$	Contract specific training factor	Not included

Dataset

Production model

Parameter_Name	Type	Value	Source
Initial Unemployment rate Manual I ft	Initial	0,062	CBS (2018d)
Initial Unemployment rate Manual L ft	Initial	0,057	CBS (2018d)
Initial Unemployment rate Routine I ft	Initial	0,044	CBS (2018d)
Initial Unemployment rate Routine L ft	Initial	0,04	CBS (2018d)
Initial Unemployment rate Abstract I ft	Initial	0,031	CBS (2018d)
Initial Unemployment rate Abstract L ft	Initial	0,03	CBS (2018d)
Initial Unemployment rate Manual I pt	Initial	0,083	CBS (2018d)
Initial Unemployment rate Manual L pt	Initial	0,074	CBS (2018d)
Initial Unemployment rate Routine I pt	Initial	0,053	CBS (2018d)
Initial Unemployment rate Routine L pt	Initial	0,049	CBS (2018d)
Initial Unemployment rate Abstract I pt	Initial	0,035	CBS (2018d)
Initial Unemployment rate Abstract L pt	Initial	0,037	CBS (2018d)
Initial Average Wage Abstract L	Initial	38600	CBS (2018f)
Initial Average Wage Abstract I	Initial	38600	CBS (2018f)
Initial Average Wage Routine L	Initial	30600	CBS (2018f)
Initial Average Wage Routine I	Initial	30600	CBS (2018f)
Initial Average Wage Manual L	Initial	28900	CBS (2018f)
Initial Average Wage Manual I	Initial	28900	CBS (2018f)
Hours fulltime contracts	Policy	38	Policy
Price elasticity of demand Abstract L	Constant	1	ASSUMPTION
Price elasticity of demand Abstract I	Constant	1	ASSUMPTION
Price elasticity of demand Routine L	Constant	1	ASSUMPTION
Price elasticity of demand Routine I	Constant	1	ASSUMPTION
Price elasticity of demand Manual L	Constant	1	ASSUMPTION
Price elasticity of demand Manual I	Constant	1	ASSUMPTION
Task substitution elasticity	Uncertainty	0,66-0,9	Gregory, Salomons, and Zierahn (2016)

Long term annual economic growth LOOKUP	Lookup	LOOKUP	OECD (2018)
Long term economic growth error margin	Uncertainty	0-0,05	OECD (2018)
Business cycle fluctuation amplitude	Uncertainty	0,001-0,0033	Based on OECD (2018)
Business cycle fluctuation period	Uncertainty	2-3	Based on OECD (2018)
Time to first recession	Uncertainty	2-5	Estimation based on OECD (2018)
Business cycle recession amplitude	Uncertainty	0,0187-0,0263	Claessens, Ayhan Kose, and Terrones (2009)
Business cycle recession duration	Uncertainty	3-3,64	Claessens, Ayhan Kose, and Terrones (2009)
Busines cycle recession period	Uncertainty	8-9,4	Estrella and Mishkin (1998) and Claessens, Ayhan Kose, and Terrones (2009)
Severe recession timing	Uncertainty	1-3	Uncertainty
Severe recession duration	Uncertainty	4-4,7	Claessens, Ayhan Kose, and Terrones (2009)
Severe recession amplitude	Uncertainty	0,0489-0,0631	Claessens, Ayhan Kose, and Terrones (2009)
Severe recession occurance	Uncertainty	0-1	Claessens, Ayhan Kose, and Terrones (2009)
Proportion of time in recession	Uncertainty	0,18-0,21	Claessens, Ayhan Kose, and Terrones (2009)
Initial Labour share	Uncertainty	0,554-0,714	Cho, Hwang, and Schreyer (2017)
Smooting period	Setting	6	Setting
SWITCH Routinisation OFF	Setting	0	Setting
SWITCH Spillover effect OFF	Setting	0	Setting

Demographic model

Parameter_Name	Type	Value	Source
Initial CH LI m	Initial	164730	CBS (2017a) together with CBS (2018a)
Initial CH LL m	Initial	49419	CBS (2017a) together with CBS (2018a)
Initial CH MI m	Initial	399470	CBS (2017a) together with CBS (2018a)
Initial CH ML m	Initial	205912	CBS (2017a) together with CBS (2018a)
Initial CH HI m	Initial	420061	CBS (2017a) together with CBS (2018a)
Initial CH HL m	Initial	174339	CBS (2017a) together with CBS (2018a)
Initial ST LI m	Initial	126041	CBS (2017a) together with CBS (2018a)
Initial ST LL m	Initial	37812	CBS (2017a) together with CBS (2018a)
Initial ST MI m	Initial	305649	CBS (2017a) together with CBS (2018a)

Initial ST ML m	Initial	157551	CBS (2017a) together with CBS (2018a)
Initial ST HI m	Initial	321405	CBS (2017a) together with CBS (2018a)
Initial ST HL m	Initial	133393	CBS (2017a) together with CBS (2018a)
Initial YA LI m	Initial	127343	CBS (2017a) together with CBS (2018a)
Initial YA LL m	Initial	38203	CBS (2017a) together with CBS (2018a)
Initial YA MI m	Initial	308808	CBS (2017a) together with CBS (2018a)
Initial YA ML m	Initial	159179	CBS (2017a) together with CBS (2018a)
Initial YA HI m	Initial	324725	CBS (2017a) together with CBS (2018a)
Initial YA HL m	Initial	134772	CBS (2017a) together with CBS (2018a)
Initial MA LI m	Initial	307034	CBS (2017a) together with CBS (2018a)
Initial MA LL m	Initial	148186	CBS (2017a) together with CBS (2018a)
Initial MA MI m	Initial	590613	CBS (2017a) together with CBS (2018a)
Initial MA ML m	Initial	395519	CBS (2017a) together with CBS (2018a)
Initial MA HI m	Initial	593811	CBS (2017a) together with CBS (2018a)
Initial MA HL m	Initial	273985	CBS (2017a) together with CBS (2018a)
Initial SA LI m	Initial	194271	CBS (2017a) together with CBS (2018a)
Initial SA LL m	Initial	121959	CBS (2017a) together with CBS (2018a)
Initial SA MI m	Initial	289248	CBS (2017a) together with CBS (2018a)
Initial SA ML m	Initial	170527	CBS (2017a) together with CBS (2018a)
Initial SA HI m	Initial	265503	CBS (2017a) together with CBS (2018a)
Initial SA HL m	Initial	102532	CBS (2017a) together with CBS (2018a)
Initial RE LI m	Initial	360499	CBS (2017a) together with CBS (2018a)
Initial RE LL m	Initial	172336	CBS (2017a) together with CBS (2018a)
Initial RE MI m	Initial	323570	CBS (2017a) together with CBS (2018a)
Initial RE ML m	Initial	203990	CBS (2017a) together with CBS (2018a)
Initial RE HI m	Initial	293675	CBS (2017a) together with CBS (2018a)
Initial RE HL m	Initial	130131	CBS (2017a) together with CBS (2018a)
Initial CH LI f	Initial	136353	CBS (2017a) together with CBS (2018a)
Initial CH LL f	Initial	3971	CBS (2017a) together with CBS (2018a)
Initial CH MI f	Initial	485841	CBS (2017a) together with CBS (2018a)

Initial CH ML f	Initial	19857	CBS (2017a) together with CBS (2018a)
Initial CH HI f	Initial	656613	CBS (2017a) together with CBS (2018a)
Initial CH HL f	Initial	43686	CBS (2017a) together with CBS (2018a)
Initial ST LI f	Initial	104994	CBS (2017a) together with CBS (2018a)
Initial ST LL f	Initial	3058	CBS (2017a) together with CBS (2018a)
Initial ST MI f	Initial	374104	CBS (2017a) together with CBS (2018a)
Initial ST ML f	Initial	15290	CBS (2017a) together with CBS (2018a)
Initial ST HI f	Initial	505601	CBS (2017a) together with CBS (2018a)
Initial ST HL f	Initial	33639	CBS (2017a) together with CBS (2018a)
Initial YA LI f	Initial	108089	CBS (2017a) together with CBS (2018a)
Initial YA LL f	Initial	3148	CBS (2017a) together with CBS (2018a)
Initial YA MI f	Initial	385133	CBS (2017a) together with CBS (2018a)
Initial YA ML f	Initial	15741	CBS (2017a) together with CBS (2018a)
Initial YA HI f	Initial	520507	CBS (2017a) together with CBS (2018a)
Initial YA HL f	Initial	34630	CBS (2017a) together with CBS (2018a)
Initial MA LI f	Initial	414045	CBS (2017a) together with CBS (2018a)
Initial MA LL f	Initial	13696	CBS (2017a) together with CBS (2018a)
Initial MA MI f	Initial	928177	CBS (2017a) together with CBS (2018a)
Initial MA ML f	Initial	66374	CBS (2017a) together with CBS (2018a)
Initial MA HI f	Initial	804911	CBS (2017a) together with CBS (2018a)
Initial MA HL f	Initial	75856	CBS (2017a) together with CBS (2018a)
Initial SA LI f	Initial	405924	CBS (2017a) together with CBS (2018a)
Initial SA LL f	Initial	10796	CBS (2017a) together with CBS (2018a)
Initial SA MI f	Initial	418879	CBS (2017a) together with CBS (2018a)
Initial SA ML f	Initial	25910	CBS (2017a) together with CBS (2018a)
Initial SA HI f	Initial	267737	CBS (2017a) together with CBS (2018a)
Initial SA HL f	Initial	18353	CBS (2017a) together with CBS (2018a)
Initial RE LI f	Initial	913177	CBS (2017a) together with CBS (2018a)
Initial RE LL f	Initial	32041	CBS (2017a) together with CBS (2018a)
Initial RE MI f	Initial	466602	CBS (2017a) together with CBS (2018a)

Initial RE ML f	Initial	46059	CBS (2017a) together with CBS (2018a)
Initial RE HI f	Initial	262338	CBS (2017a) together with CBS (2018a)
Initial RE HL f	Initial	10013	CBS (2017a) together with CBS (2018a)
Retirement age	Policy	780	Policy
Life expectancy H f	Constant	1069,2	CBS (2018b)
Life expectancy M f	Constant	1052,4	CBS (2018b)
Life expectancy L f	Constant	1027,2	CBS (2018b)
Life expectancy H m	Constant	1035,6	CBS (2018b)
Life expectancy M m	Constant	1006,8	CBS (2018b)
Life expectancy L m	Constant	987,6	CBS (2018b)
Death rate infants H	Constant	0,0023	CBS (2018b)
Death rate infants M	Constant	0,0029	CBS (2018b)
Death rate infants L	Constant	0,0074	CBS (2018b)
Death rate CH	Constant	0	CBS (2018b)
Death rate ST	Constant	0	CBS (2018b)
Death rate YA	Constant	0	CBS (2018b)
Death rate MA	Constant	0	CBS (2018b)
Death rate SA	Constant	0	CBS (2018b)
Normal ratio HL to HI at birth f	Constant	0,062	CBS (2018a)
Normal ratio ML to MI at birth f	Constant	0,039	CBS (2018a)
Normal ratio LL to LI at birth f	Constant	0,028	CBS (2018a)
Normal ratio HL to HI at birth m	Constant	0,293	CBS (2018a)
Normal ratio ML to MI at birth m	Constant	0,34	CBS (2018a)
Normal ratio LL to LI at birth m	Constant	0,293	CBS (2018a)
ratio of no SL level difference	Constant	0,432	CBS (2017c)
ratio of 1 SL level difference	Constant	0,409	CBS (2017c)
ratio of 2 SL level difference	Constant	0,145	CBS (2017c)
ratio YA f higher SL than YA m	Constant	0,322	CBS (2017c)
ratio YA f same SL as YA m	Constant	0,466	CBS (2017c)
ratio YA f lower SL than YA m	Constant	0,212	CBS (2017c)

Correlation strenght YA SL f on CH f	Constant	0,117	CBS (2011b)
Correlation strenght YA SL m on CH f	Constant	0,132	CBS (2011b)
Correlation strenght YA SL f on CH m	Constant	0,099	CBS (2011b)
Correlation strenght YA SL m on CH m	Constant	0,132	CBS (2011b)
ratio YA H f birth H f	Constant	0,502	CBS (2011a)
ratio YA H f birth M f	Constant	0,338	CBS (2011a)
ratio YA H f birth L f	Constant	0,16	CBS (2011a)
ratio YA M f birth H f	Constant	0,418	CBS (2011a)
ratio YA M f birth M f	Constant	0,334	CBS (2011a)
ratio YA M f birth L f	Constant	0,248	CBS (2011a)
ratio YA L f birth H f	Constant	0,244	CBS (2011a)
ratio YA L f birth M f	Constant	0,332	CBS (2011a)
ratio YA L f birth L f	Constant	0,424	CBS (2011a)
ratio YA H f birth H m	Constant	0,525	CBS (2011a)
ratio YA H f birth M m	Constant	0,3	CBS (2011a)
ratio YA H f birth L m	Constant	0,175	CBS (2011a)
ratio YA M f birth H m	Constant	0,366	CBS (2011a)
ratio YA M f birth M m	Constant	0,355	CBS (2011a)
ratio YA M f birth L m	Constant	0,28	CBS (2011a)
ratio YA L f birth H m	Constant	0,217	CBS (2011a)
ratio YA L f birth M m	Constant	0,327	CBS (2011a)
ratio YA L f birth L m	Constant	0,457	CBS (2011a)
ratio YA H m birth H f	Constant	0,505	CBS (2011a)
ratio YA H m birth M f	Constant	0,318	CBS (2011a)
ratio YA H m birth L f	Constant	0,177	CBS (2011a)
ratio YA M m birth H f	Constant	0,373	CBS (2011a)
ratio YA M m birth M f	Constant	0,35	CBS (2011a)
ratio YA M m birth L f	Constant	0,277	CBS (2011a)
ratio YA L m birth H f	Constant	0,269	CBS (2011a)
ratio YA L m birth M f	Constant	0,325	CBS (2011a)

ratio YA L m birth L f	Constant	0,406	CBS (2011a)
ratio YA H m birth H m	Constant	0,523	CBS (2011a)
ratio YA H m birth M m	Constant	0,302	CBS (2011a)
ratio YA H m birth L m	Constant	0,175	CBS (2011a)
ratio YA M m birth H m	Constant	0,359	CBS (2011a)
ratio YA M m birth M m	Constant	0,354	CBS (2011a)
ratio YA M m birth L m	Constant	0,287	CBS (2011a)
ratio YA L m birth H m	Constant	0,211	CBS (2011a)
ratio YA L m birth M m	Constant	0,327	CBS (2011a)
ratio YA L m birth L m	Constant	0,462	CBS (2011a)
ratio female to male at birth	Constant	0,95	CBS (2017a)
Normal fertility rate per f	Uncertainty	1,62	CBS (2018c)
Fertility index LOOKUP	LOOKUP	LOOKUP	LOOKUP (see 11.2)
Fertility correction H f	Variable	0,89	CBS (2012a)
Fertility correction M f	Variable	1	CBS (2012a)
Fertility correction L f	Variable	1,08	CBS (2012a)
t upto CH to ST	Constant	180	Based on labour market dataset
t upto ST to YA H	Constant	120	Based on labour market dataset
t upto ST to YA M	Constant	120	Based on labour market dataset
t upto ST to YA L	Constant	120	Based on labour market dataset
t upto ST to MA	Constant	240	Based on labour market dataset
t upto MA to SA	Constant	240	Based on labour market dataset
POPULATION TEST SETTING	Setting	1	Setting
Fraction of delay	Setting	0,1	Setting
Delay order	Setting	15	Setting
Set Initial reskill and upskill flows to zero	Setting	0	Setting
SWITCH SL segregation in society	Setting	0	Setting

Labour market

Parameter_Name	**Type**	**Value**	**Source**

ST L m participation	Constant	0,615	CBS (2018d)
ST M m participation	Constant	0,73	CBS (2018d)
ST H m participation	Constant	0,724	CBS (2018d)
YA L m participation	Constant	0,808	CBS (2018d)
YA M m participation	Constant	0,912	CBS (2018d)
YA H m participation	Constant	0,949	CBS (2018d)
MA L m participation	Constant	0,82	CBS (2018d)
MA M m participation	Constant	0,919	CBS (2018d)
MA H m participation	Constant	0,968	CBS (2018d)
SA L m participation	Constant	0,699	CBS (2018d)
SA M m participation	Constant	0,799	CBS (2018d)
SA H m participation	Constant	0,867	CBS (2018d)
RE L m participation	Constant	0,078	CBS (2018d)
RE M m participation	Constant	0,102	CBS (2018d)
RE H m participation	Constant	0,146	CBS (2018d)
ST L f participation	Constant	0,614	CBS (2018d)
ST M f participation	Constant	0,753	CBS (2018d)
ST H f participation	Constant	0,804	CBS (2018d)
YA L f participation	Constant	0,569	CBS (2018d)
YA M f participation	Constant	0,817	CBS (2018d)
YA H f participation	Constant	0,922	CBS (2018d)
MA L f participation	Constant	0,608	CBS (2018d)
MA M f participation	Constant	0,83	CBS (2018d)
MA H f participation	Constant	0,905	CBS (2018d)
SA L f participation	Constant	0,453	CBS (2018d)
SA M f participation	Constant	0,656	CBS (2018d)
SA H f participation	Constant	0,755	CBS (2018d)
RE L f participation	Constant	0,023	CBS (2018d)
RE M f participation	Constant	0,04	CBS (2018d)
RE H f participation	Constant	0,068	CBS (2018d)

ST L m ratio fulltime	Constant	0,182	CBS (2018d)
ST M m ratio fulltime	Constant	0,36	CBS (2018d)
ST H m ratio fulltime	Constant	0,492	CBS (2018d)
YA L m ratio fulltime	Constant	0,806	CBS (2018d)
YA M m ratio fulltime	Constant	0,812	CBS (2018d)
YA H m ratio fulltime	Constant	0,833	CBS (2018d)
MA L m ratio fulltime	Constant	0,869	CBS (2018d)
MA M m ratio fulltime	Constant	0,865	CBS (2018d)
MA H m ratio fulltime	Constant	0,845	CBS (2018d)
SA L m ratio fulltime	Constant	0,787	CBS (2018d)
SA M m ratio fulltime	Constant	0,76	CBS (2018d)
SA H m ratio fulltime	Constant	0,75	CBS (2018d)
RE L m ratio fulltime	Constant	0,308	CBS (2018d)
RE M m ratio fulltime	Constant	0,28	CBS (2018d)
RE H m ratio fulltime	Constant	0,196	CBS (2018d)
ST L f ratio fulltime	Constant	0,041	CBS (2018d)
ST M f ratio fulltime	Constant	0,149	CBS (2018d)
ST H f ratio fulltime	Constant	0,354	CBS (2018d)
YA L f ratio fulltime	Constant	0,263	CBS (2018d)
YA M f ratio fulltime	Constant	0,271	CBS (2018d)
YA H f ratio fulltime	Constant	0,499	CBS (2018d)
MA L f ratio fulltime	Constant	0,194	CBS (2018d)
MA M f ratio fulltime	Constant	0,214	CBS (2018d)
MA H f ratio fulltime	Constant	0,33	CBS (2018d)
SA L f ratio fulltime	Constant	0,149	CBS (2018d)
SA M f ratio fulltime	Constant	0,186	CBS (2018d)
SA H f ratio fulltime	Constant	0,297	CBS (2018d)
RE L f ratio fulltime	Constant	0,1	CBS (2018d)
RE M f ratio fulltime	Constant	0,111	CBS (2018d)
RE H f ratio fulltime	Constant	0,118	CBS (2018d)

Sensitivity Wage reallocation	Uncertainty	0-0, 999	Uncertainty space
Wage sacrifice ratio for employment	Uncertainty	0,01-0,5	Uncertainty space
Sensitivity Unemployment reallocation	Uncertainty	0-1	Uncertainty space
Normal Labour Supply Demand Mismatch ratio	Constant	0,02	ASSUMTION: Effective minimum unemployment due to regional and sectoral mismatches
Labour reallocation delay	Uncertainty	12	Uncertainty space 6 to 24
SWITCH Wage discrete criteria OR relative factor	Setting	0	Setting
SWITCH Equal Labour market OR Skill level preference	Setting	0	Setting
Error MINMAX corrector	Setting	1,00E+16	Setting
SWITCH part time labour market OFF	Constant	0	Setting
Minimum Labour Supply	Setting	1	Setting

Education model

Parameter_Name	Type	Value	Source
Time to introduction STEM program	Policy	60	Policy
Period for STEM program to become fully integrated	Constant	120	Bybee (2010)
STEM initial program score	Constant	0	-
CH Edu performance Reskill equivalent	Variable	30	Woessmann (2016)
CH Edu performance Upskill equivalent	Variable	30	Woessmann (2016)
STEM educated vs STEM graduated ratio	Policy	0,4	Wells, Sanchez, and Attridge (2007)
Time to realise CH Edu capacity expansion	Policy	48	Ministry of Education, Culture and Science (2018b)
Minimum fixed period CH Edu capacity expansion	Constant	36	Ministry of Education, Culture and Science (2018b)
CH Edu capacity planning	Policy	1	Policy
ST STEM stimulation and awareness	Policy	1	Policy
ST High Edu stimulation and awareness	Policy	1	Policy
ST Labour market awareness and sensitivity	Uncertainty	0-1	Uncertainty space
ST knowledge YA Unemployment delay	Uncertainty	12-48	Uncertainty space
ST STEM Edu capacity expansion stimulation	Policy	1	ASSUMPTION: STEM creation can not be done faster
Time to realise ST Edu capacity expansion	Policy	60	Policy
Fixed period ST Edu capacity expansion	Constant	12	ASSUMPTION: it takes one year to find the required resources, financially (due to annual budget), staff

			(contracts), and find (temporary) space
ST Edu capacity planning	Policy	1	Policy
WA STEM stimulation and awareness	Policy	1	Policy
WA High Edu stimulation and awareness	Policy	1	Policy
WAu reskill and upskill sensitivity	Uncertainty	0-1	Uncertainty space
WAe reskill and upskill sensitivity	Uncertainty	0-1	Uncertainty space
SA and RE LF relative reduction in training	Variable	1-0,952	CBS (2018d)
Socioeconomic influence education and training H	Constant	1,297	CBS (2018d)
Socioeconomic influence education and training M	Constant	0,895	CBS (2018d)
Socioeconomic influence education and training L	Constant	0,561	CBS (2018d)
MANUAL CH Edu performance overall improvement H	Policy	0	Policy
MANUAL CH Edu performance overall improvement M	Policy	0	Policy
MANUAL CH Edu performance overall improvement L	Policy	0	Policy
MANUAL CH Edu performance STEM improvement H	Policy	0	Policy
MANUAL CH Edu performance STEM improvement M	Policy	0	Policy
MANUAL CH Edu performance STEM improvement L	Policy	0	Policy
SWITCH Overall Education factors OR MANUAL performance increase	Setting	0	Setting
SWITCH STEM Education factors OR MANUAL performance increase	Setting	0	Setting
Time to realise CH Edu HL demographic growth	Setting	1	Setting
Time to realise CH Edu HI demographic growth	Setting	1	Setting
Time to realise CH Edu ML demographic growth	Setting	1	Setting
Time to realise CH Edu MI demographic growth	Setting	1	Setting
Time to realise CH Edu LL demographic growth	Setting	1	Setting
Time to realise CH Edu LI demographic growth	Setting	1	Setting
Time to realise ST Edu HL demographic growth	Setting	1	Setting
Time to realise ST Edu HI demographic growth	Setting	1	Setting
Time to realise ST Edu ML demographic growth	Setting	1	Setting
Time to realise ST Edu MI demographic growth	Setting	1	Setting
Time to realise ST Edu LL demographic growth	Setting	1	Setting
Time to realise ST Edu LI demographic growth	Setting	1	Setting

Technology model

Parameter_Name	Type	Value	Source
Prior Substituted Labour demand	Uncertainty	8,9-10,1	Gregory, Salomons, and Zierahn (2016)
Prior stock of Labour demand	Initial	180	Gregory, Salomons, and Zierahn (2016)
Prior period of labour substitution	Initial	11	Gregory, Salomons, and Zierahn (2016)
Current rate of substitution Abstract correction	Initial	0,4	Setting
Long term annual TFP growth LOOKUP	Lookup	LOOKUP	OECD (2015a)
Macro economic Technological TFP growth	Constant	0,0067	Graetz & Michaels (2017)
Skill mismatch GDP factor	Constant	0	OECD (2015a)
Innovation allocation GDP factor	Constant	0	OECD (2015a)
Initial Economic Innovation allocation	Initial	0,02013	The World Bank (2015)
Productivity growth Profit allocation	Constant	0,233	Graetz and Michaels (2017)
Productivity growth Competitive allocation	Constant	0,667	Graetz and Michaels (2017)
Productivity growth Wage allocation	Constant	0,1	Graetz and Michaels (2017)
Proportion profit invested in innovation	Uncertainty	0-1	Uncertainty space
Solow Paradox multiplier	Uncertainty	0-1	Uncertainty space
Wage decline in relation to substitution	Constant	0	Nedelkoska and Quintini (2018)
Innovation allocation sensivitity to business cycle	Uncertainty	0-0,1	Uncertainty space
Minimum Economic Innovation allocation	Constant	0,7	ASSUMPTION
SWITCH net OECD TFP vs Technology corrected TFP	Setting	0	Setting
SWITCH Difference automation vs substitution	Setting	0	Setting
Time difference automation and substitution	Uncertainty	Table 2	Uncertainty
Upper bound technological bottleneck proportion of tasks	Uncertainty	0,01-0,1	Setting
SWITCH Relief Solow Paradox	Setting	0	Setting
TFP Wage allocation Manual I	Uncertainty	0-1	Uncertainty
TFP Wage allocation Manual L	Uncertainty	0-1	Uncertainty
TFP Wage allocation Routine I	Uncertainty	0-1	Uncertainty
TFP Wage allocation Routine L	Uncertainty	0-1	Uncertainty
TFP Wage allocation Abstract I	Uncertainty	0-1	Uncertainty

TFP Wage allocation Abstract L	Uncertainty	0-1	Uncertainty

III SD Model

A high resolution of the SD model overview image (Figure 34 to Figure 38) can be found here[108].

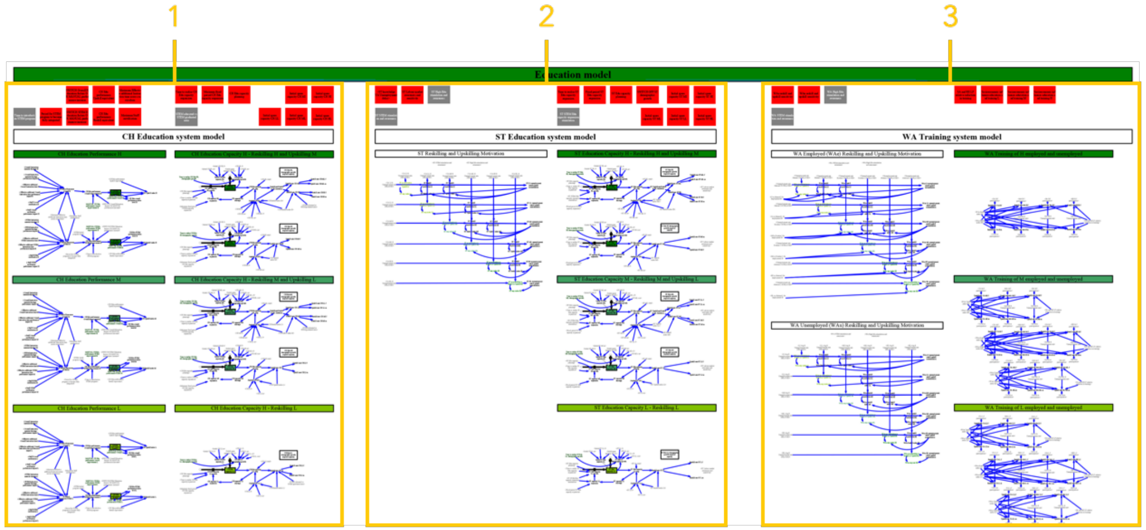


Figure 34 SD model - Education model overview

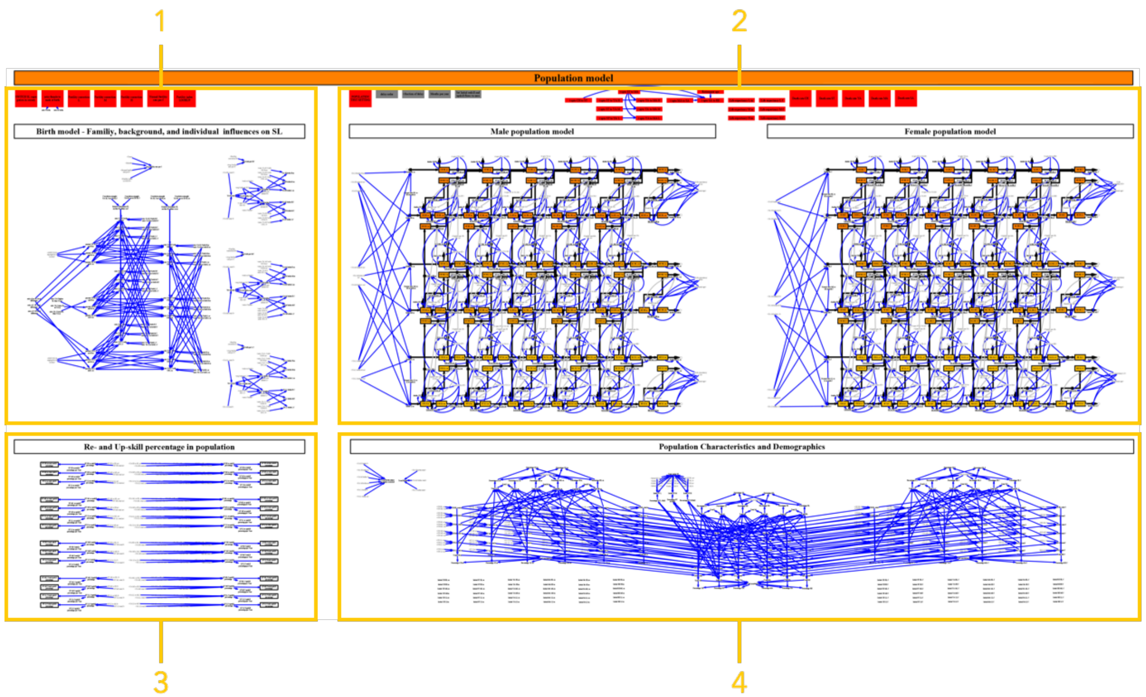
Education Model

1 = CH education based on stimulation program per skill level resulting in re- and up-skilling depending on the available capacity

2 = ST education based on relative unemployment rate of young adults as an incentive to re- or up-skill depending on the available capacity

3 = WA training based on relative unemployment and influenced by demographic factors

[108] If the link does not work, copy and paste the following address: https://drive.google.com/open?id=1FPkYn0sRTRkiVz4PAEPdnQKjCz28qo7d



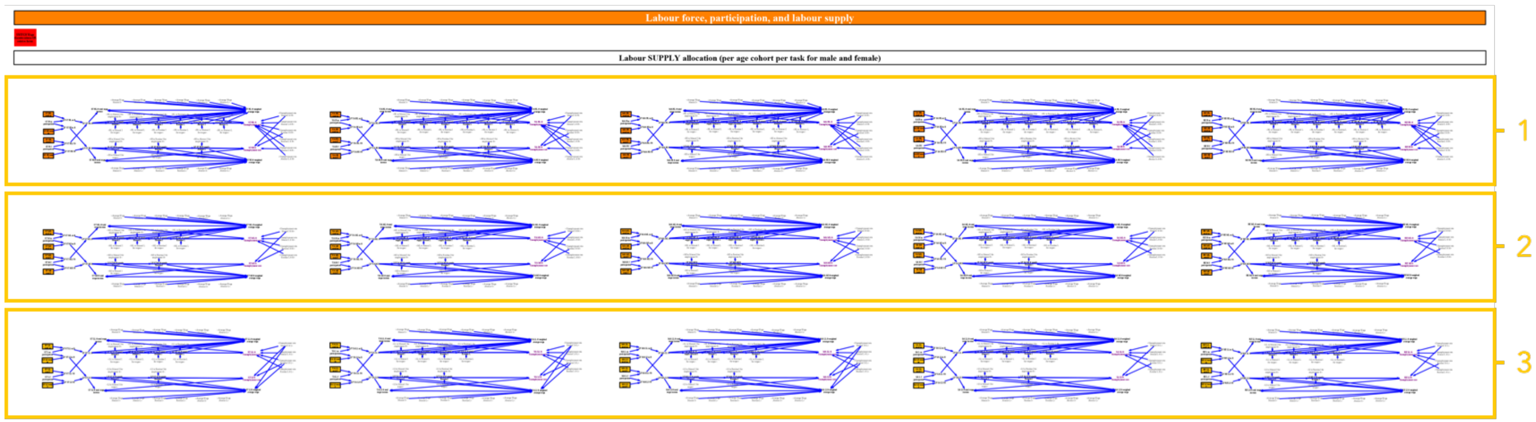
Demographic Model (1)

1 = Births based on

2 = Male and Female populations across skill levels and age cohorts

3 = Re- and up-skilling outcomes for $\mathbb{ST}$ and $\mathbb{WA}$

4 = Population properties



Demographic Model (2)

1 = High skilled ($L_{\varepsilon_{\mathbb{H}}}$, $L_{\xi_{\mathbb{H}}}$) labour force, supply allocation, and unemployment and wage per age cohort

2 = Middle skilled ($L_{\varepsilon_{\mathbb{M}}}$, $L_{\xi_{\mathbb{M}}}$) labour force, supply allocation, and unemployment and wage per age cohort

3 = Low skilled ($L_{\varepsilon_{\mathbb{L}}}$, $L_{\xi_{\mathbb{L}}}$) labour force, supply allocation, and unemployment and wage per age cohort

Figure 35 SD model – Demographic model overview (Population (1) and Labour force (2))

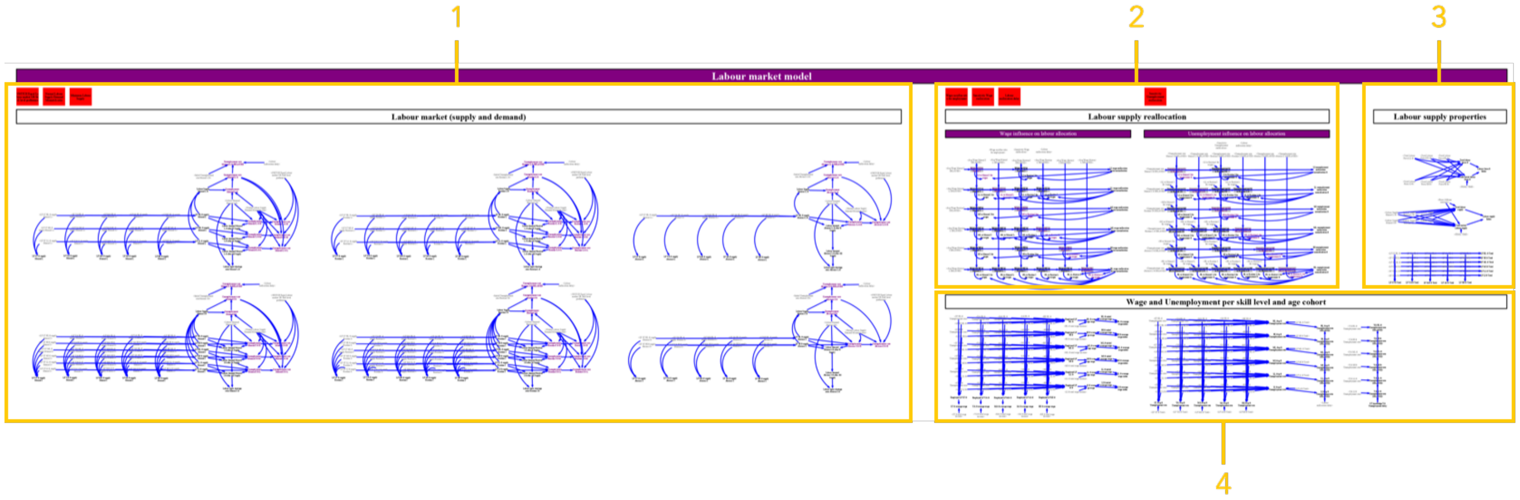


Figure 36 SD model – Labour market model overview

Labour Market Model

1 = Labour market per task

2 = Labour allocation based on wages and unemployment

3 = Labour supply properties

4 = Wage and unemployment outcomes per skill level and age cohort

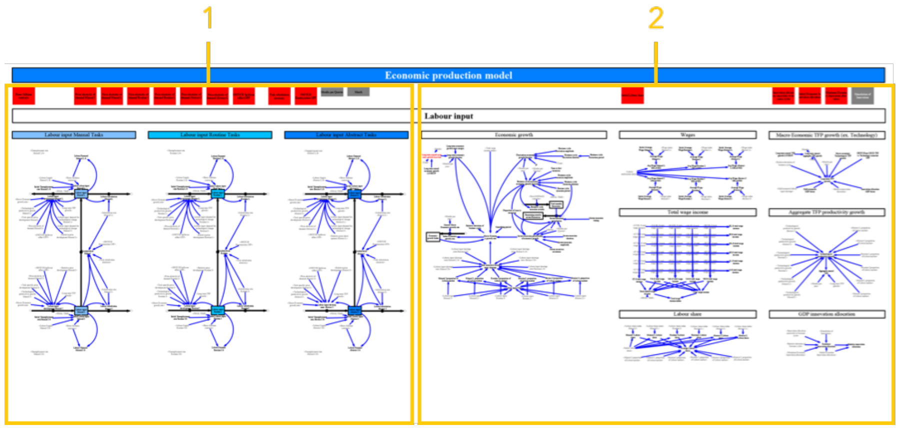


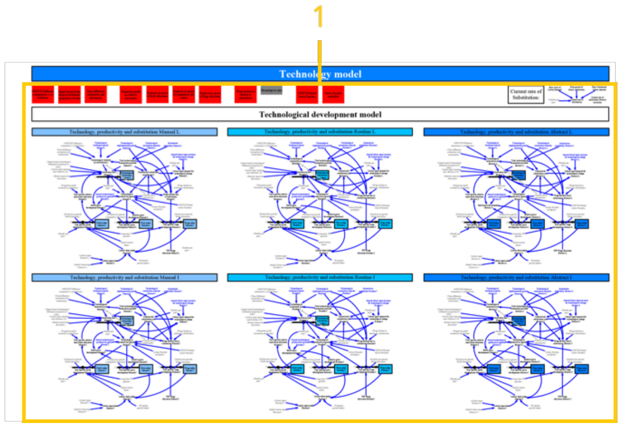
Figure 37 SD model - Production model overview

Production Model

1 = Labour input per task and routinisation between tasks

2 = Macro economic growth projection, Labour share, TFP, innovation investment, and total wage income

Figure 38 SD model - Technology model overview



Technology Model

1 = Technological substitution, productivity growth, and spill-overs (profit, price, wage) per task

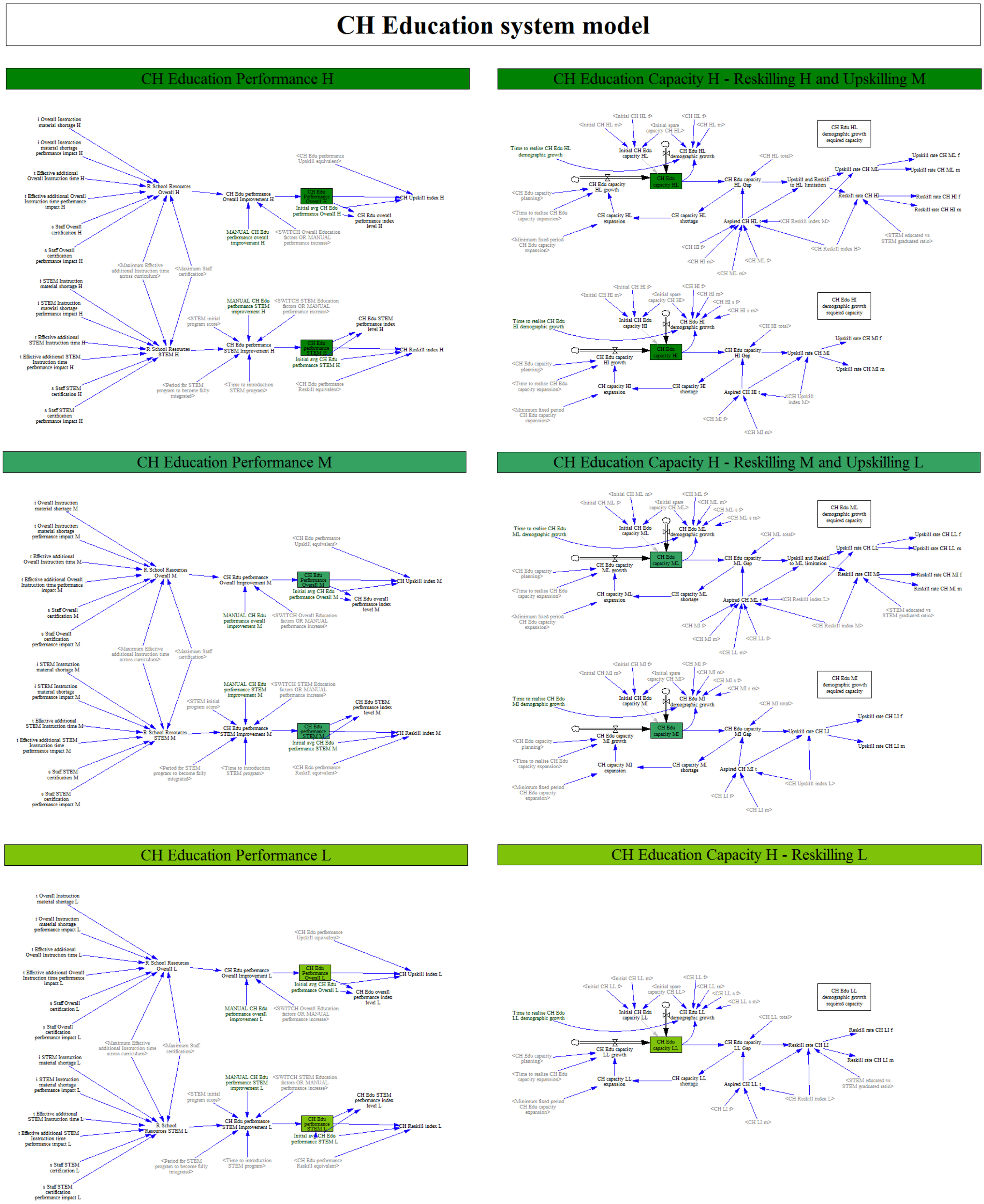


Figure 39 SD Model – Enlarged Children education

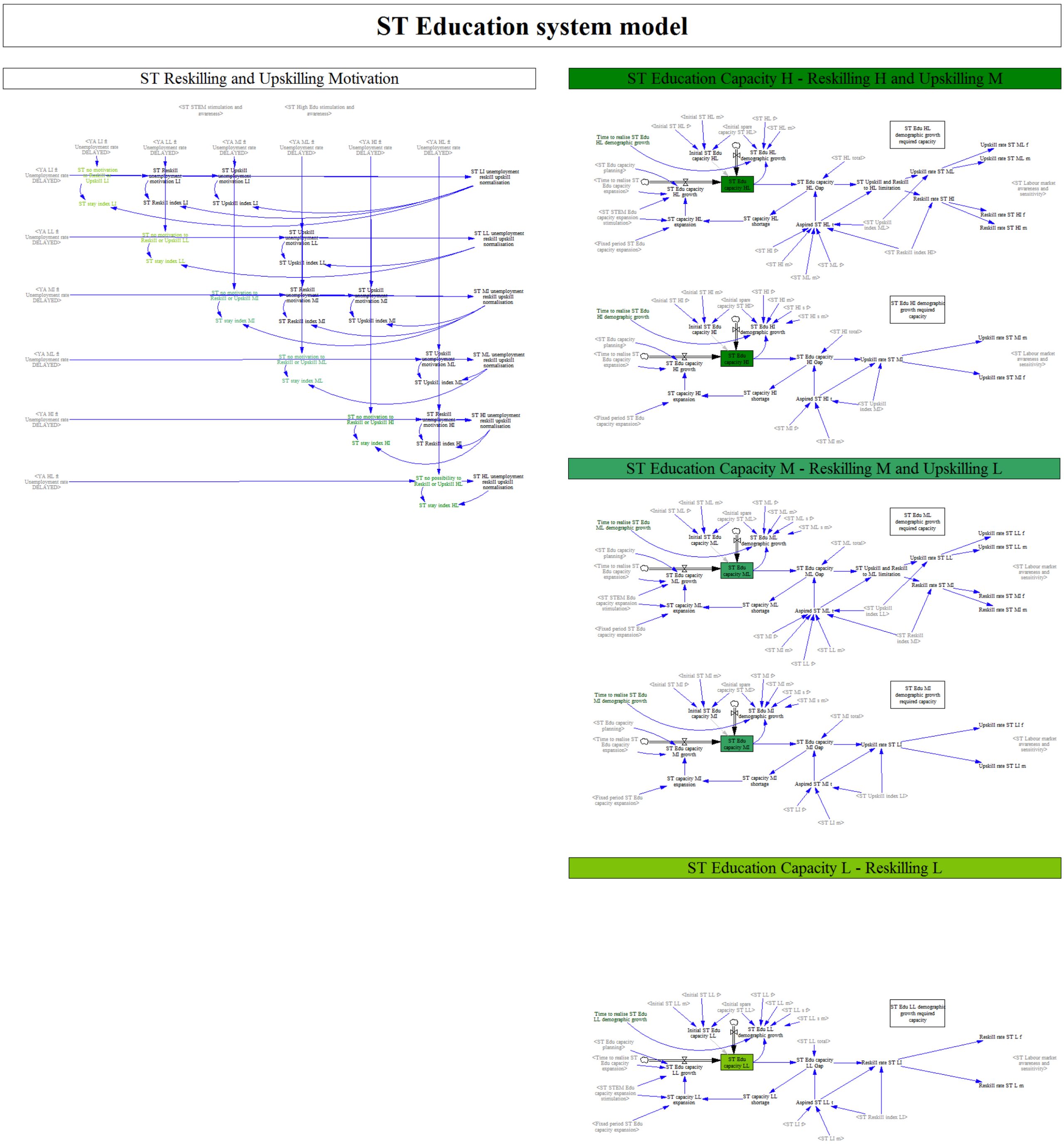


Figure 40 SD Model – Enlarged Student education

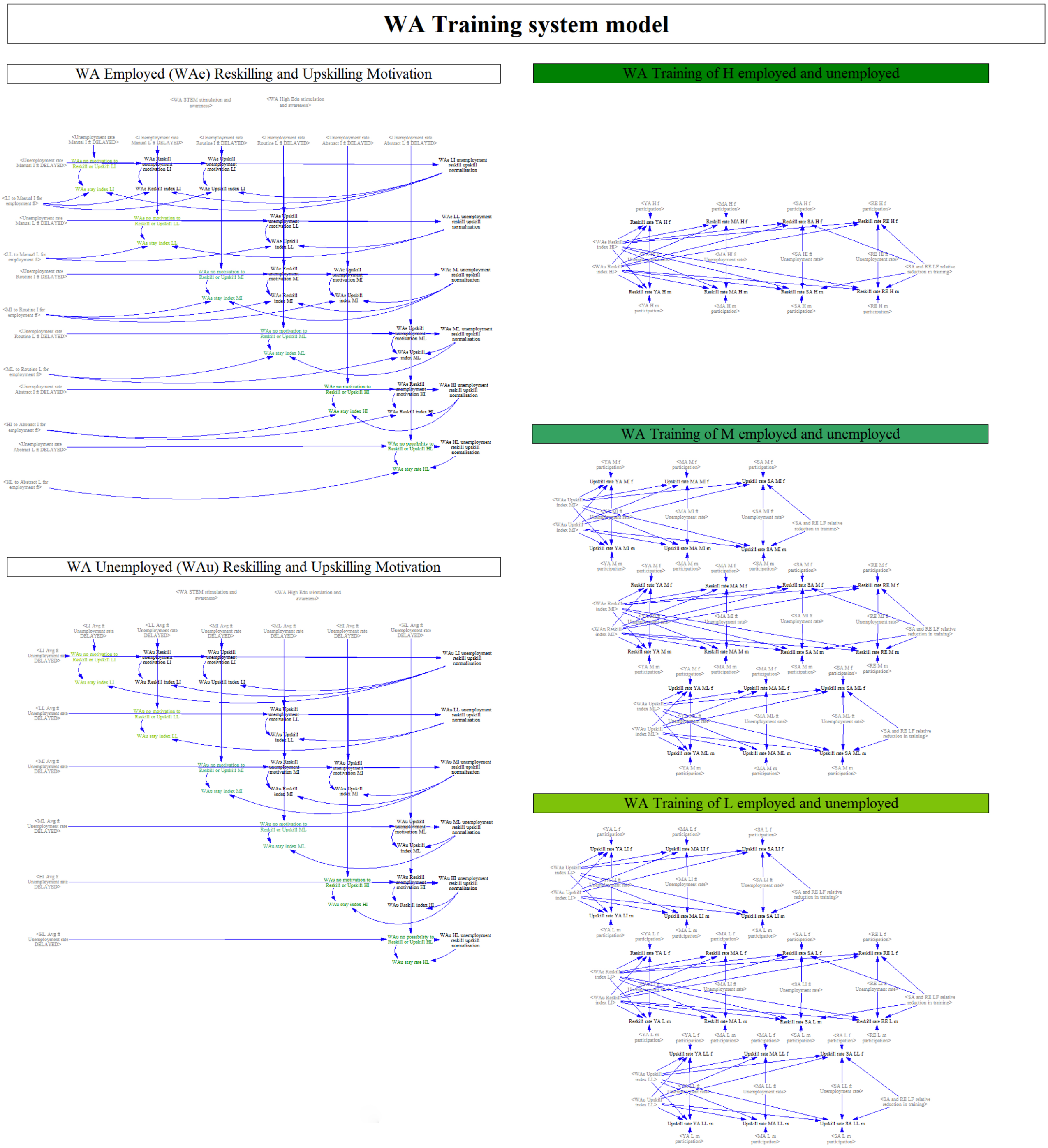


Figure 41 SD Model – Enlarged Working age training

Birth model - Familiy, background, and individual influences on SL

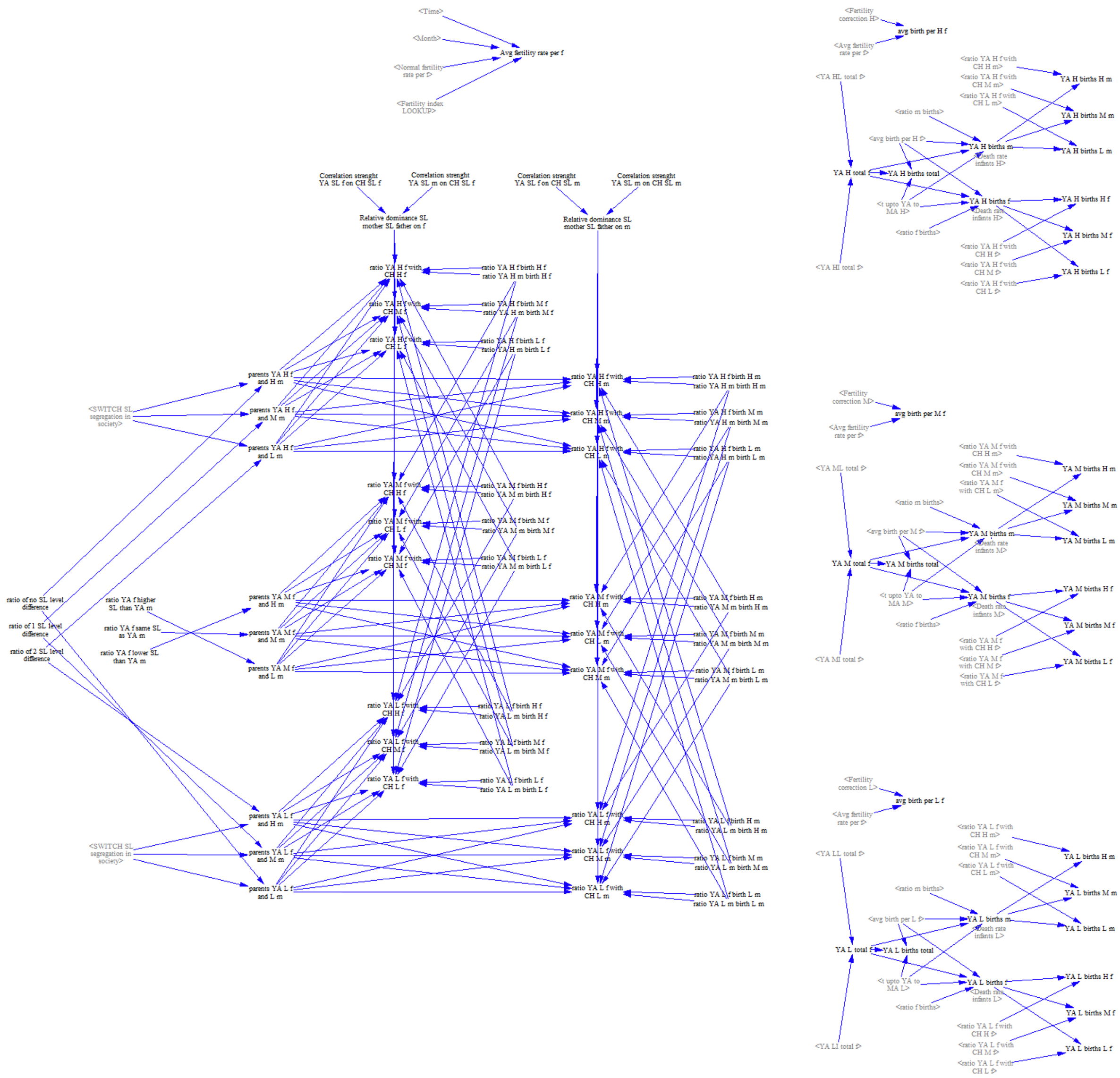


Figure 42 SD model – Birth component

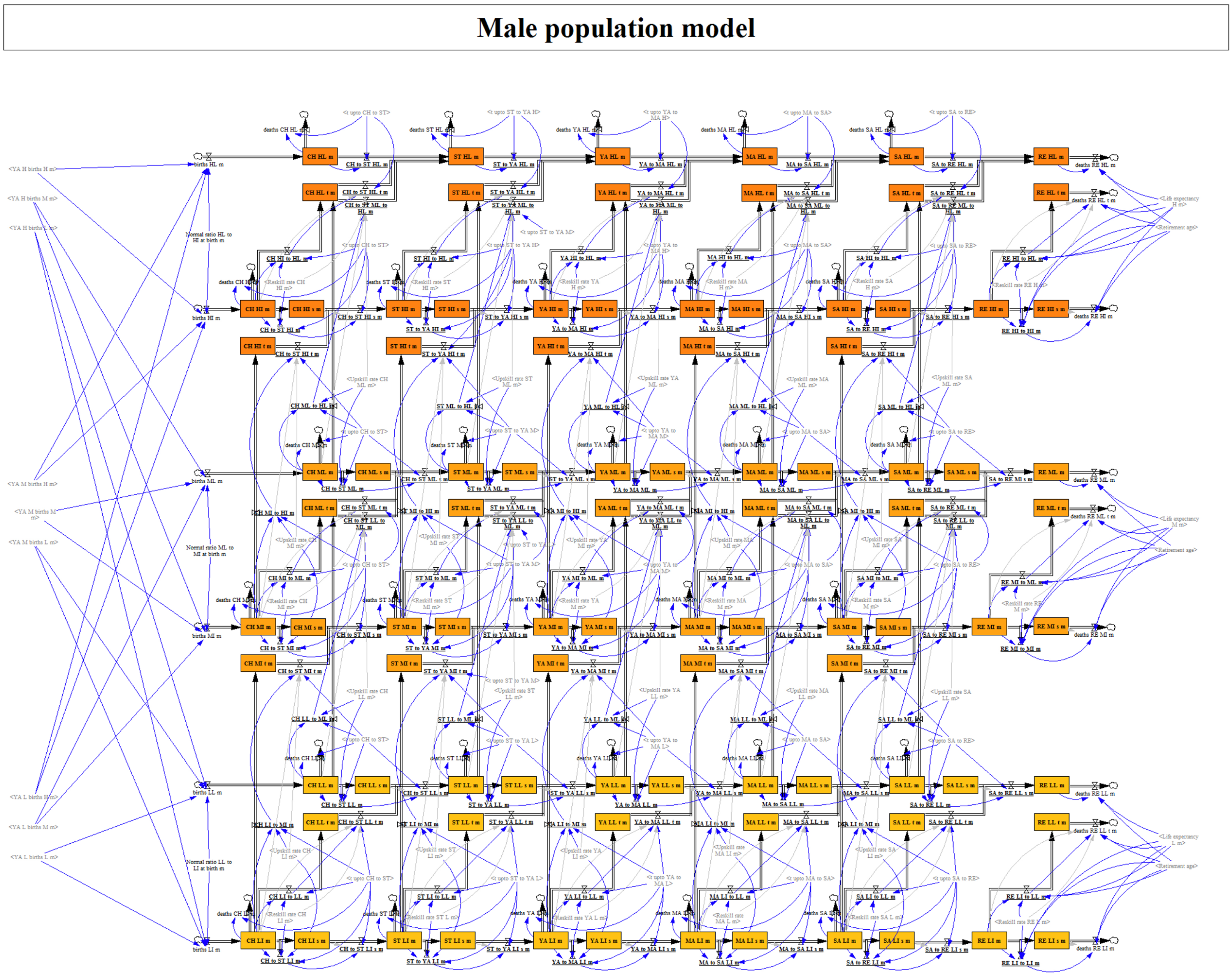


Figure 43 SD Model – Male population

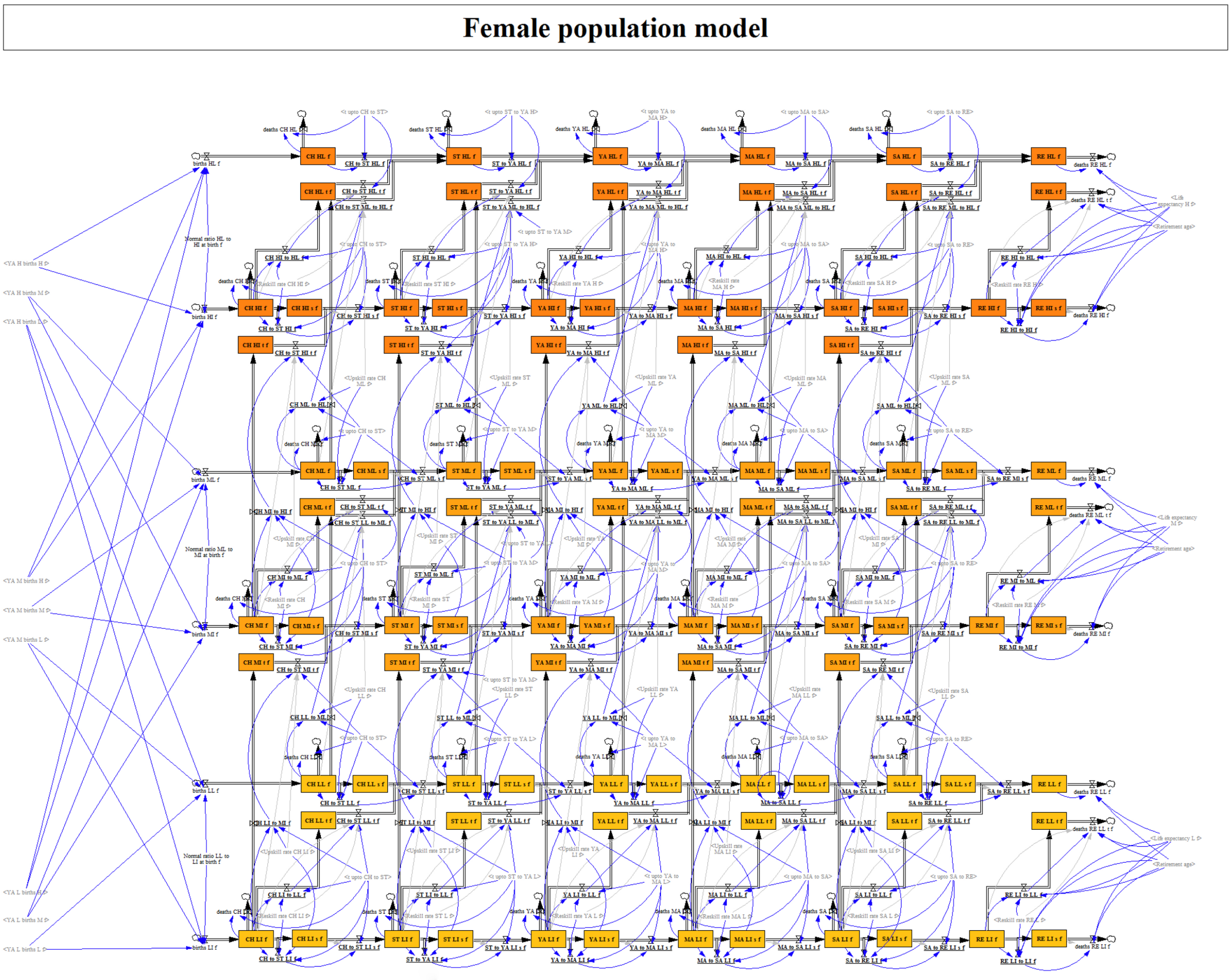


Figure 44 SD Model – Female population

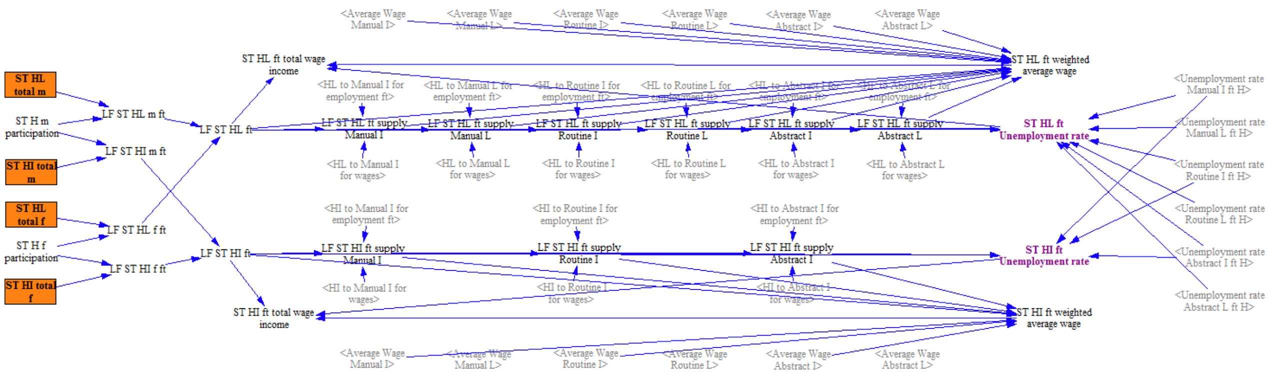


Figure 45 SD model – Labour force and labour supply allocation (sample of component per skill level per age cohort)

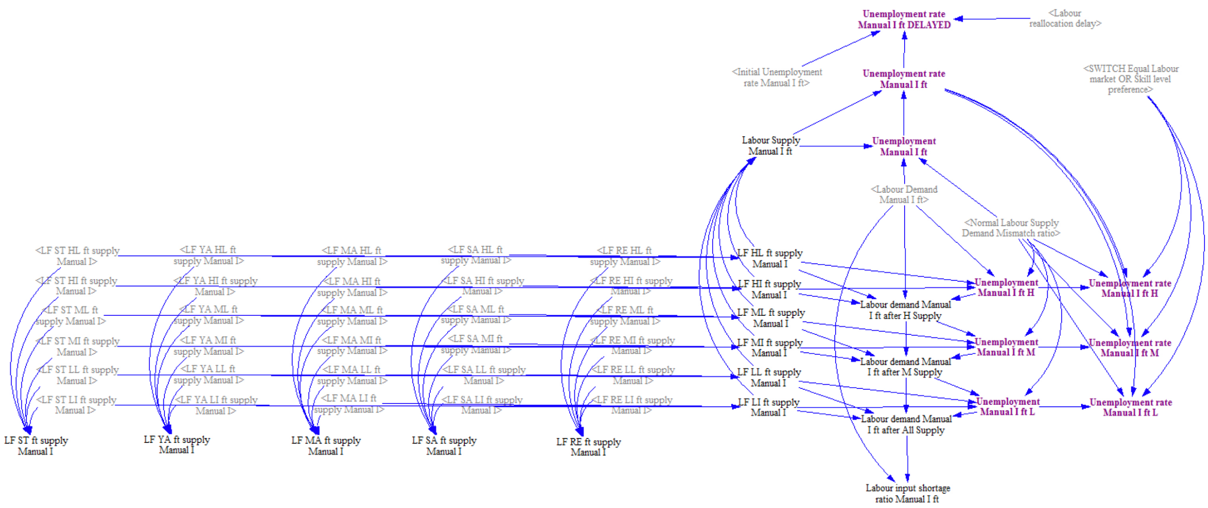


Figure 46 SD model – Labour market (sample of component per task)

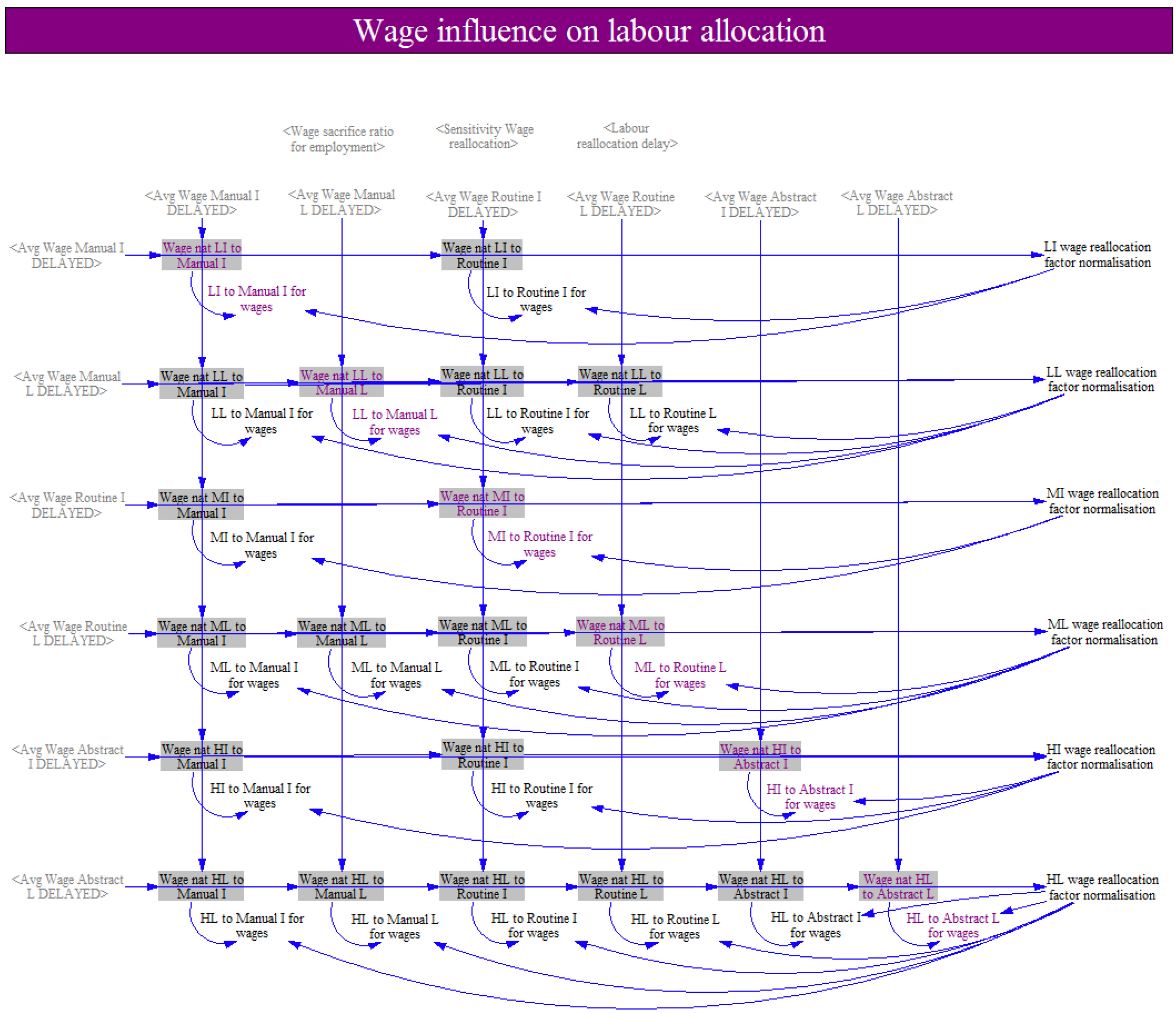


Figure 47 SD model – Labour market supply reallocation based on wages

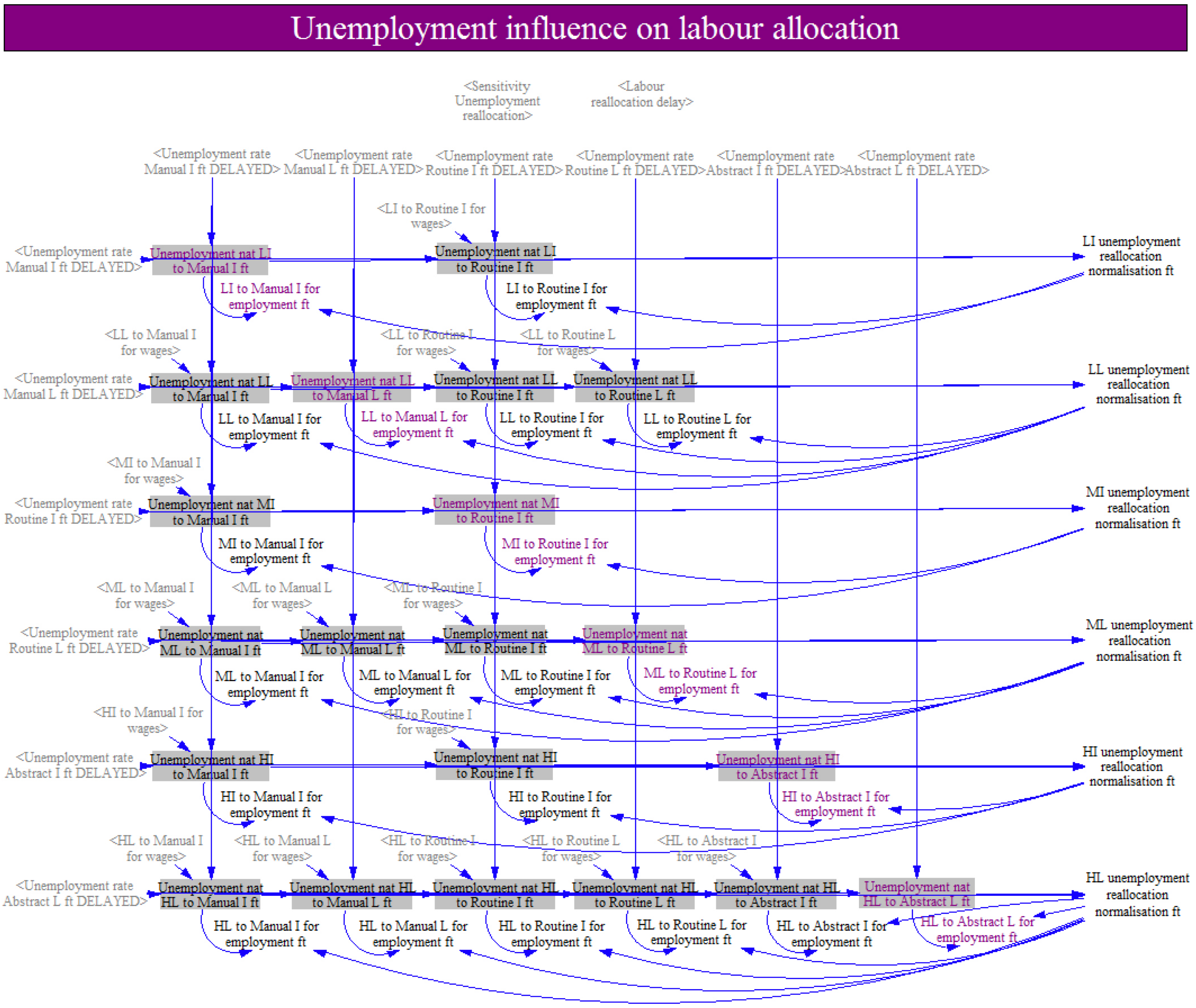


Figure 48 SD model – Labour market supply reallocation based on unemployment

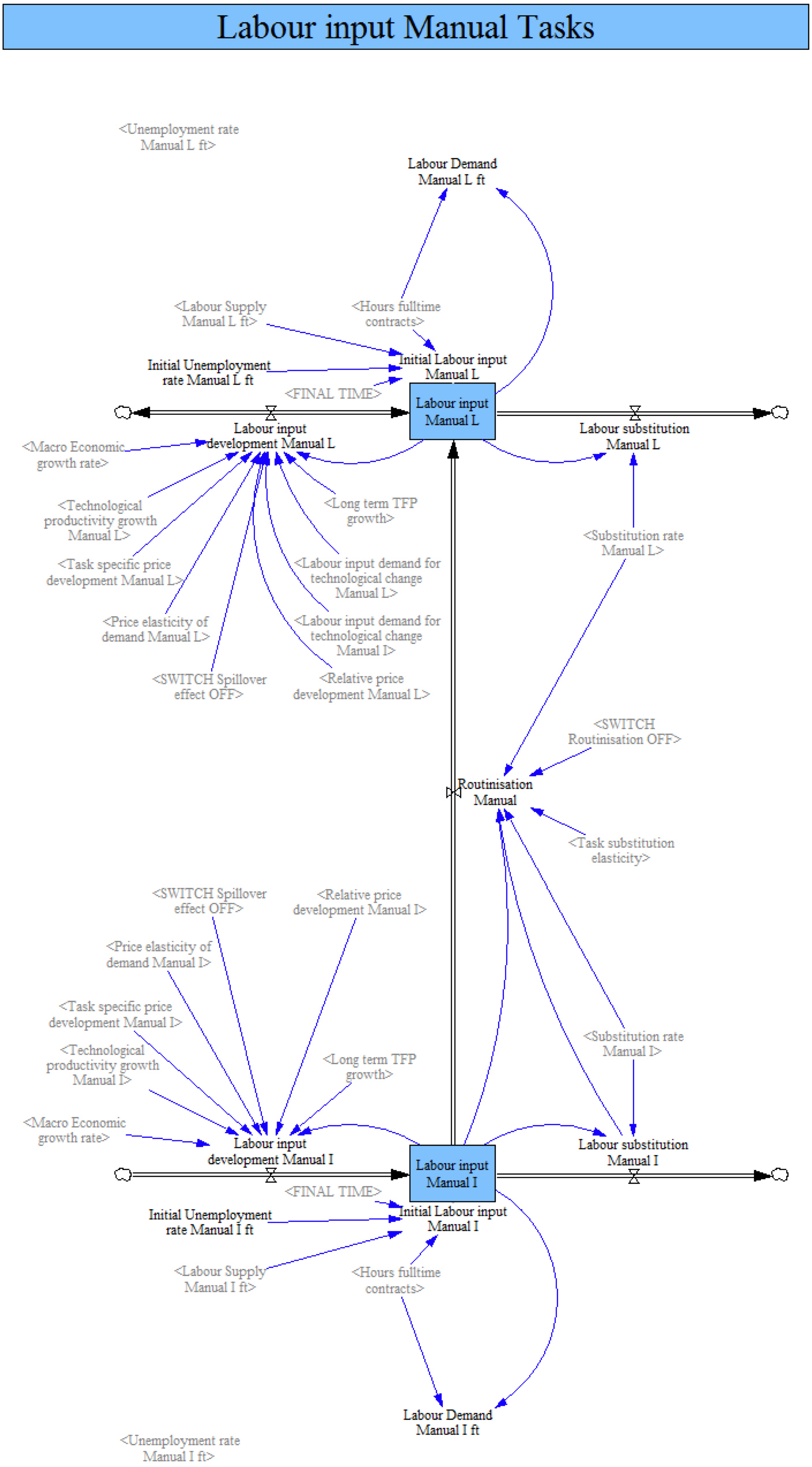


Figure 49 SD model – Production model labour input with spill-overs and routinisation (sample of component per task)

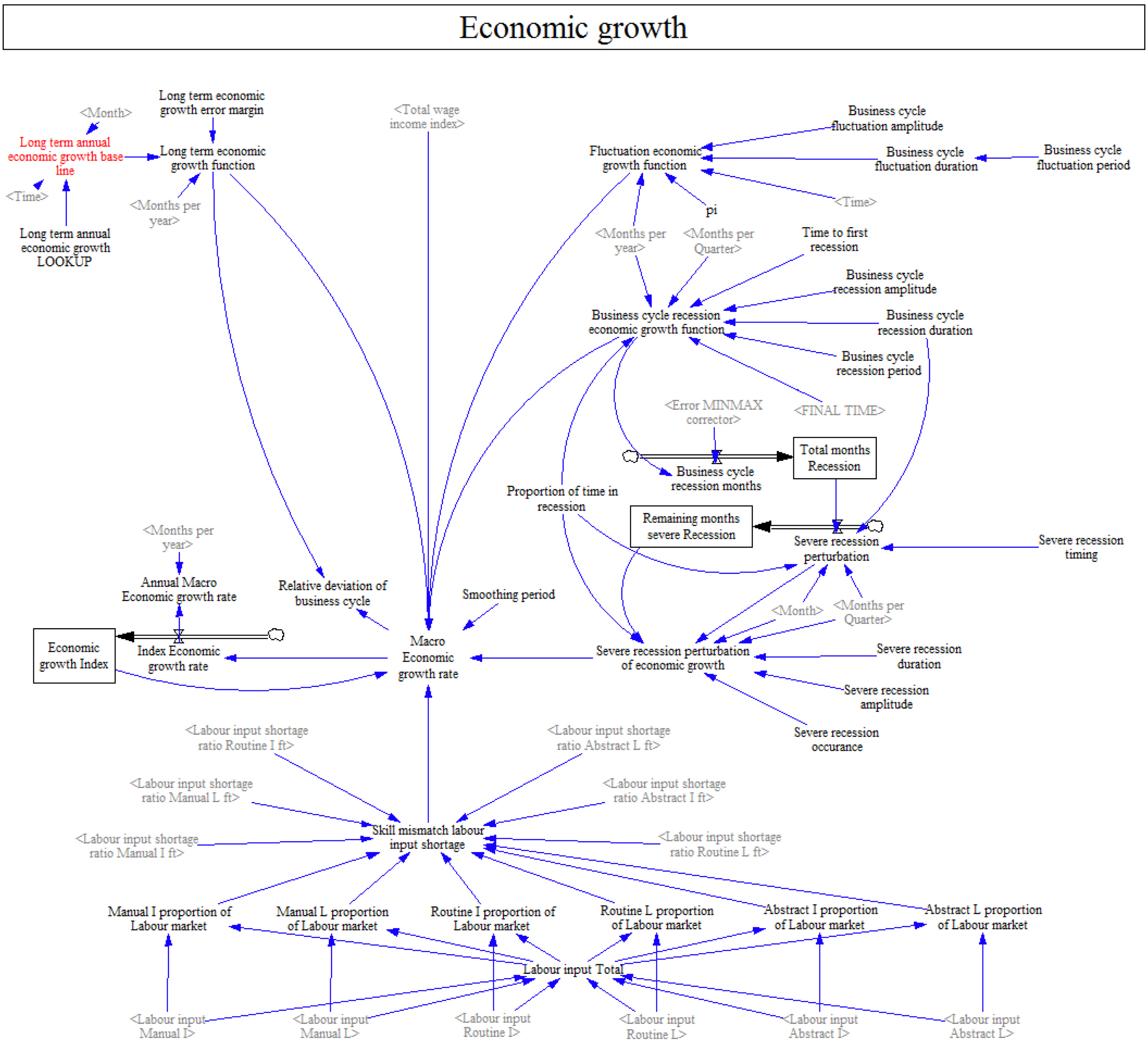


Figure 50 SD model – Production model corrected economic growth projection with feedback-mechanisms

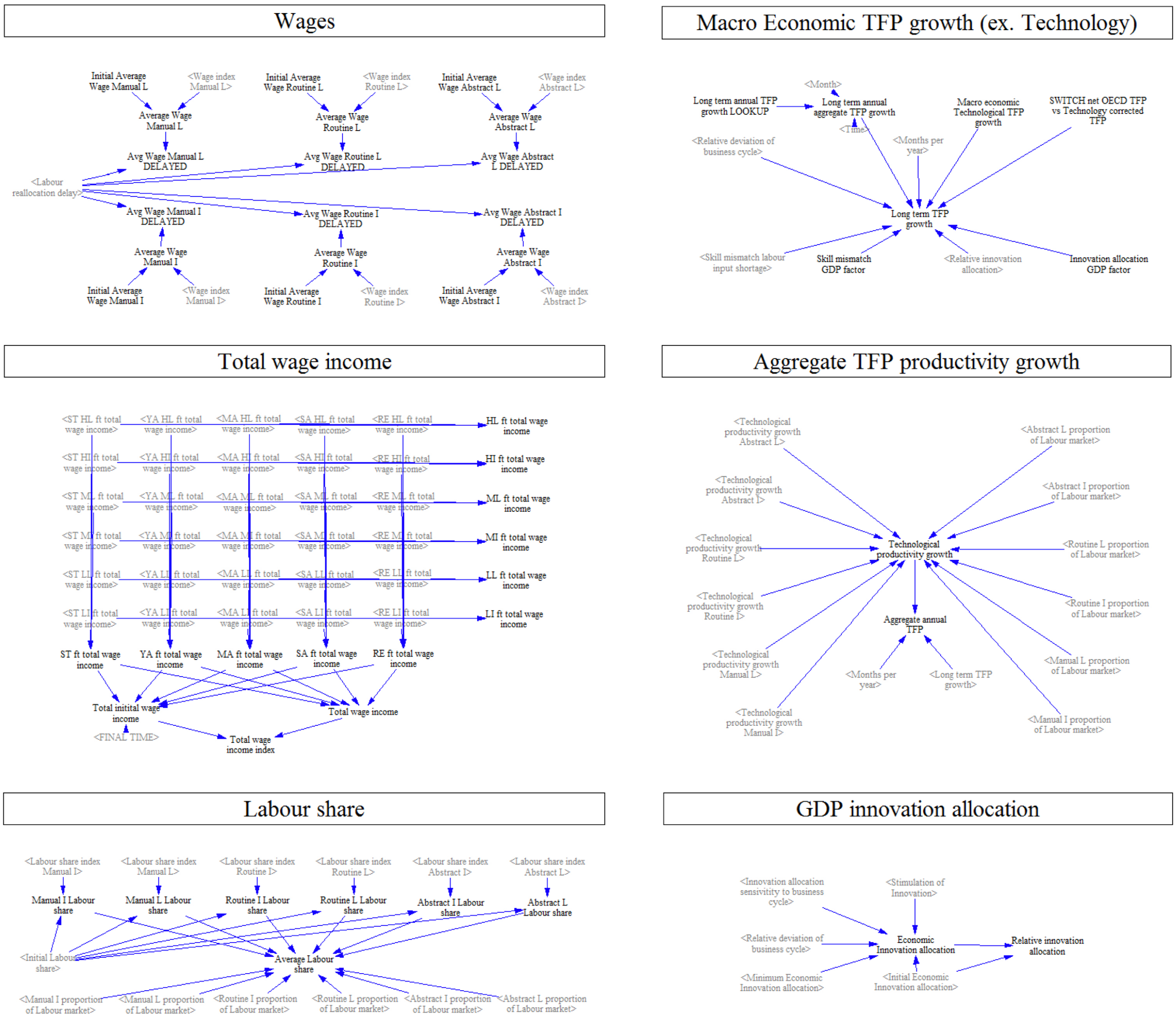


Figure 51 SD model – Production model Labour share, TFP, innovation investment, and total wage income

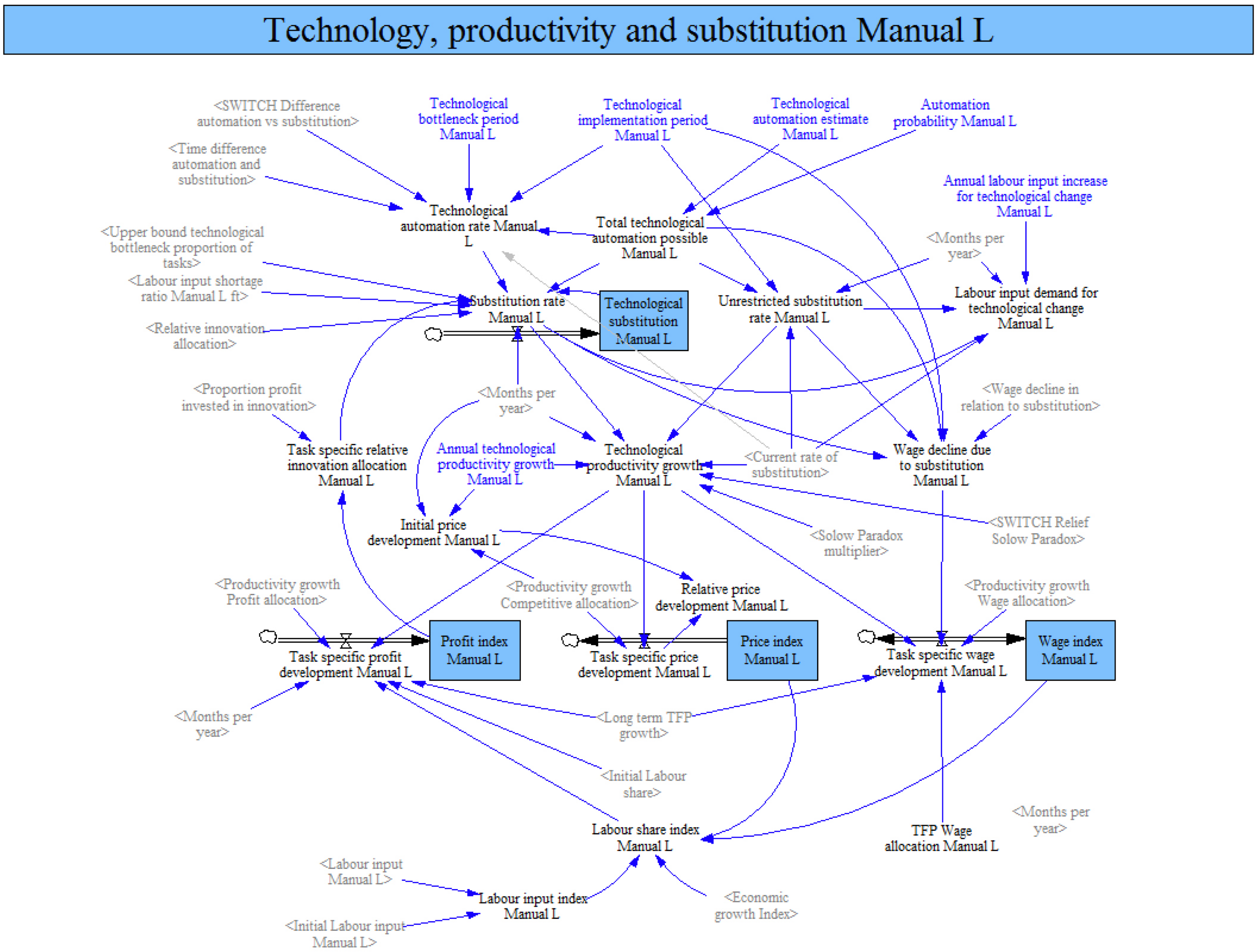


Figure 52 SD model – Technology model (sample of component per task)

IV OECD Economic growth inter-recession fluctuation

Based on OECD data, the fluctuations have a half-period (- -) between 1 and 1,5 years between recessions (—) with an amplitude (from —) ranging between approximately between 0,05% and 0,33% (OECD, 2018):

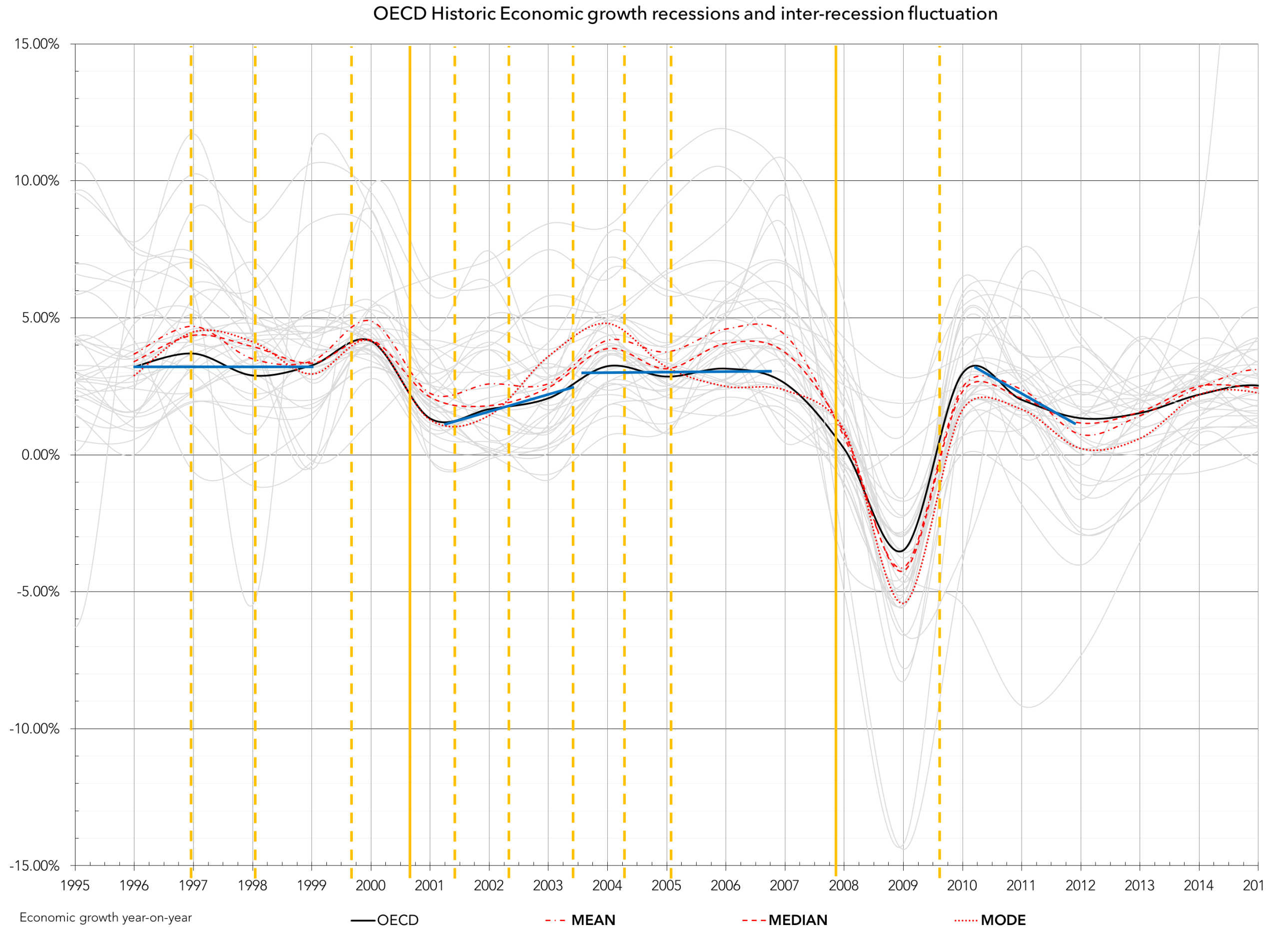


Figure 53 OECD Economic growth inter-recession fluctutation

V Demographic configuration

Initial 5-year age cohort demographic representation

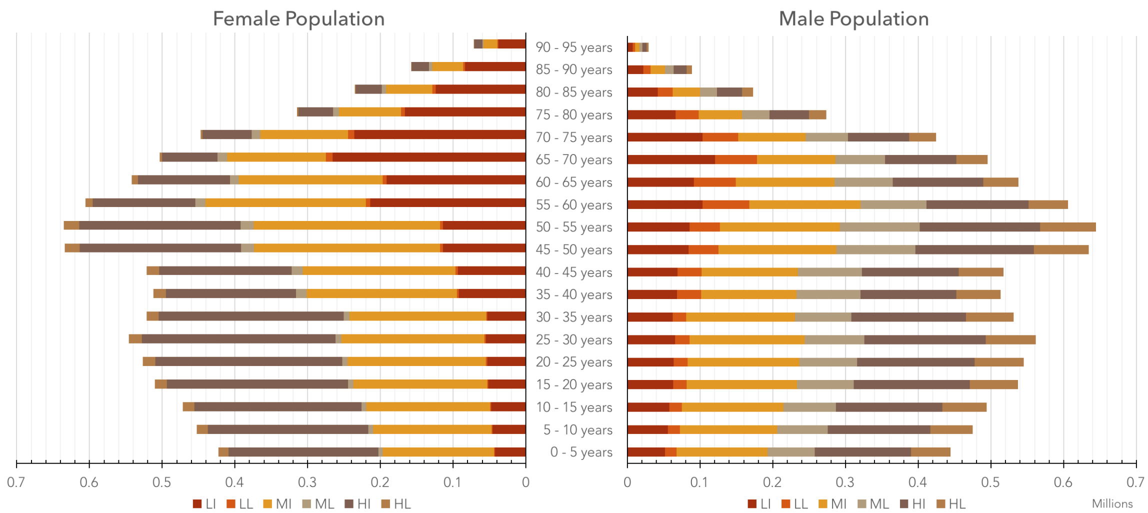


Figure 54 Initial 5-year age cohort demographic representation

Incorrect population configuration

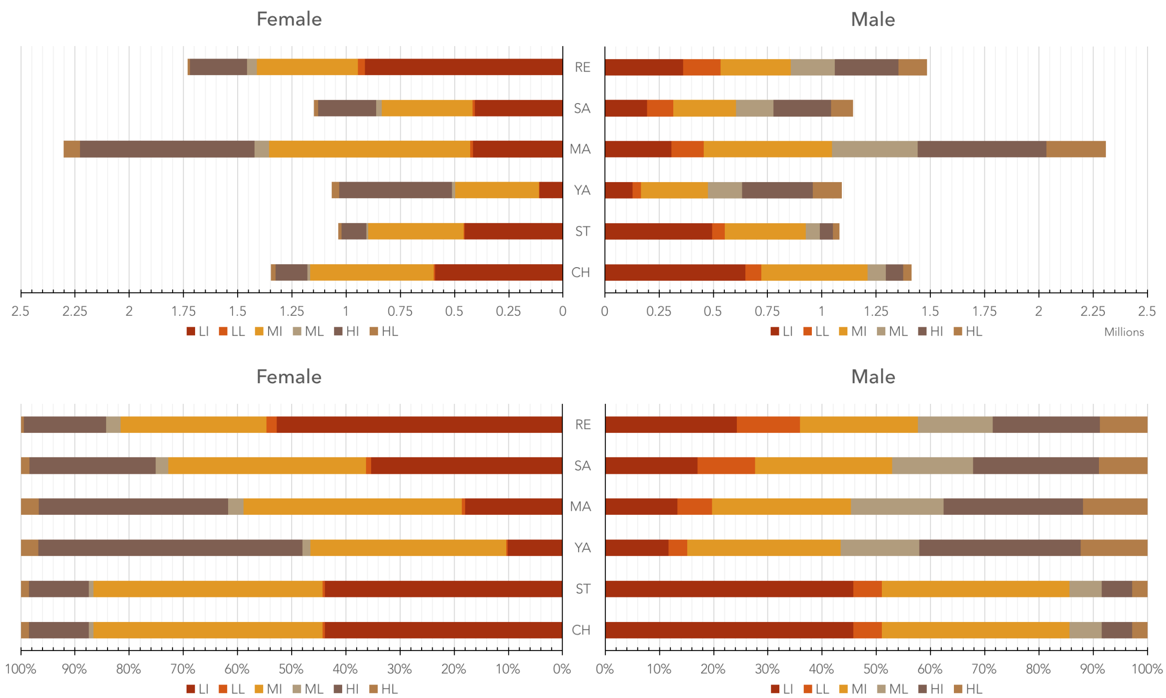


Figure 55 Incorrect initial population

Corrected population configuration

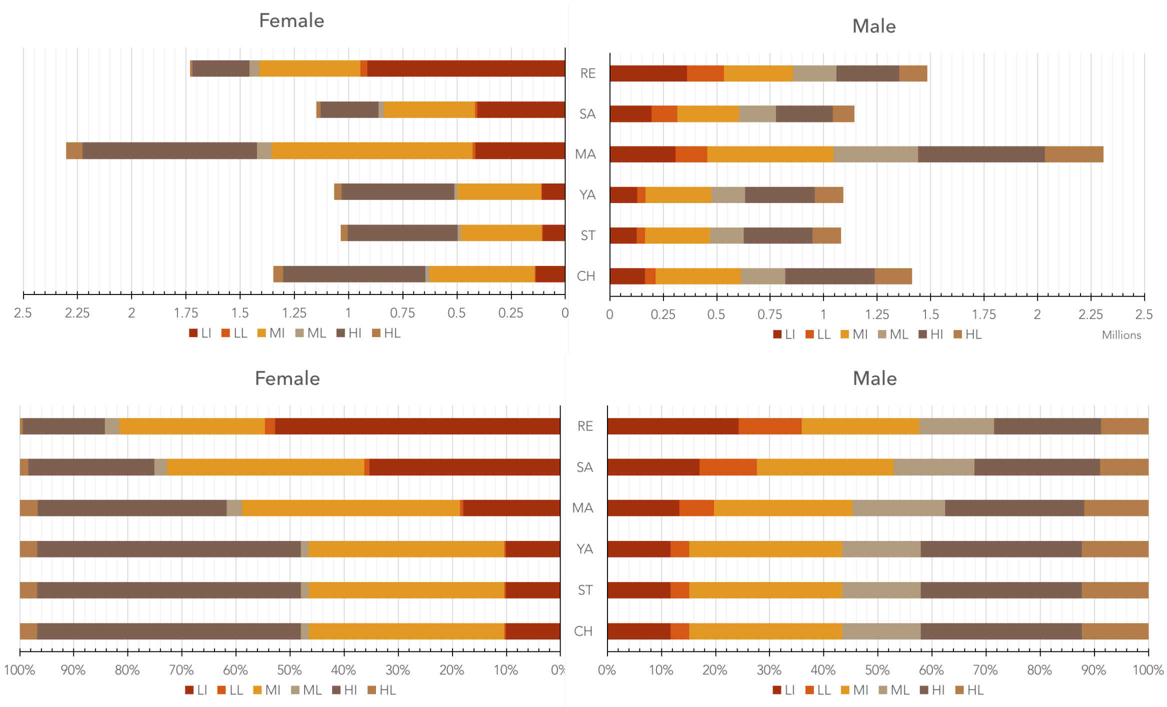


Figure 56 Corrected initial population

VI Behaviour Anomaly Test

Data set from Gregory, Salomons, and Zierahn (2016)

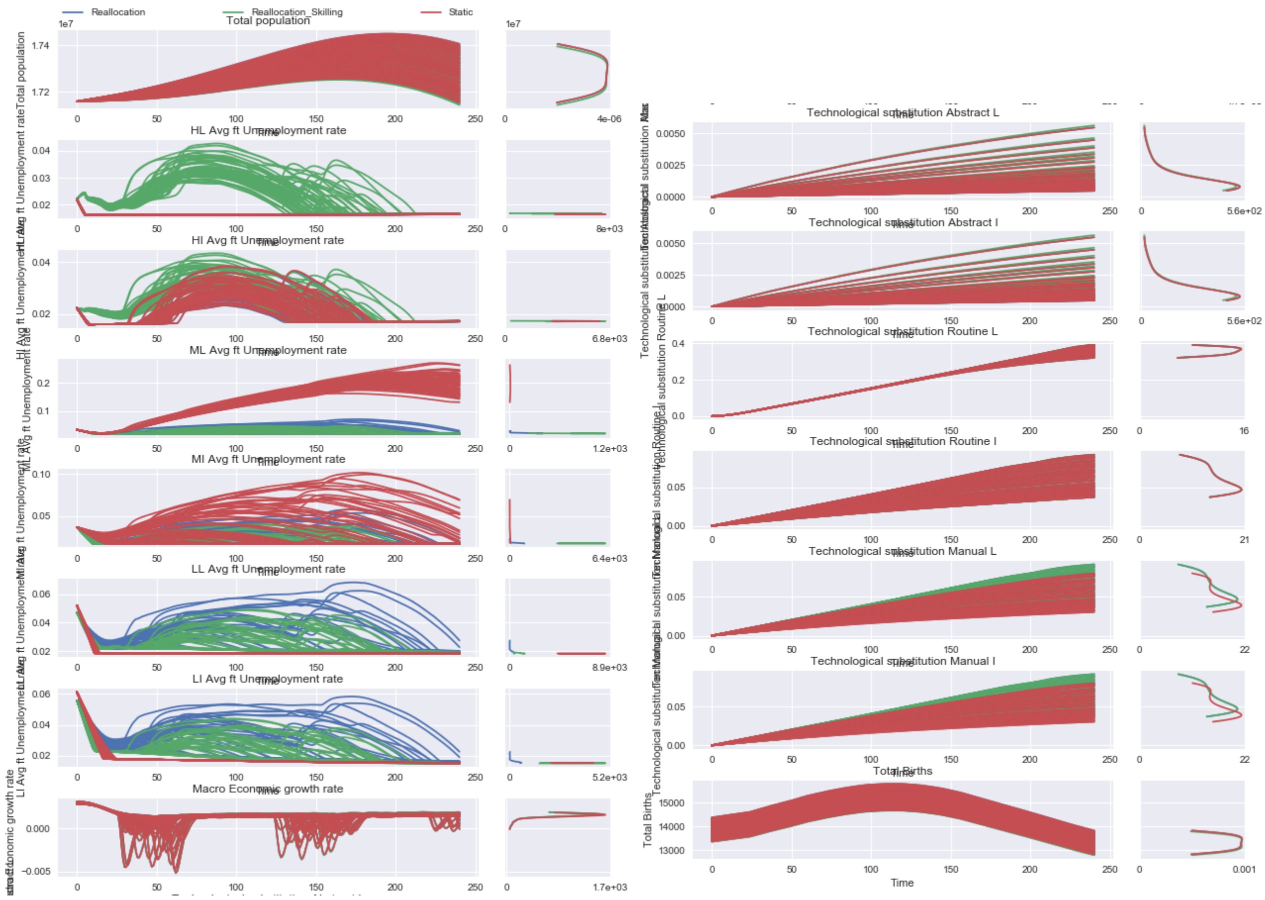


Figure 57 Behaviour Anomaly Test using substitution estimates from Gregory, Salomons, and Zierahn (Gregory, Salomons & Zierahn, 2016)

Data set from Frey and Osborne (2017)

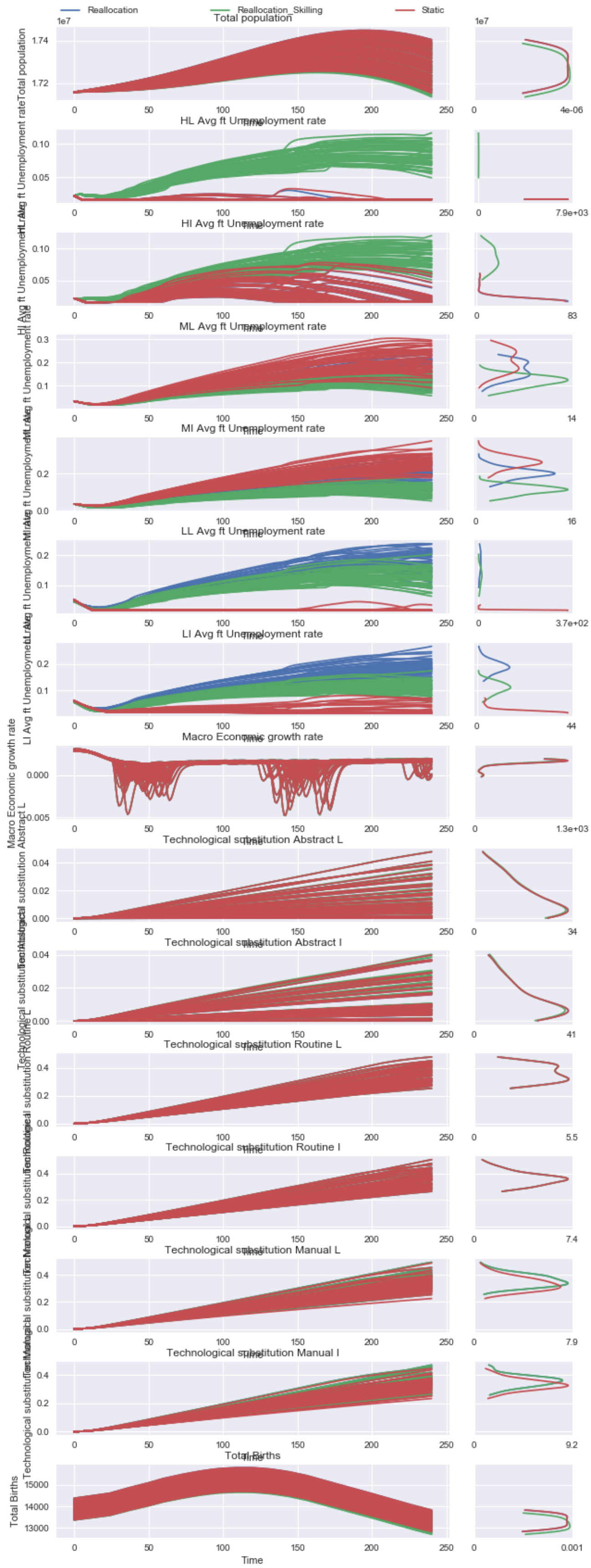


Figure 58 Behaviour Anomaly Test using substitution estimates from Frey and Osborne (Frey & Osborne, 2017)

Data set from Arntz, Gregory, and Zierahn (2016)

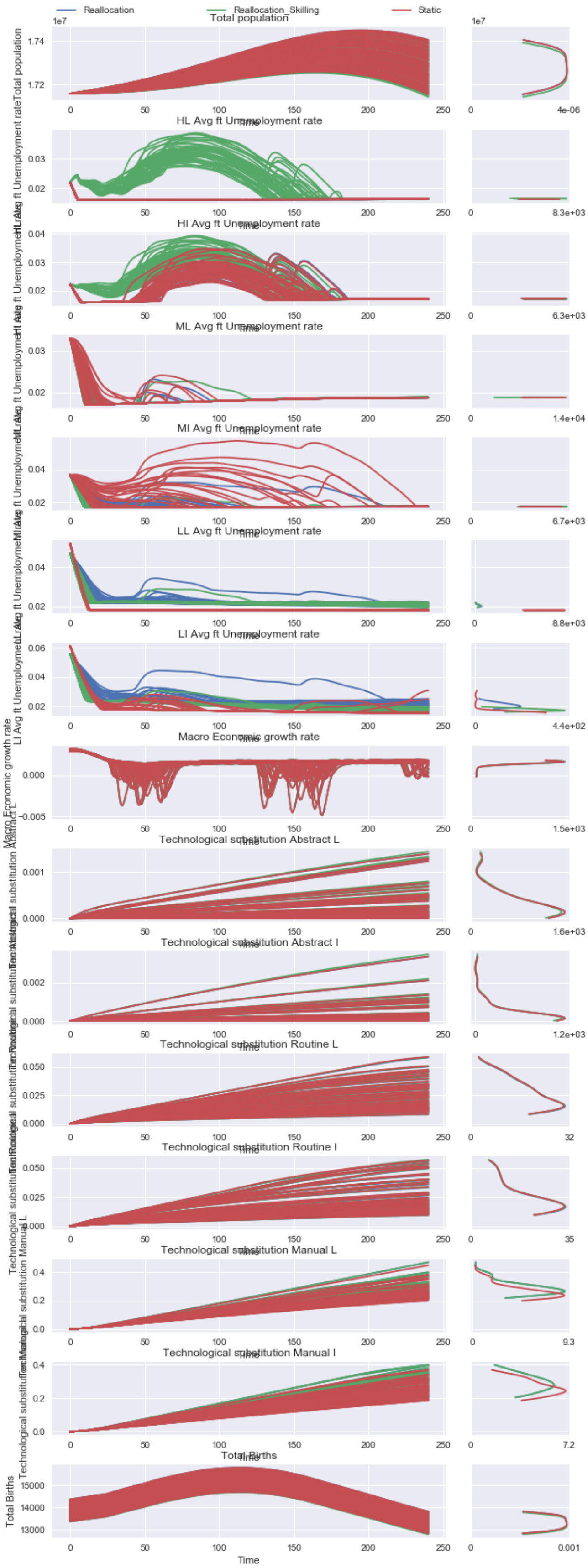


Figure 59 Behaviour Anomaly Test using substitution estimates from Arntz, Gregory, and Zierahn (Arntz, Gregory, Zierahn, 2016)

Data set from Nedelkoska and Quintini (2018)

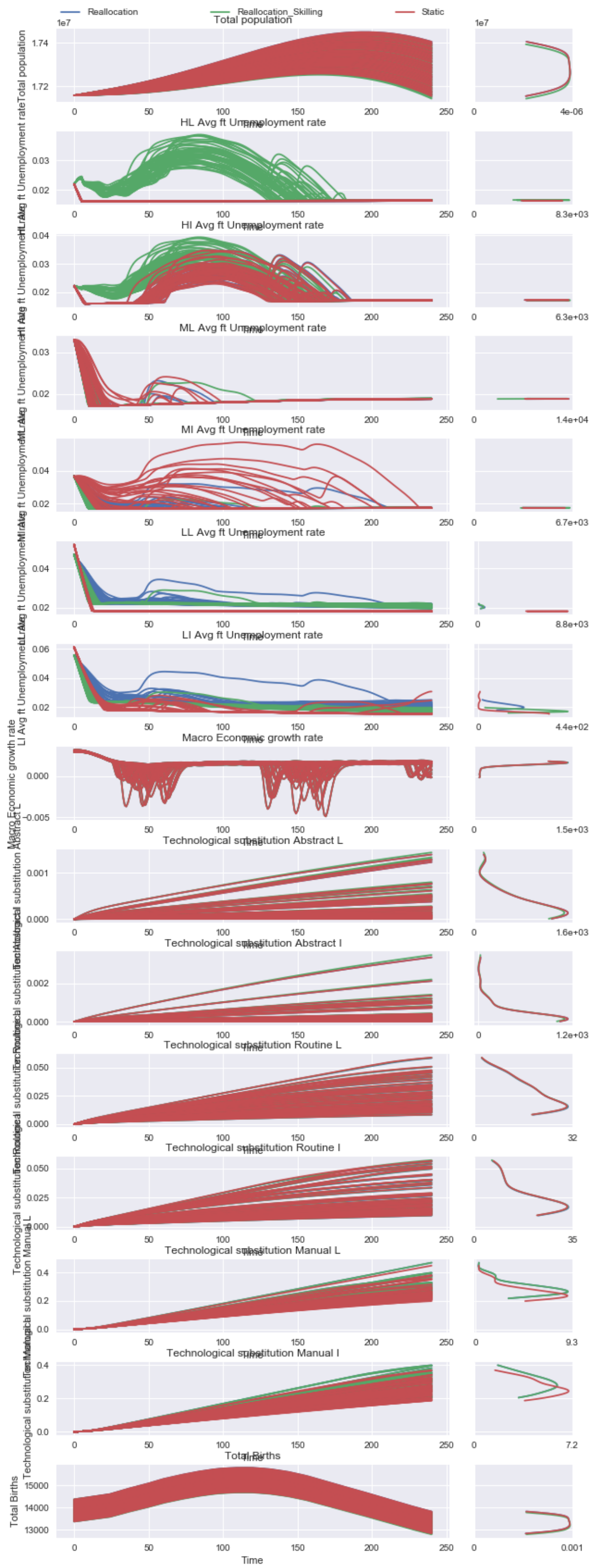


Figure 60 Behaviour Anomaly Test using substitution estimates from Nedelkoska and Quintini (Nedelkoska & Quintini, 2018)

VII Population Behaviour

Model behaviour test across model integration settings for time fraction of delay (T fraction =) and re- and up-skilling compared to Netherlands Central Bureau of Statistics (CBS) projections:

Population

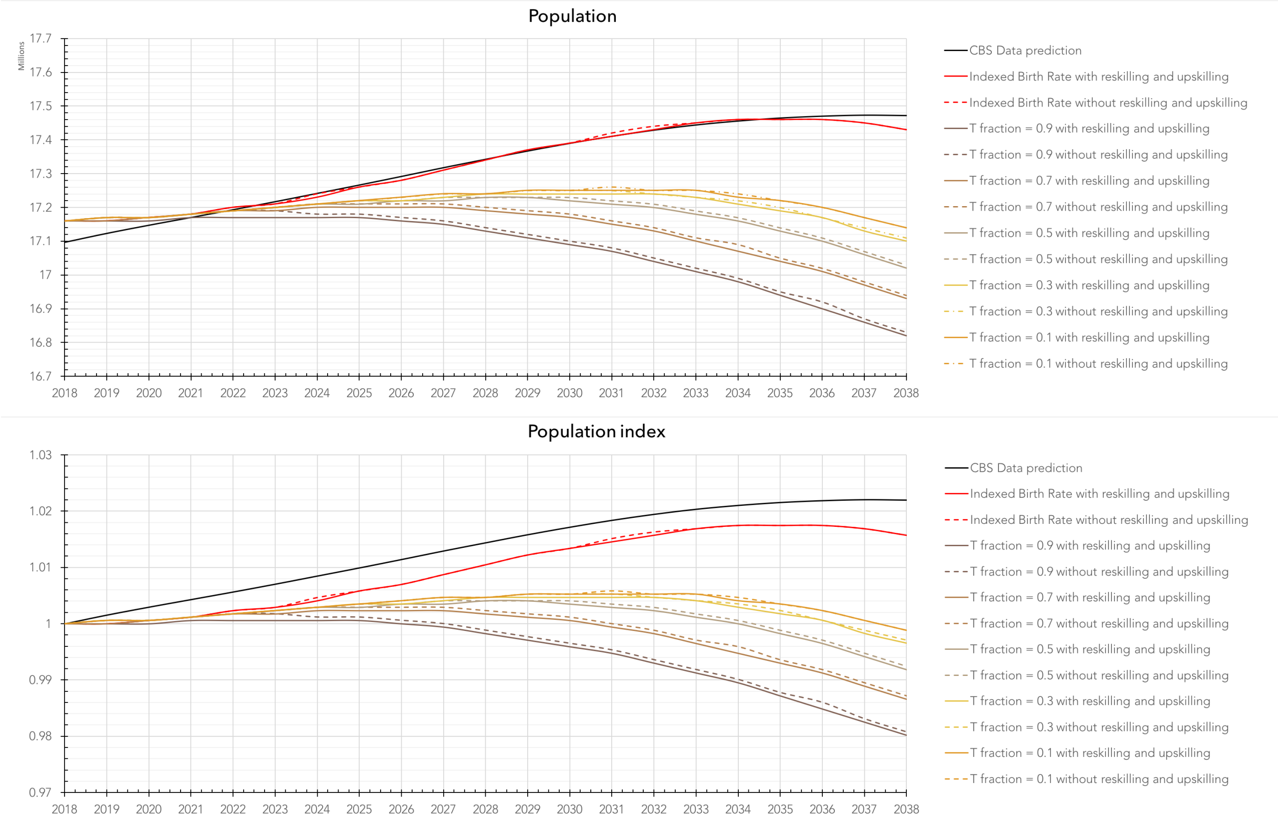


Figure 61 Model validation Population behaviour under different settings

Births

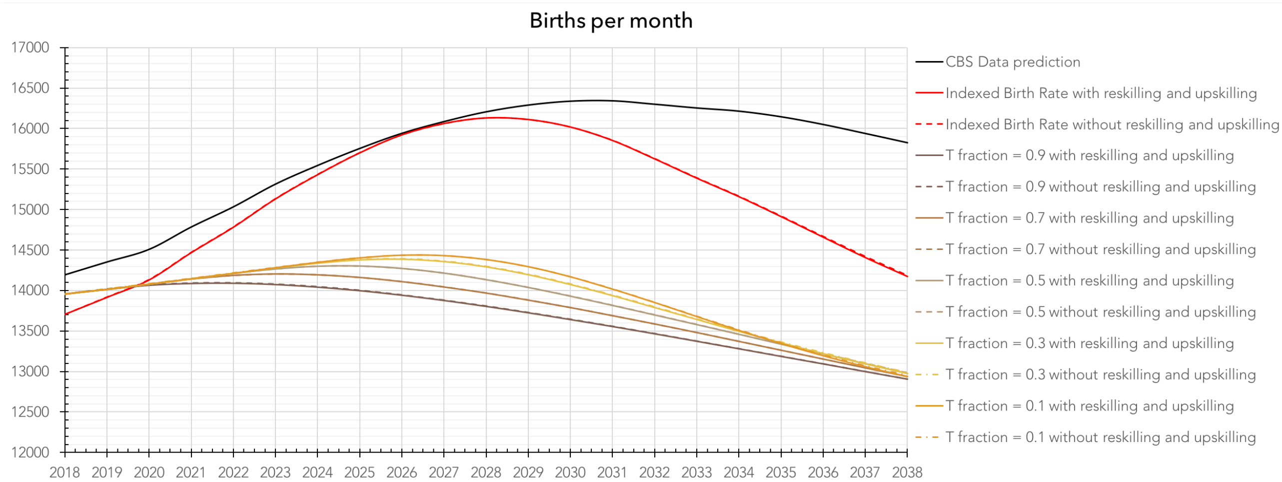


Figure 62 Model validation Births behaviour under different settings

CH Population

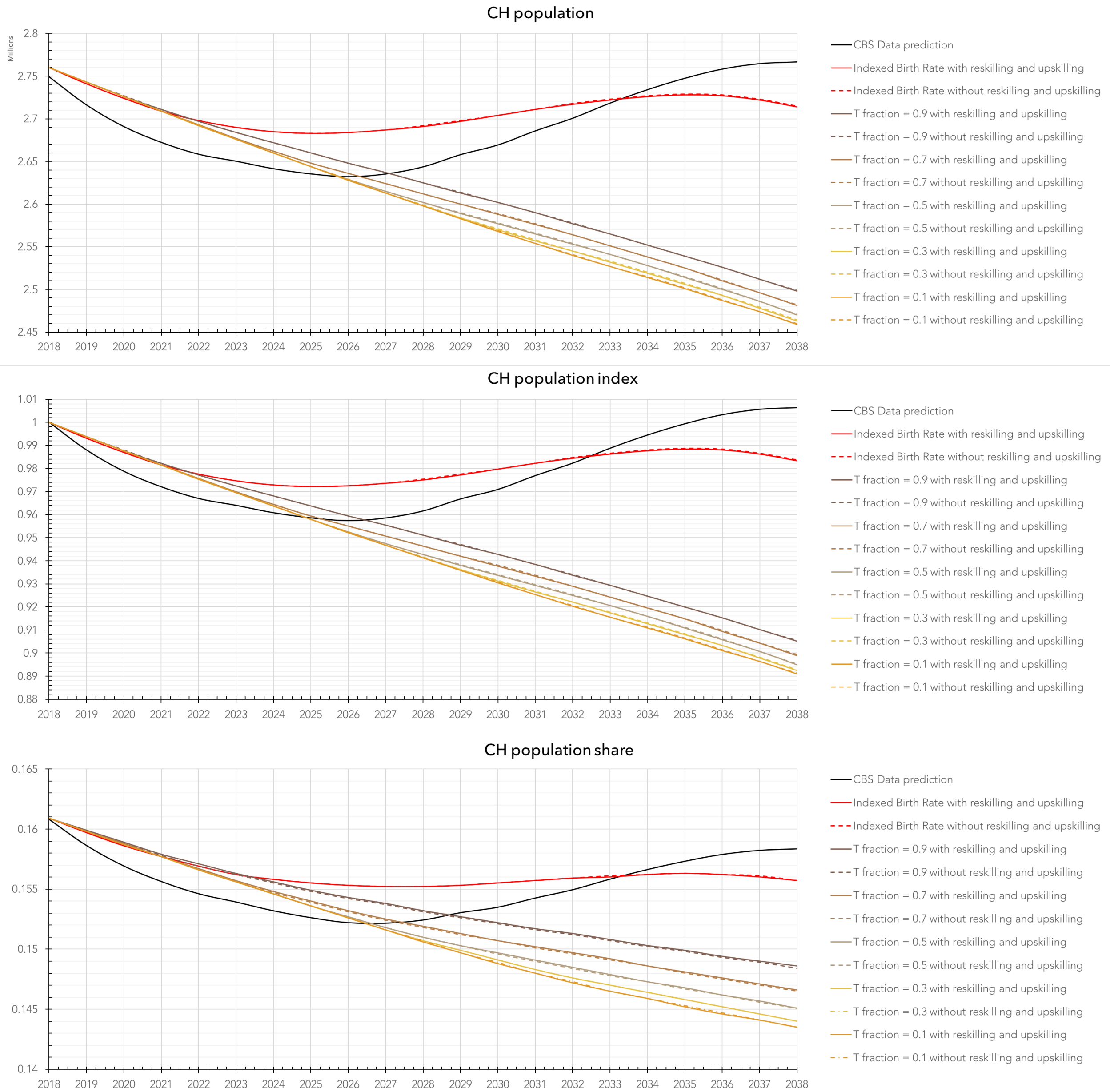


Figure 63 Model validation Children (CH) Population behaviour under different settings)

ST Population

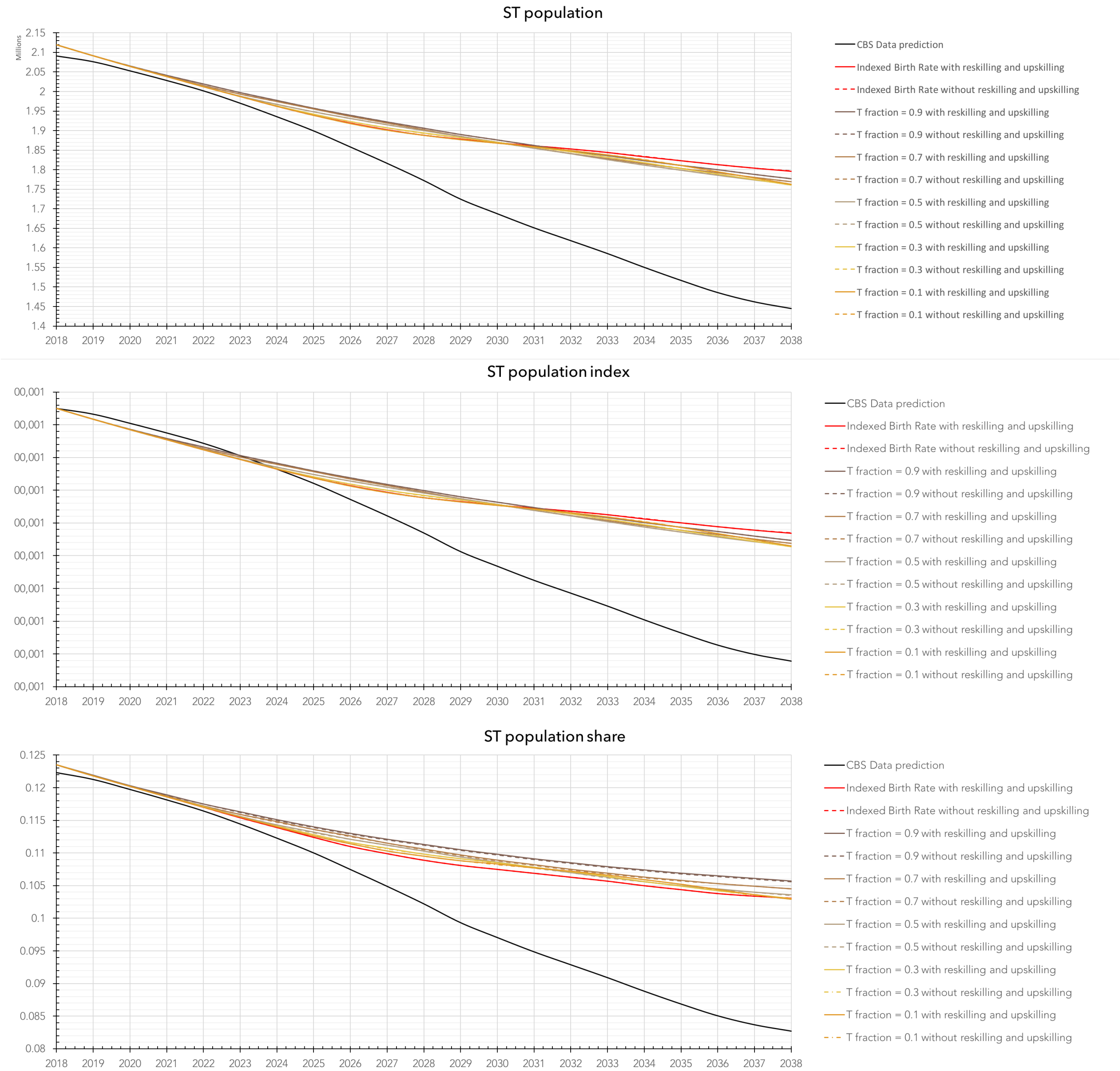


Figure 64 Model validation Student (ST) Population behaviour under different settings

YA Population

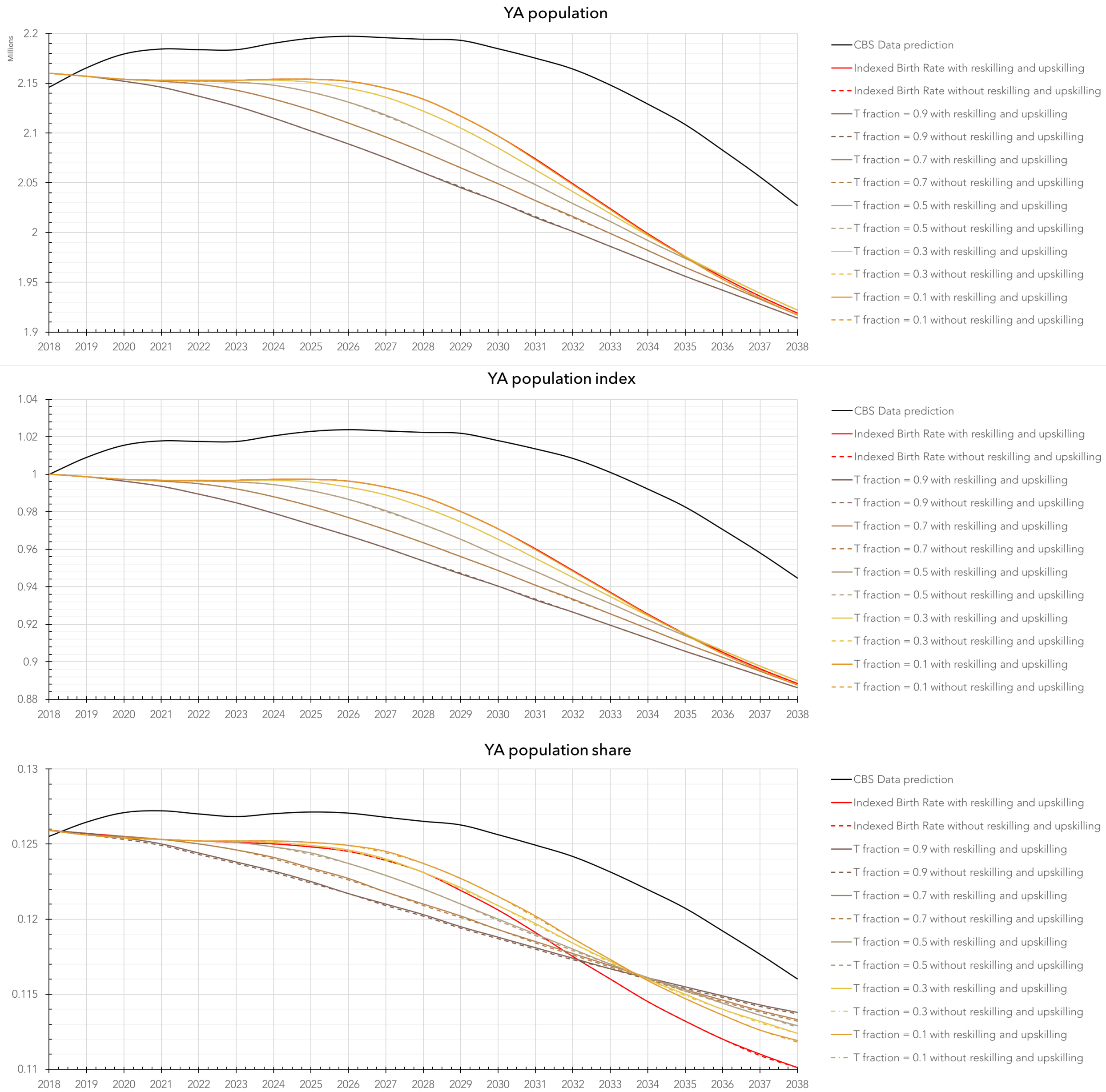


Figure 65 Model validation Young Adult (YA) Population behaviour under different settings

MA Population

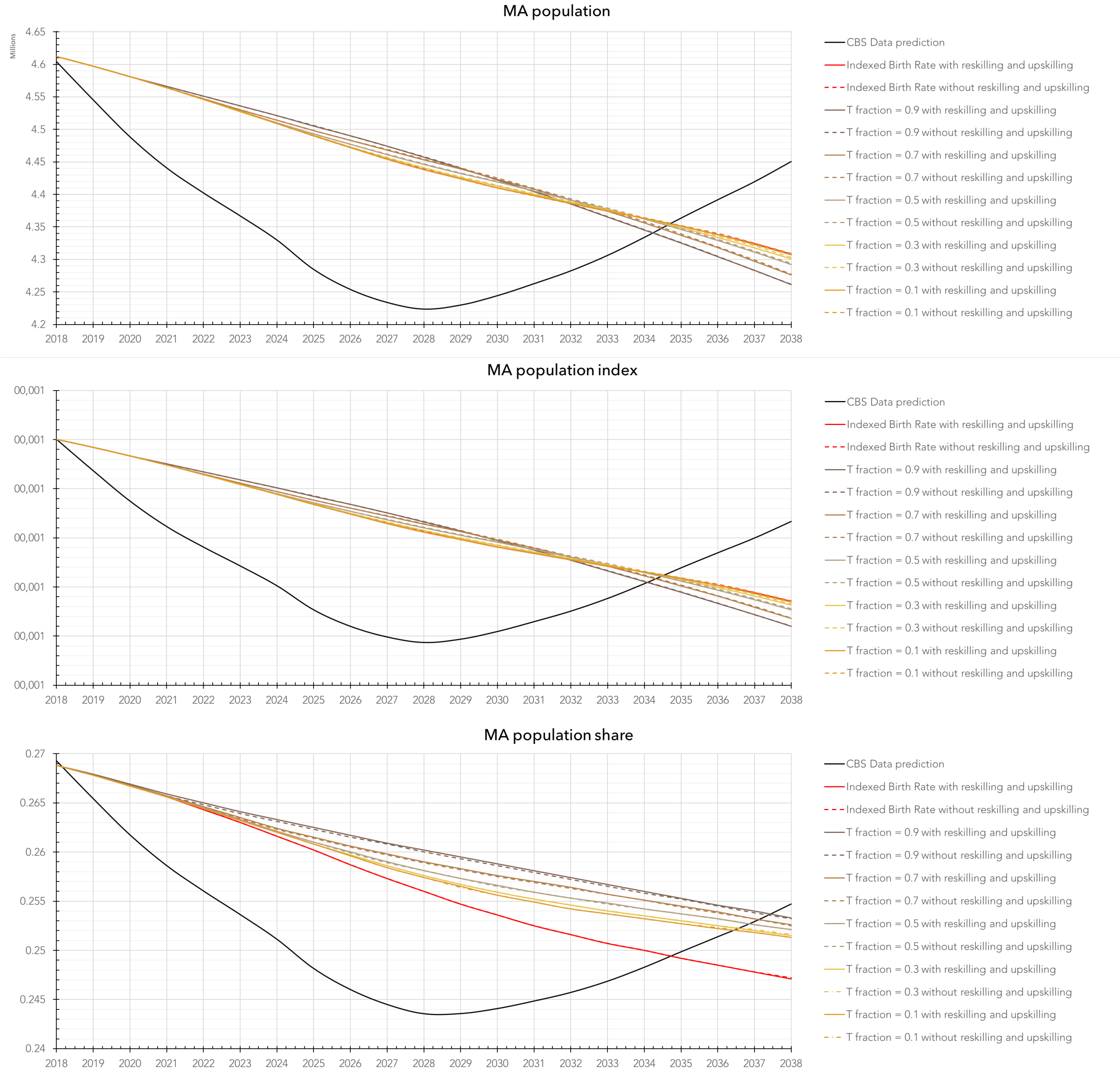


Figure 66 Model validation Mature Adult (MA) Population behaviour under different settings

SA Population

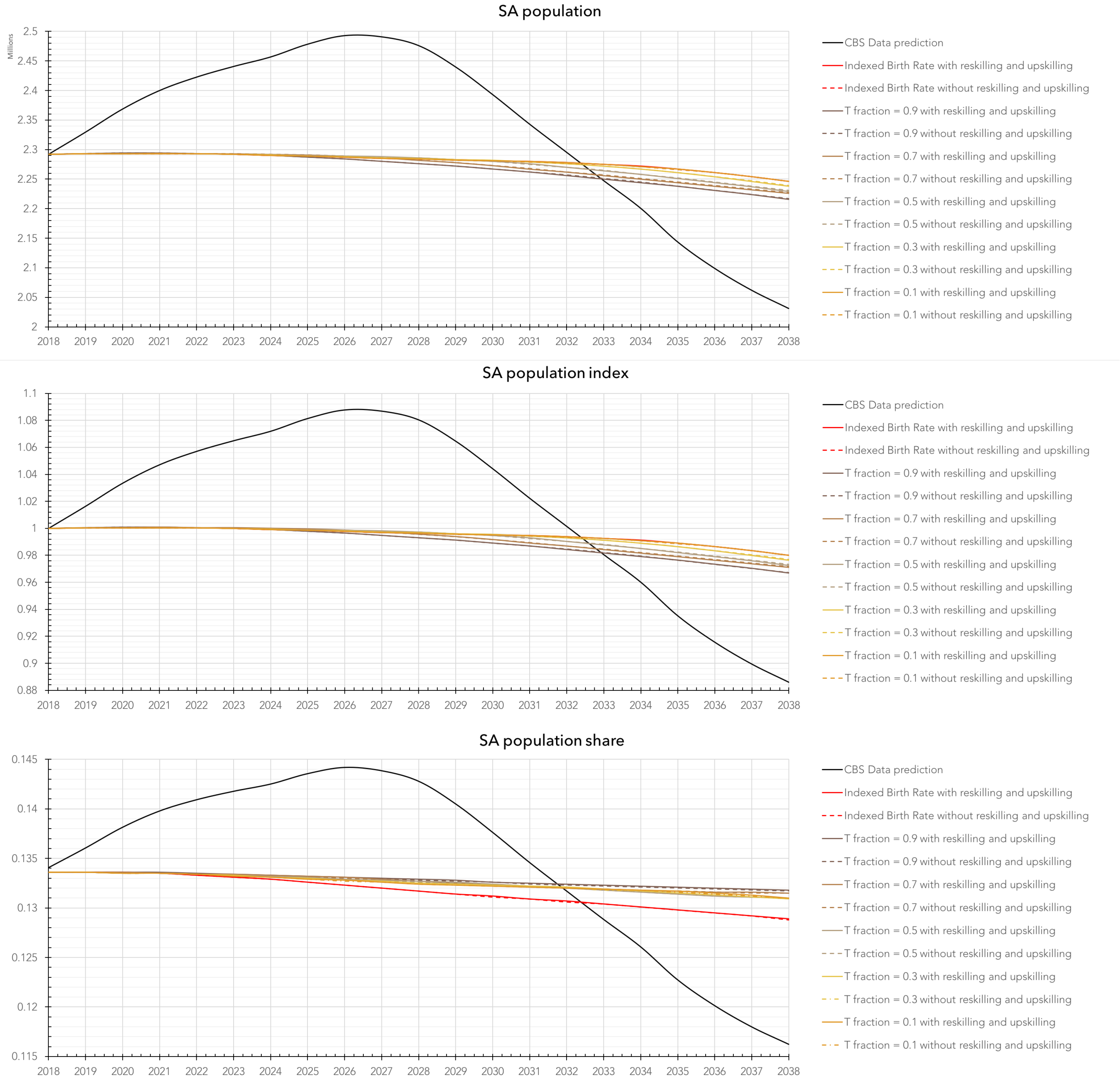
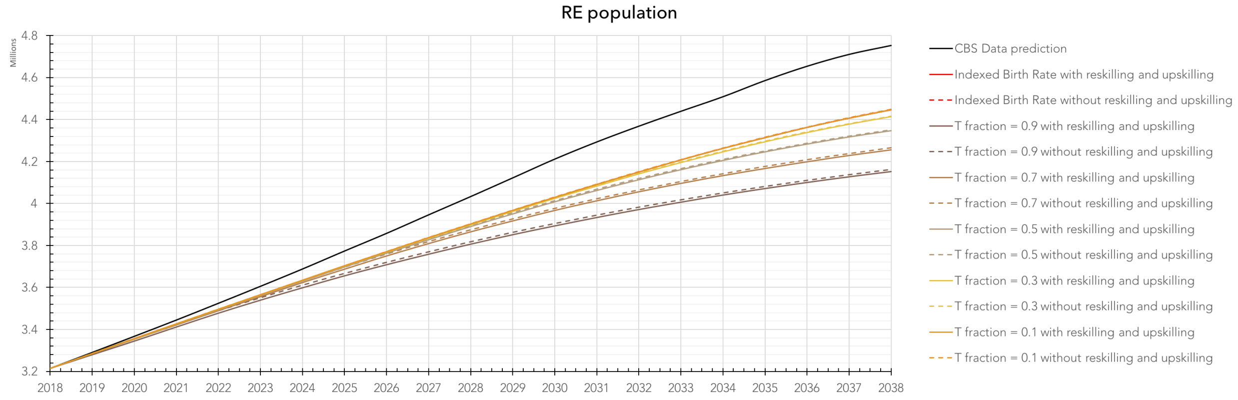
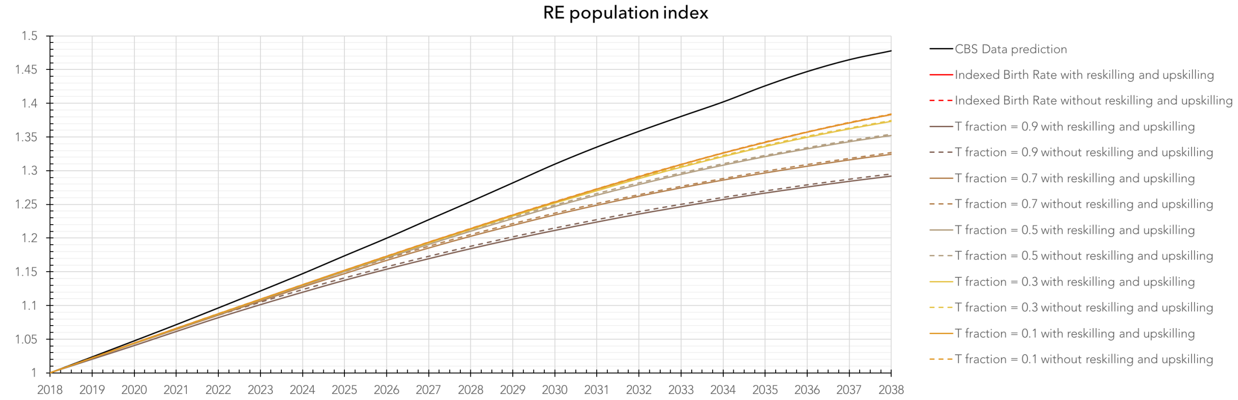


Figure 67 Model validation Senior Adult (SA) Population behaviour under different settings

RE Population





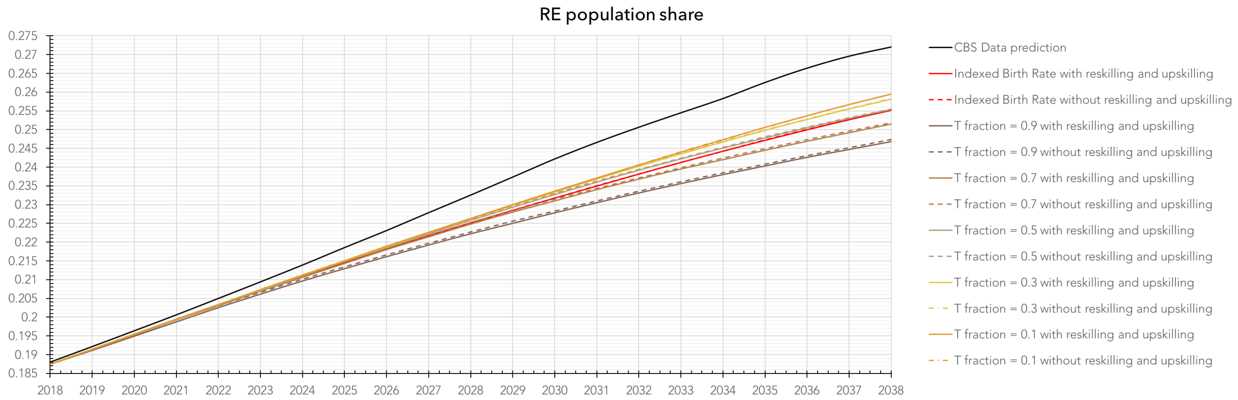


Figure 68 Model validation Retired (RE) Population behaviour under different settings

VIII SD Model configuration settings for feedback mechanisms

Table 6 Model configuration feedback mechanism parameter settings

Feedback	Parameter	Model Configuration I	II	III	IV	V
Labour supply reallocation	Sensitivity Wage reallocation	0	0.999	0.999	0.999	0.999
	Wage sacrifice ratio for employment	0	0.999	0.999	0.999	0.999
	Sensitivity Unemployment reallocation	0	1	1	1	1
Re- and up-skilling	ST Labour market awareness and sensitivity	0	0	1	1	1
	WAu reskill and upskill sensitivity	0	0	1	1	1
	WAe reskill and upskill sensitivity	0	0	1	1	1
Spillover	SWITCH Spillover effect OFF	0	0	0	1	1
Routinisation	SWITCH Routinisation OFF	0	0	0	1	1
Solow Paradox	SWITCH Relief Solow Paradox	0	0	0	0	1

IX Uncertainty Scenarios

A. Gregory, Salomons, and Zierahn (2016)

```
#Substitution
 #Abstract L:
    #RealParameter("Technological bottleneck period Abstract L", 0, 12),
    RealParameter("Technological implementation period Abstract L", 240, 241),
    RealParameter("Technological automation estimate Abstract L", 0.009, 0.0102),
    RealParameter("Automation probability Abstract L", 0.999, 1),
    #RealParameter("Annual labour input increase for technological change Abstract L", 0.0042, 0.015),
    RealParameter("Annual technological productivity growth Abstract L", 0.006, 0.01),
 #Abstract I:
    #RealParameter("Technological bottleneck period Abstract I", 0, 12),
    RealParameter("Technological implementation period Abstract I", 240, 241),
    RealParameter("Technological automation estimate Abstract I", 0.009, 0.0102),
    RealParameter("Automation probability Abstract I", 0.999, 1),
    #RealParameter("Annual labour input increase for technological change Abstract I", 0.0042, 0.015),
    RealParameter("Annual technological productivity growth Abstract I", 0.006, 0.01),
 #Routine L:
    #RealParameter("Technological bottleneck period Routine L", 0, 12),
    RealParameter("Technological implementation period Routine L", 240, 241),
    RealParameter("Technological automation estimate Routine L", 0.09, 0.102),
    RealParameter("Automation probability Routine L", 0.999, 1),
    #RealParameter("Annual labour input increase for technological change Routine L", 0.0042, 0.015),
    RealParameter("Annual technological productivity growth Routine L", 0.006, 0.01),
 #Routine I:
    #RealParameter("Technological bottleneck period Routine I", 0, 12),
    RealParameter("Technological implementation period Routine I", 240, 241),
    RealParameter("Technological automation estimate Routine I", 0.09, 0.102),
    RealParameter("Automation probability Routine I", 0.999, 1),
    #RealParameter("Annual labour input increase for technological change Routine I", 0.0042, 0.015),
    RealParameter("Annual technological productivity growth Routine I", 0.006,0.01),
 #Manual L:
    #RealParameter("Technological bottleneck period Manual L", 0, 12),
    RealParameter("Technological implementation period Manual L", 240, 241),
    RealParameter("Technological automation estimate Manual L", 0.09, 0.102),
    RealParameter("Automation probability Manual L", 0.999, 1),
    #RealParameter("Annual labour input increase for technological change Manual L", 0.0042, 0.015),
    RealParameter("Annual technological productivity growth Manual L", 0.006, 0.01),
 #Manual I:
    #RealParameter("Technological bottleneck period Manual I", 0, 12),
    RealParameter("Technological implementation period Manual I", 240, 241),
    RealParameter("Technological automation estimate Manual I", 0.09, 0.102),
    RealParameter("Automation probability Manual I", 0.999, 1),
    #RealParameter("Annual labour input increase for technological change Manual I", 0.0042, 0.015),
    RealParameter("Annual technological productivity growth Manual I", 0.006, 0.01),
```

B. Frey and Osborne (2017)

```
#Abstract L:
        #RealParameter("Technological bottleneck period Abstract L", 0, 12),
        RealParameter("Technological implementation period Abstract L", 360, 600),
        RealParameter("Technological automation estimate Abstract L", 0.329, 0.331),
        RealParameter("Automation probability Abstract L", 0.01, 0.3),
        #RealParameter("Annual labour input increase for technological change Abstract L", 0.0042, 0.015),
        RealParameter("Annual technological productivity growth Abstract L", 0.006, 0.01),
    #Abstract I:
      #RealParameter("Technological bottleneck period Abstract I", 0, 12),
      RealParameter("Technological implementation period Abstract I", 360, 600),
      RealParameter("Technological automation estimate Abstract I", 0.329, 0.331),
      RealParameter("Automation probability Abstract I", 0.01, 0.3),
      #RealParameter("Annual labour input increase for technological change Abstract I", 0.0042, 0.015),
      RealParameter("Annual technological productivity growth Abstract I", 0.006, 0.01),
    #Routine L:
      #RealParameter("Technological bottleneck period Routine L", 0, 12),
      RealParameter("Technological implementation period Routine L", 216, 264),
      RealParameter("Technological automation estimate Routine L", 0.524, 0.559),
      RealParameter("Automation probability Routine L", 0.7, 1.0),
      #RealParameter("Annual labour input increase for technological change Routine L", 0.0042, 0.015),
      RealParameter("Annual technological productivity growth Routine L", 0.006, 0.01),
    #Routine I:
      #RealParameter("Technological bottleneck period Routine I", 0, 12),
      RealParameter("Technological implementation period Routine I", 216, 264),
      RealParameter("Technological automation estimate Routine I", 0.524, 0.559),
      RealParameter("Automation probability Routine I", 0.7, 1.0),
      #RealParameter("Annual labour input increase for technological change Routine I", 0.0042, 0.015),
      RealParameter("Annual technological productivity growth Routine I", 0.006,0.01),
    #Manual L:
      #RealParameter("Technological bottleneck period Manual L", 0, 12),
      RealParameter("Technological implementation period Manual L", 216, 264),
      RealParameter("Technological automation estimate Manual L", 0.524, 0.559),
      RealParameter("Automation probability Manual L", 0.7, 1.0),
      #RealParameter("Annual labour input increase for technological change Manual L", 0.0042, 0.015),
      RealParameter("Annual technological productivity growth Manual L", 0.006, 0.01),
    #Manual I:
      #RealParameter("Technological bottleneck period Manual I", 0, 12),
      RealParameter("Technological implementation period Manual I", 216, 264),
      RealParameter("Technological automation estimate Manual I", 0.524, 0.559),
      RealParameter("Automation probability Manual I", 0.7, 1.0),
      #RealParameter("Annual labour input increase for technological change Manual I", 0.0042, 0.015),
      RealParameter("Annual technological productivity growth Manual I", 0.006, 0.01),
```

C. Arntz, Gregory, and Zierahn (2016)

```
    #Substitution
     #Abstract L:
        #RealParameter("Technological bottleneck period Abstract L", 0, 12),
        RealParameter("Technological implementation period Abstract L", 216, 264),
        RealParameter("Technological automation estimate Abstract L", 0.001, 0.01),
```

```
        RealParameter("Automation probability Abstract L", 0.7, 1.0),
        #RealParameter("Annual labour input increase for technological change Abstract L", 0.0042, 0.015),
        RealParameter("Annual technological productivity growth Abstract L", 0.006, 0.01),
    #Abstract I:
       #RealParameter("Technological bottleneck period Abstract I", 0, 12),
       RealParameter("Technological implementation period Abstract I", 216, 264),
       RealParameter("Technological automation estimate Abstract I", 0.001, 0.01),
       RealParameter("Automation probability Abstract I", 0.7, 1.0),
       #RealParameter("Annual labour input increase for technological change Abstract I", 0.0042, 0.015),
       RealParameter("Annual technological productivity growth Abstract I", 0.006, 0.01),
    #Routine L:
       #RealParameter("Technological bottleneck period Routine L", 0, 12),
       RealParameter("Technological implementation period Routine L", 216, 264),
       RealParameter("Technological automation estimate Routine L", 0.06825, 0.07175),
       RealParameter("Automation probability Routine L", 0.7, 1.0),
       #RealParameter("Annual labour input increase for technological change Routine L", 0.0042, 0.015),
       RealParameter("Annual technological productivity growth Routine L", 0.006, 0.01),
    #Routine I:
       #RealParameter("Technological bottleneck period Routine I", 0, 12),
       RealParameter("Technological implementation period Routine I", 216, 264),
       RealParameter("Technological automation estimate Routine I", 0.06825, 0.07175),
       RealParameter("Automation probability Routine I", 0.7, 1.0),
       #RealParameter("Annual labour input increase for technological change Routine I", 0.0042, 0.015),
       RealParameter("Annual technological productivity growth Routine I", 0.006,0.01),
    #Manual L:
       #RealParameter("Technological bottleneck period Manual L", 0, 12),
       RealParameter("Technological implementation period Manual L", 216, 264),
       RealParameter("Technological automation estimate Manual L", 0.37, 0.51),
       RealParameter("Automation probability Manual L", 0.7, 1.0),
       #RealParameter("Annual labour input increase for technological change Manual L", 0.0042, 0.015),
       RealParameter("Annual technological productivity growth Manual L", 0.006, 0.01),
    #Manual I:
       #RealParameter("Technological bottleneck period Manual I", 0, 12),
       RealParameter("Technological implementation period Manual I", 216, 264),
       RealParameter("Technological automation estimate Manual I", 0.37, 0.51),
       RealParameter("Automation probability Manual I", 0.7, 1.0),
       #RealParameter("Annual labour input increase for technological change Manual I", 0.0042, 0.015),
       RealParameter("Annual technological productivity growth Manual I", 0.006, 0.01),
```

D. Nedelkoska and Quintini (2018)

```
#Substitution
     #Abstract L:
        #RealParameter("Technological bottleneck period Abstract L", 0, 12),
        RealParameter("Technological implementation period Abstract L", 216, 264),
        RealParameter("Technological automation estimate Abstract L", 0.001, 0.01),
        RealParameter("Automation probability Abstract L", 0.27, 0.85),
        #RealParameter("Annual labour input increase for technological change Abstract L", 0.0042, 0.015),
        RealParameter("Annual technological productivity growth Abstract L", 0.006, 0.01),
    #Abstract I:
       #RealParameter("Technological bottleneck period Abstract I", 0, 12),
       RealParameter("Technological implementation period Abstract I", 216, 264),
```

```
        RealParameter("Technological automation estimate Abstract I", 0.001, 0.01),
        RealParameter("Automation probability Abstract I", 0.27, 0.85),
        #RealParameter("Annual labour input increase for technological change Abstract I", 0.0042, 0.015),
        RealParameter("Annual technological productivity growth Abstract I", 0.006, 0.01),
    #Routine L:
        #RealParameter("Technological bottleneck period Routine L", 0, 12),
        RealParameter("Technological implementation period Routine L", 216, 264),
        RealParameter("Technological automation estimate Routine L", 0.289, 0.326),
        RealParameter("Automation probability Routine L", 0.59, 0.94),
        #RealParameter("Annual labour input increase for technological change Routine L", 0.0042, 0.015),
        RealParameter("Annual technological productivity growth Routine L", 0.006, 0.01),
    #Routine I:
        #RealParameter("Technological bottleneck period Routine I", 0, 12),
        RealParameter("Technological implementation period Routine I", 216, 264),
        RealParameter("Technological automation estimate Routine I", 0.289, 0.326),
        RealParameter("Automation probability Routine I", 0.59, 0.94),
        #RealParameter("Annual labour input increase for technological change Routine I", 0.0042, 0.015),
        RealParameter("Annual technological productivity growth Routine I", 0.006,0.01),
    #Manual L:
        #RealParameter("Technological bottleneck period Manual L", 0, 12),
        RealParameter("Technological implementation period Manual L", 216, 264),
        RealParameter("Technological automation estimate Manual L", 0.289, 0.326),
        RealParameter("Automation probability Manual L", 0.59, 0.94),
        #RealParameter("Annual labour input increase for technological change Manual L", 0.0042, 0.015),
        RealParameter("Annual technological productivity growth Manual L", 0.006, 0.01),
    #Manual I:
        #RealParameter("Technological bottleneck period Manual I", 0, 12),
        RealParameter("Technological implementation period Manual I", 216, 264),
        RealParameter("Technological automation estimate Manual I", 0.245, 0.422),
        RealParameter("Automation probability Manual I", 0.7, 1.0),
        #RealParameter("Annual labour input increase for technological change Manual I", 0.0042, 0.015),
        RealParameter("Annual technological productivity growth Manual I", 0.006, 0.01),
```

G. Deloitte (2016)

```
#Substitution
    #Abstract L:
        #RealParameter("Technological bottleneck period Abstract L", 0, 12),
        RealParameter("Technological implementation period Abstract L", 216, 264),
        RealParameter("Technological automation estimate Abstract L", 0.104, 0.193),
        RealParameter("Automation probability Abstract L", 0.7, 1.0),
        #RealParameter("Annual labour input increase for technological change Abstract L", 0.0042, 0.015),
        RealParameter("Annual technological productivity growth Abstract L", 0.006, 0.01),
    #Abstract I:
        #RealParameter("Technological bottleneck period Abstract I", 0, 12),
        RealParameter("Technological implementation period Abstract I", 216, 264),
        RealParameter("Technological automation estimate Abstract I", 0.104, 0.193),
        RealParameter("Automation probability Abstract I", 0.7, 1.0),
        #RealParameter("Annual labour input increase for technological change Abstract I", 0.0042, 0.015),
        RealParameter("Annual technological productivity growth Abstract I", 0.006, 0.01),
    #Routine L:
        #RealParameter("Technological bottleneck period Routine L", 0, 12),
```

```
        RealParameter("Technological implementation period Routine L", 216, 264),
        RealParameter("Technological automation estimate Routine L", 0.412425, 0.433575),
        RealParameter("Automation probability Routine L", 0.7, 1.0),
        #RealParameter("Annual labour input increase for technological change Routine L", 0.0042, 0.015),
        RealParameter("Annual technological productivity growth Routine L", 0.006, 0.01),
    #Routine I:
        #RealParameter("Technological bottleneck period Routine I", 0, 12),
        RealParameter("Technological implementation period Routine I", 216, 264),
        RealParameter("Technological automation estimate Routine I", 0.412425, 0.433575),
        RealParameter("Automation probability Routine I", 0.7, 1.0),
        #RealParameter("Annual labour input increase for technological change Routine I", 0.0042, 0.015),
        RealParameter("Annual technological productivity growth Routine I", 0.006,0.01),
    #Manual L:
        #RealParameter("Technological bottleneck period Manual L", 0, 12),
        RealParameter("Technological implementation period Manual L", 216, 264),
        RealParameter("Technological automation estimate Manual L", 0.412425, 0.433575),
        RealParameter("Automation probability Manual L", 0.7, 1.0),
        #RealParameter("Annual labour input increase for technological change Manual L", 0.0042, 0.015),
        RealParameter("Annual technological productivity growth Manual L", 0.006, 0.01),
    #Manual I:
        #RealParameter("Technological bottleneck period Manual I", 0, 12),
        RealParameter("Technological implementation period Manual I", 216, 264),
        RealParameter("Technological automation estimate Manual I", 0.412425, 0.433575),
        RealParameter("Automation probability Manual I", 0.7, 1.0),
        #RealParameter("Annual labour input increase for technological change Manual I", 0.0042, 0.015),
        RealParameter("Annual technological productivity growth Manual I", 0.006, 0.01),
```

X EMA Python script Adaptibility

```
# Simulation configuration

import numpy as np
import matplotlib
import matplotlib.pyplot as plt
import pandas as pd
import SALib
import seaborn as sns
import mpl_toolkits.axisartist as AA
import scipy as sp
import copy
import matplotlib.ticker as ticker

from ema_workbench import (Model,
                    RealParameter,
                    IntegerParameter,
                    CategoricalParameter,
                    Constant,
                    TimeSeriesOutcome,
                    ScalarOutcome,
                    perform_experiments,
                    ema_logging,
                    save_results,
                    load_results)
from ema_workbench import (Policy)
from ema_workbench import (MultiprocessingEvaluator)
from ema_workbench.connectors import vensimDLLwrapper
from ema_workbench.connectors.vensim import VensimModel
from ema_workbench.em_framework.samplers import sample_levers, sample_uncertainties
from ema_workbench.util import load_results
from ema_workbench.util import ema_logging

from ema_workbench.analysis import prim
import matplotlib.pyplot as plt
from ema_workbench.analysis.plotting import lines, multiple_densities, kde_over_time
from ema_workbench.analysis.plotting_util import KDE
from ema_workbench.analysis.plotting_util import determine_time_dimension
from ema_workbench.analysis.pairs_plotting import pairs_scatter

from SALib.sample import saltelli
from SALib.analyze import sobol, morris
from SALib.test_functions import Ishigami

from mpl_toolkits.axes_grid1 import host_subplot

from scipy.stats import linregress
```

```
ema_logging.log_to_stderr(ema_logging.INFO)
```

```
vensimModel = VensimModel("ThesisModel", model_file=r"C:\Users\LocalAdmin\Documents\Koen\Final\Final_Models\Thesis_model_Final.vpm" )
```

```
# Uncertainty configuration Technological Substitution Dataset Frey, Osborne (2013-2017)

vensimModel.uncertainties = [
    #POPULATION MODEL UNCERTAINTIES
        RealParameter("Normal fertility rate per f", 1.58, 1.7),

    #EDUCATION MODEL UNCERTAINTIES
#       #CH Education
#           RealParameter("CH Edu performance Reskill equivalent", 25, 30),
#           RealParameter("CH Edu performance Upskill equivalent", 25, 30),
#         #Policy
#           #RealParameter("Time to introduction STEM program", 0, 300),
#           #RealParameter("Minimum fixed period CH Edu capacity expansion", 1, 36),
#           #RealParameter("Time to realise CH Edu capacity expansion", 1, 48),
#           #RealParameter("STEM educated vs STEM graduated ratio", 0.4, 1),
#           #RealParameter("MANUAL CH Edu performance overall improvement H", 0, 25),
#           #RealParameter("MANUAL CH Edu performance overall improvement M", 0, 25),
#           #RealParameter("MANUAL CH Edu performance overall improvement L", 0, 25),
#           #RealParameter("MANUAL CH Edu performance STEM improvement H", 0, 16.75),
#           #RealParameter("MANUAL CH Edu performance STEM improvement M", 0, 16.75),
#           #RealParameter("MANUAL CH Edu performance STEM improvement L", 0, 16.75),
#       #ST Education
#           RealParameter("ST Labour market awareness and sensitivity", 0, 1),
#           RealParameter("ST knowledge YA Unemployment delay", 12, 48),
#         #Policy
#           #RealParameter("ST STEM stimulation and awareness", 1, 2),
#           #RealParameter("ST High Edu stimulation and awareness", 1, 2),
#           #RealParameter("Time to realise ST Edu capacity expansion", 12, 60),
#           #RealParameter("Fixed period ST Edu capacity expansion", 1, 12),
#       #WA Education
#           RealParameter("WAu reskill and upskill sensitivity", 0, 1),
#           RealParameter("WAe reskill and upskill sensitivity", 0, 1),
#         #Policy
#           #RealParameter("WA STEM stimulation and awareness", 1, 2),
#           #RealParameter("WA High Edu stimulation and awareness", 1, 2),
#           #RealParameter("Socioeconomic influence education and training H", 1, 2),
#           #RealParameter("Socioeconomic influence education and training M", 0.895, 2),
#           #RealParameter("Socioeconomic influence education and training L", 0.561, 2),

    #LABOUR MARKET MODEL UNCERTAINTIES
        #Labour reallocation
#           RealParameter("Sensitivity Wage reallocation", 0, 0.999),
#           RealParameter("Wage sacrifice ratio for employment", 0.01, 0.5),
#           RealParameter("Sensitivity Unemployment reallocation", 0, 1),
#         #Policy
#           #RealParameter("Labour reallocation delay", 12, 48),
#         #Setting
        RealParameter("Error MINMAX corrector", 10000000000000000, 100000000000000000),

    #PRODUCTION MODEL UNCERTAINTIES
```

```
        #Labour input
#           RealParameter("Price elasticity of demand Abstract L", 0, 1),
#           RealParameter("Price elasticity of demand Abstract I", 0, 1),
#           RealParameter("Price elasticity of demand Routine L", 0, 1),
#           RealParameter("Price elasticity of demand Routine I", 0, 1),
#           RealParameter("Price elasticity of demand Manual L", 0, 1),
#           RealParameter("Price elasticity of demand Manual I", 0, 1),
        #GDP growth
            RealParameter("Long term economic growth error margin", 0, 0.05),
            RealParameter("Business cycle fluctuation amplitude", 0.001, 0.0033),
            RealParameter("Business cycle fluctuation period", 2, 3),
            RealParameter("Time to first recession", 2, 5),
            RealParameter("Business cycle recession amplitude", 0.0187, 0.0263),
            RealParameter("Business cycle recession duration", 3, 3.64),
            RealParameter("Busines cycle recession period", 8, 9.4),
            RealParameter("Severe recession timing", 1, 3),
            RealParameter("Severe recession duration", 4, 4.7),
            RealParameter("Severe recession amplitude", 0.0489, 0.0631),
            RealParameter("Severe recession occurance", 0, 1),
            RealParameter("Proportion of time in recession", 0.18, 0.21),
            RealParameter("Initial Labour share", 0.554, 0.714),
        #Others
#           RealParameter("Macro economic Technological TFP growth", 0.004, 0.0067),
            RealParameter("Task substitution elasticity", 0.66, 0.9),
          #Policy
            #RealParameter("Hours fulltime contracts", 32, 38),

    #TECHNOLOGY MODEL UNCERTAINTIES
            RealParameter("Proportion profit invested in innovation", 0.02, 1),
            RealParameter("Innovation allocation sensivitity to business cycle", 0, 0.1),
            RealParameter("Prior Substituted Labour demand", 8.9, 10.1),
            RealParameter("Solow Paradox multiplier", 0, 0.5),
            RealParameter("Time difference automation and substitution", 0.999, 1.001),
            RealParameter("TFP Wage allocation Abstract L", 0.1, 1),
            RealParameter("TFP Wage allocation Abstract I", 0.1, 1),
            RealParameter("TFP Wage allocation Routine L", 0.1, 1),
            RealParameter("TFP Wage allocation Routine I", 0.1, 1),
            RealParameter("TFP Wage allocation Manual L", 0.1, 1),
            RealParameter("TFP Wage allocation Manual I", 0.1, 1),
    #Substitution
         #Abstract L:
            #RealParameter("Technological bottleneck period Abstract L", 0, 12),
            RealParameter("Technological implementation period Abstract L", 360, 600),
            RealParameter("Technological automation estimate Abstract L", 0.329, 0.331),
            RealParameter("Automation probability Abstract L", 0.01, 0.3),
            #RealParameter("Annual labour input increase for technological change Abstract L", 0.0042, 0.015),
            RealParameter("Annual technological productivity growth Abstract L", 0.006, 0.01),
        #Abstract I:
            #RealParameter("Technological bottleneck period Abstract I", 0, 12),
            RealParameter("Technological implementation period Abstract I", 360, 600),
            RealParameter("Technological automation estimate Abstract I", 0.329, 0.331),
            RealParameter("Automation probability Abstract I", 0.01, 0.3),
            #RealParameter("Annual labour input increase for technological change Abstract I", 0.0042, 0.015),
```

```
        RealParameter("Annual technological productivity growth Abstract I", 0.006, 0.01),
    #Routine L:
        #RealParameter("Technological bottleneck period Routine L", 0, 12),
        RealParameter("Technological implementation period Routine L", 216, 264),
        RealParameter("Technological automation estimate Routine L", 0.524, 0.559),
        RealParameter("Automation probability Routine L", 0.7, 1.0),
        #RealParameter("Annual labour input increase for technological change Routine L", 0.0042, 0.015),
        RealParameter("Annual technological productivity growth Routine L", 0.006, 0.01),
    #Routine I:
        #RealParameter("Technological bottleneck period Routine I", 0, 12),
        RealParameter("Technological implementation period Routine I", 216, 264),
        RealParameter("Technological automation estimate Routine I", 0.524, 0.559),
        RealParameter("Automation probability Routine I", 0.7, 1.0),
        #RealParameter("Annual labour input increase for technological change Routine I", 0.0042, 0.015),
        RealParameter("Annual technological productivity growth Routine I", 0.006,0.01),
    #Manual L:
        #RealParameter("Technological bottleneck period Manual L", 0, 12),
        RealParameter("Technological implementation period Manual L", 216, 264),
        RealParameter("Technological automation estimate Manual L", 0.524, 0.559),
        RealParameter("Automation probability Manual L", 0.7, 1.0),
        #RealParameter("Annual labour input increase for technological change Manual L", 0.0042, 0.015),
        RealParameter("Annual technological productivity growth Manual L", 0.006, 0.01),
    #Manual I:
        #RealParameter("Technological bottleneck period Manual I", 0, 12),
        RealParameter("Technological implementation period Manual I", 216, 264),
        RealParameter("Technological automation estimate Manual I", 0.524, 0.559),
        RealParameter("Automation probability Manual I", 0.7, 1.0),
        #RealParameter("Annual labour input increase for technological change Manual I", 0.0042, 0.015),
        RealParameter("Annual technological productivity growth Manual I", 0.006, 0.01),

        RealParameter("Upper bound technological bottleneck proportion of tasks", 0.001, 0.01)
]

vensimModel.outcomes = [
  #POPULATION MODEL OUTCOMES
#        TimeSeriesOutcome('Total population'),
  #EDUCATION MODEL OUTCOMES
  #LABOUR MARKET OUTCOMES
        TimeSeriesOutcome('HL Avg ft Unemployment rate'),
        TimeSeriesOutcome('HI Avg ft Unemployment rate'),
        TimeSeriesOutcome('ML Avg ft Unemployment rate'),
        TimeSeriesOutcome('MI Avg ft Unemployment rate'),
        TimeSeriesOutcome('LL Avg ft Unemployment rate'),
        TimeSeriesOutcome('LI Avg ft Unemployment rate'),
  #PRODUCTION MODEL OUTCOMES
        TimeSeriesOutcome('Annual Macro Economic growth rate'),
        TimeSeriesOutcome('Total wage income index'),
        TimeSeriesOutcome('Aggregate annual TFP'),
        TimeSeriesOutcome('Average Labour share'),
        TimeSeriesOutcome('Relative price development Abstract L'),
        TimeSeriesOutcome('Relative price development Abstract I'),
        TimeSeriesOutcome('Relative price development Routine L'),
        TimeSeriesOutcome('Relative price development Routine I'),
```

```
        TimeSeriesOutcome('Relative price development Manual L'),
        TimeSeriesOutcome('Relative price development Manual I'),
   #TECHNOLOGY MODEL OUTCOMES
        TimeSeriesOutcome('Technological substitution Abstract L'),
        TimeSeriesOutcome('Technological substitution Abstract I'),
        TimeSeriesOutcome('Technological substitution Routine L'),
        TimeSeriesOutcome('Technological substitution Routine I'),
        TimeSeriesOutcome('Technological substitution Manual L'),
        TimeSeriesOutcome('Technological substitution Manual I')
]

policies = [
        Policy('Model_I',

model_file=r"C:\Users\LocalAdmin\Documents\Koen\Final\Final_Models\Thesis_model_Final_I.vpm"),
        Policy('Model_II',

model_file=r"C:\Users\LocalAdmin\Documents\Koen\Final\Final_Models\Thesis_model_Final_II.vpm"),
        Policy('Model_III',

model_file=r"C:\Users\LocalAdmin\Documents\Koen\Final\Final_Models\Thesis_model_Final_III.vpm"),
        Policy('Model_IV'

        ]
```

```
# Model simulation

results = perform_experiments(vensimModel, 1000, policies= policies)
```

```
# Save results

results_name = './EMA_Adaptibility_Uncertainty_B_Results.tar.gz'
save_results(results, results_name)
```

XI Labour force adaptability effect

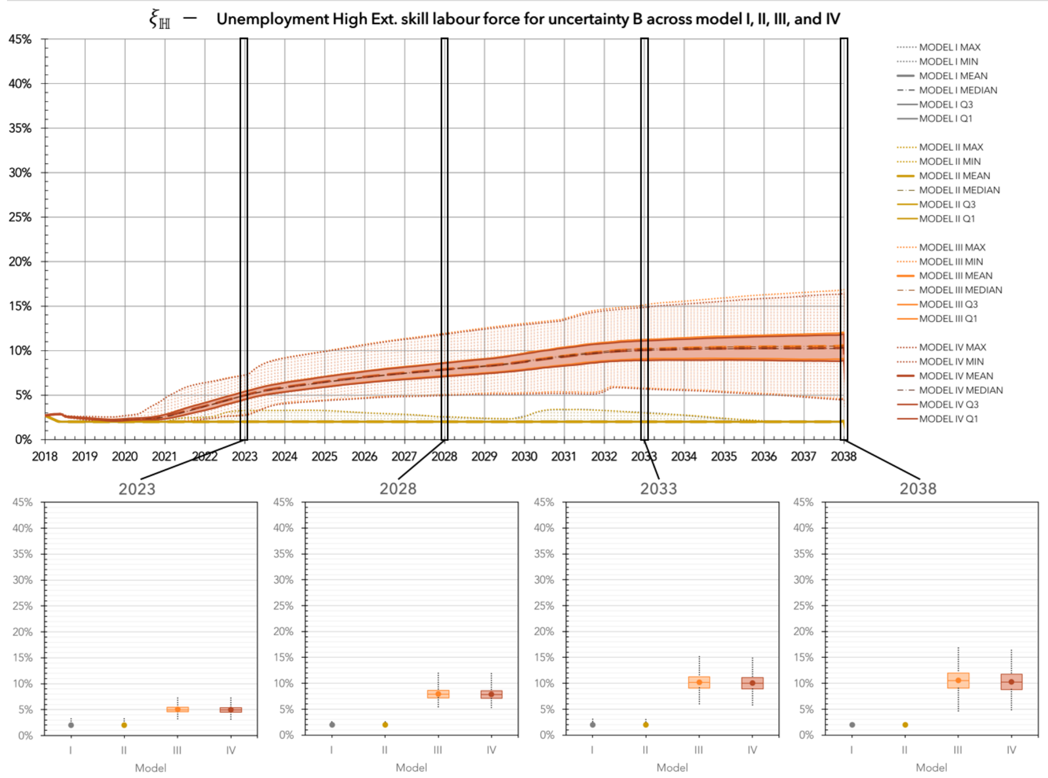


Figure 69 Unemployment projections $\xi_{\mathbb{H}}$ for uncertainty B with and without adaptability and spill-over (models I, II, III, and IV)

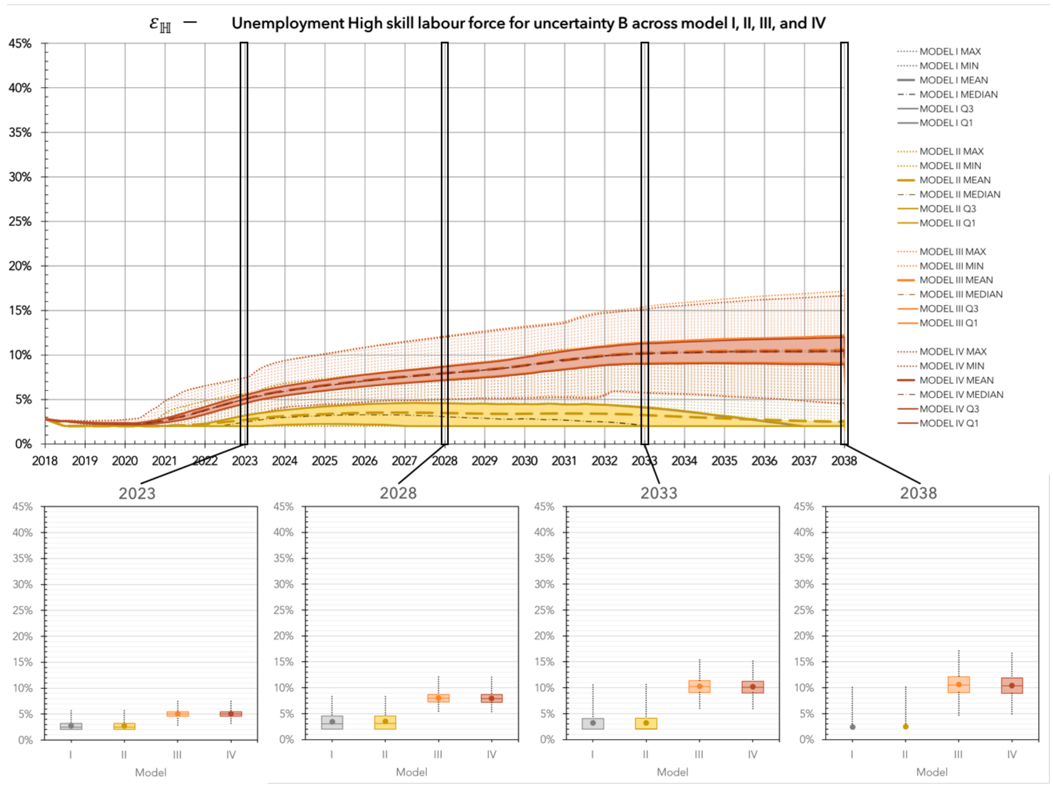


Figure 70 Unemployment projections $\varepsilon_{\mathbb{H}}$ for uncertainty B with and without adaptability and spill-over (models I, II, III, and IV)

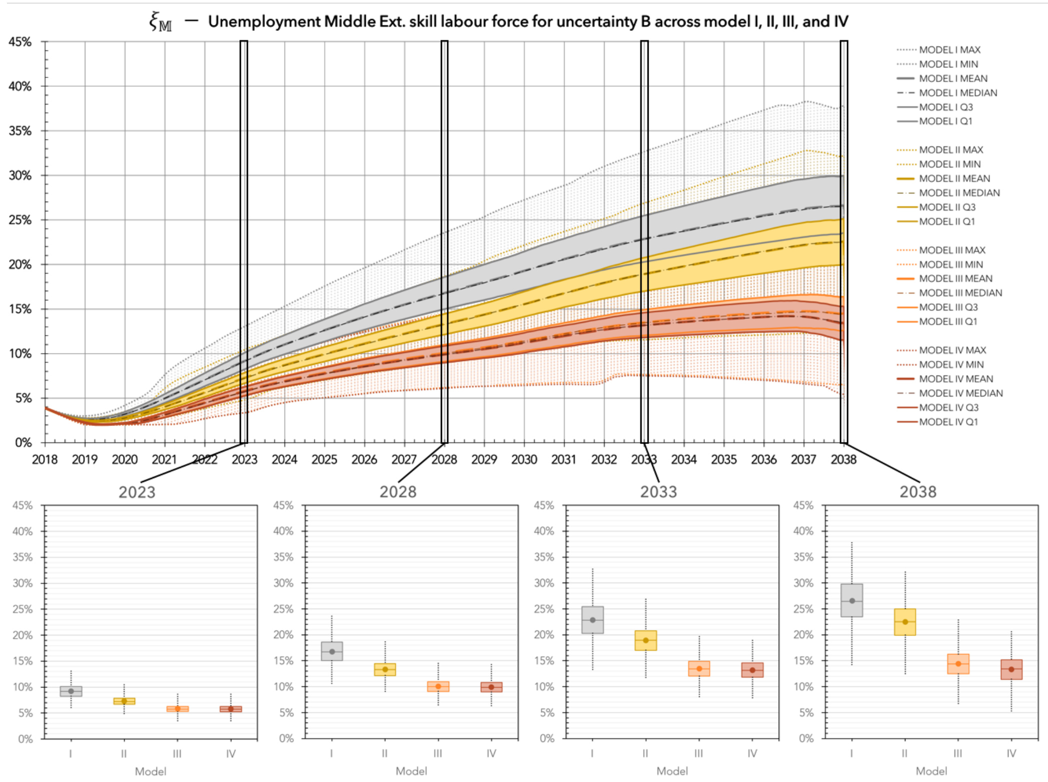


Figure 71 Unemployment projections $\xi_{\mathbb{M}}$ for uncertainty B with and without adaptability and spill-over (models I, II, III, and IV)

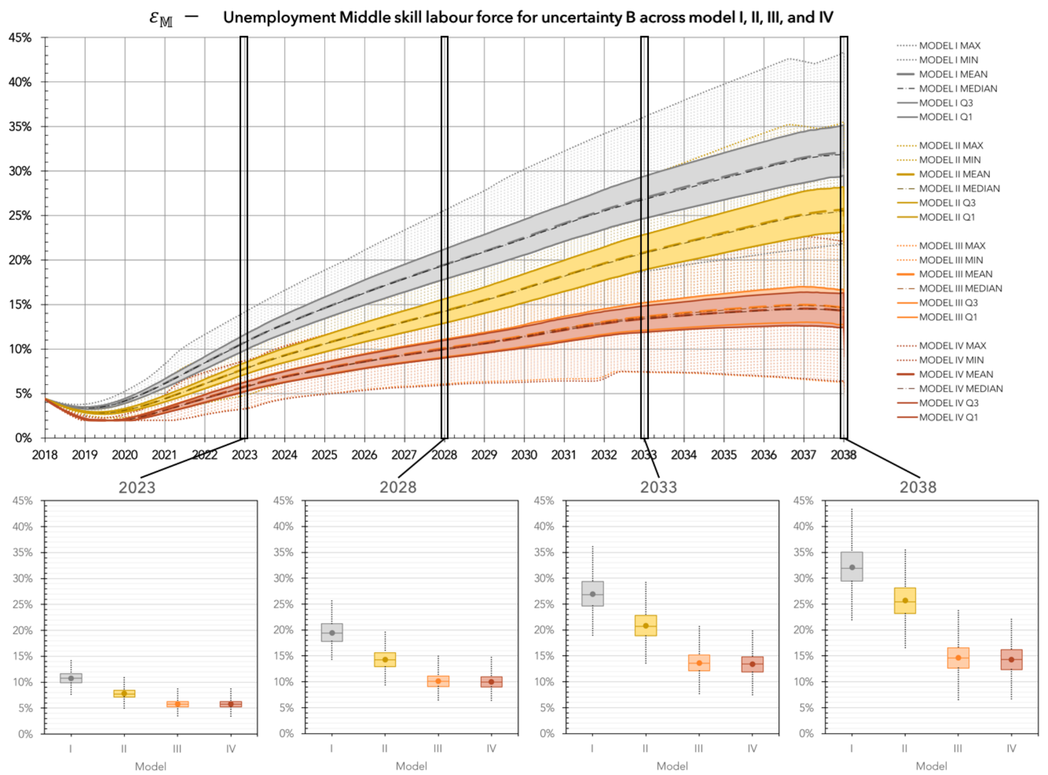


Figure 72 Unemployment projections $\varepsilon_{\mathbb{M}}$ for uncertainty B with and without adaptability and spill-over (models I, II, III, and IV)

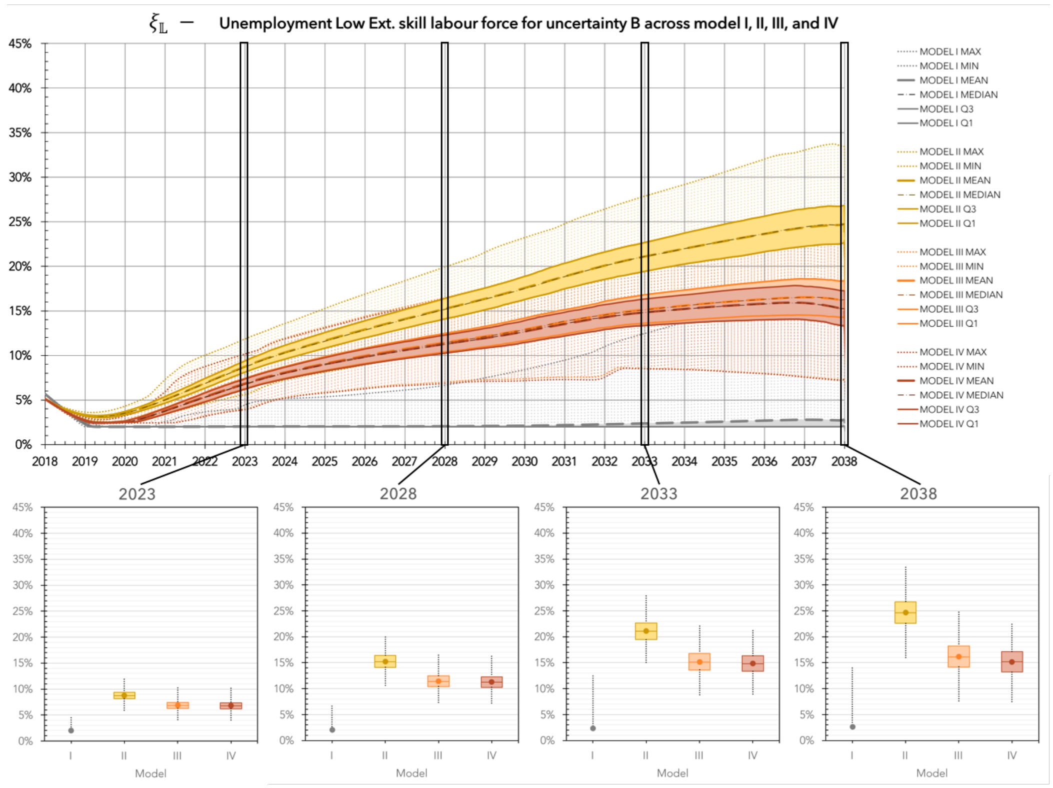


Figure 73 Unemployment projections $\xi_{\mathbb{L}}$ for uncertainty B with and without adaptability and spill-over (models I, II, III, and IV)

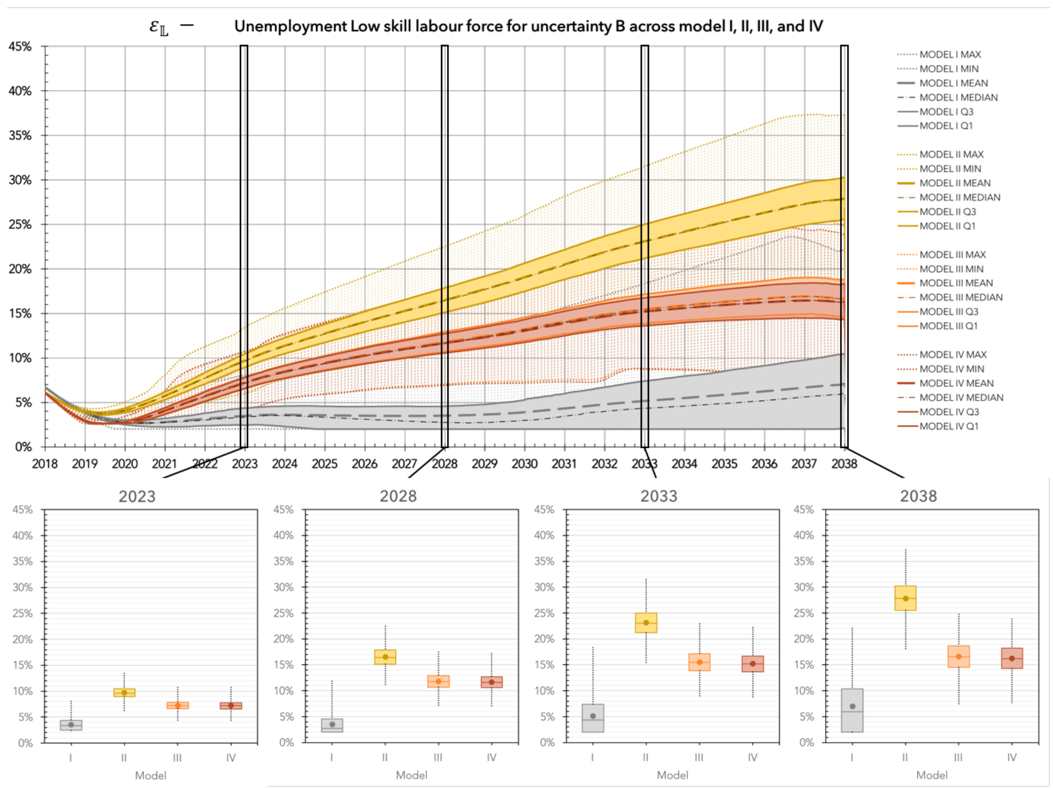


Figure 74 Unemployment projections $\varepsilon_{\mathbb{L}}$ for uncertainty B with and without adaptability and spill-over (models I, II, III, and IV)

XII EMA Python script Unemployment

For uncertainty A:

```
# Simulation configuration

import numpy as np
import matplotlib
import matplotlib.pyplot as plt
import pandas as pd
import SALib
import seaborn as sns
import mpl_toolkits.axisartist as AA
import scipy as sp
import copy
import matplotlib.ticker as ticker

from ema_workbench import (Model,
                    RealParameter,
                    IntegerParameter,
                    CategoricalParameter,
                    Constant,
                    TimeSeriesOutcome,
                    ScalarOutcome,
                    perform_experiments,
                    ema_logging,
                    save_results,
                    load_results)
from ema_workbench import (Policy)
from ema_workbench import (MultiprocessingEvaluator)
from ema_workbench.connectors import vensimDLLwrapper
from ema_workbench.connectors.vensim import VensimModel
from ema_workbench.em_framework.samplers import sample_levers, sample_uncertainties
from ema_workbench.util import load_results
from ema_workbench.util import ema_logging

from ema_workbench.analysis import prim
import matplotlib.pyplot as plt
from ema_workbench.analysis.plotting import lines, multiple_densities, kde_over_time
from ema_workbench.analysis.plotting_util import KDE
from ema_workbench.analysis.plotting_util import determine_time_dimension
from ema_workbench.analysis.pairs_plotting import pairs_scatter

from SALib.sample import saltelli
from SALib.analyze import sobol, morris
from SALib.test_functions import Ishigami

from mpl_toolkits.axes_grid1 import host_subplot

from scipy.stats import linregress

ema_logging.log_to_stderr(ema_logging.INFO)
```

```
vensimModel = VensimModel("ThesisModel", model_file=r"C:\Users\LocalAdmin\Documents\Koen\Final\Final_Models\Thesis_model_Final.vpm" )
```

```
# Uncertainty configuration Technological Substitution Dataset Gregory, Salomons, & Zierahn (2016) for the Netherlands

vensimModel.uncertainties = [
   #POPULATION MODEL UNCERTAINTIES
         RealParameter("Normal fertility rate per f", 1.58, 1.7),

   #EDUCATION MODEL UNCERTAINTIES
#       #CH Education
#          RealParameter("CH Edu performance Reskill equivalent", 25, 30),
#          RealParameter("CH Edu performance Upskill equivalent", 25, 30),
#         #Policy
#          #RealParameter("Time to introduction STEM program", 0, 300),
#          #RealParameter("Minimum fixed period CH Edu capacity expansion", 1, 36),
#          #RealParameter("Time to realise CH Edu capacity expansion", 1, 48),
#          #RealParameter("STEM educated vs STEM graduated ratio", 0.4, 1),
#          #RealParameter("MANUAL CH Edu performance overall improvement H", 0, 25),
#          #RealParameter("MANUAL CH Edu performance overall improvement M", 0, 25),
#          #RealParameter("MANUAL CH Edu performance overall improvement L", 0, 25),
#          #RealParameter("MANUAL CH Edu performance STEM improvement H", 0, 16.75),
#          #RealParameter("MANUAL CH Edu performance STEM improvement M", 0, 16.75),
#          #RealParameter("MANUAL CH Edu performance STEM improvement L", 0, 16.75),
#       #ST Education
          RealParameter("ST Labour market awareness and sensitivity", 0, 1),
          RealParameter("ST knowledge YA Unemployment delay", 12, 48),
#         #Policy
#          #RealParameter("ST STEM stimulation and awareness", 1, 2),
#          #RealParameter("ST High Edu stimulation and awareness", 1, 2),
#          #RealParameter("Time to realise ST Edu capacity expansion", 12, 60),
#          #RealParameter("Fixed period ST Edu capacity expansion", 1, 12),
#       #WA Education
          RealParameter("WAu reskill and upskill sensitivity", 0, 1),
          RealParameter("WAe reskill and upskill sensitivity", 0, 1),
#         #Policy
#          RealParameter("WA STEM stimulation and awareness", 1, 2),
#          RealParameter("WA High Edu stimulation and awareness", 1, 2),
#          RealParameter("Socioeconomic influence education and training H", 1, 2),
#          RealParameter("Socioeconomic influence education and training M", 0.895, 2),
#          RealParameter("Socioeconomic influence education and training L", 0.561, 2),

   #LABOUR MARKET MODEL UNCERTAINTIES
      #Labour reallocation
          RealParameter("Sensitivity Wage reallocation", 0, 0.999),
          RealParameter("Wage sacrifice ratio for employment", 0.01, 0.5),
          RealParameter("Sensitivity Unemployment reallocation", 0, 1),
         #Policy
          RealParameter("Labour reallocation delay", 12, 48),
         #Setting
          RealParameter("Error MINMAX corrector", 1000000000000000, 10000000000000000),
```

```
    #PRODUCTION MODEL UNCERTAINTIES
      #Labour input
#           RealParameter("Price elasticity of demand Abstract L", 0, 1),
#           RealParameter("Price elasticity of demand Abstract I", 0, 1),
#           RealParameter("Price elasticity of demand Routine L", 0, 1),
#           RealParameter("Price elasticity of demand Routine I", 0, 1),
#           RealParameter("Price elasticity of demand Manual L", 0, 1),
#           RealParameter("Price elasticity of demand Manual I", 0, 1),
      #GDP growth
        RealParameter("Long term economic growth error margin", 0, 0.05),
        RealParameter("Business cycle fluctuation amplitude", 0.001, 0.0033),
        RealParameter("Business cycle fluctuation period", 2, 3),
        RealParameter("Time to first recession", 2, 5),
        RealParameter("Business cycle recession amplitude", 0.0187, 0.0263),
        RealParameter("Business cycle recession duration", 3, 3.64),
        RealParameter("Busines cycle recession period", 8, 9.4),
        RealParameter("Severe recession timing", 1, 3),
        RealParameter("Severe recession duration", 4, 4.7),
        RealParameter("Severe recession amplitude", 0.0489, 0.0631),
        RealParameter("Severe recession occurance", 0, 1),
        RealParameter("Proportion of time in recession", 0.18, 0.21),
        RealParameter("Initial Labour share", 0.554, 0.714),
      #Others
#          RealParameter("Macro economic Technological TFP growth", 0.004, 0.0067),
        RealParameter("Task substitution elasticity", 0.66, 0.9),
      #Policy
        #RealParameter("Hours fulltime contracts", 32, 38),

    #TECHNOLOGY MODEL UNCERTAINTIES
        RealParameter("Proportion profit invested in innovation", 0.02, 1),
        RealParameter("Innovation allocation sensivitity to business cycle", 0, 0.1),
        RealParameter("Prior Substituted Labour demand", 8.9, 10.1),
        RealParameter("Time difference automation and substitution", 0.999, 1.001),
        RealParameter("TFP Wage allocation Abstract L", 0.1, 1),
        RealParameter("TFP Wage allocation Abstract I", 0.1, 1),
        RealParameter("TFP Wage allocation Routine L", 0.1, 1),
        RealParameter("TFP Wage allocation Routine I", 0.1, 1),
        RealParameter("TFP Wage allocation Manual L", 0.1, 1),
        RealParameter("TFP Wage allocation Manual I", 0.1, 1),
    #Substitution
       #Abstract L:
         #RealParameter("Technological bottleneck period Abstract L", 0, 12),
         RealParameter("Technological implementation period Abstract L", 240, 241),
         RealParameter("Technological automation estimate Abstract L", 0.009, 0.0102),
         RealParameter("Automation probability Abstract L", 0.999, 1),
         #RealParameter("Annual labour input increase for technological change Abstract L", 0.0042, 0.015),
         RealParameter("Annual technological productivity growth Abstract L", 0.006, 0.01),
      #Abstract I:
        #RealParameter("Technological bottleneck period Abstract I", 0, 12),
        RealParameter("Technological implementation period Abstract I", 240, 241),
        RealParameter("Technological automation estimate Abstract I", 0.009, 0.0102),
        RealParameter("Automation probability Abstract I", 0.999, 1),
```

```
        #RealParameter("Annual labour input increase for technological change Abstract I", 0.0042, 0.015),
        RealParameter("Annual technological productivity growth Abstract I", 0.006, 0.01),
      #Routine L:
        #RealParameter("Technological bottleneck period Routine L", 0, 12),
        RealParameter("Technological implementation period Routine L", 240, 241),
        RealParameter("Technological automation estimate Routine L", 0.09, 0.102),
        RealParameter("Automation probability Routine L", 0.999, 1),
        #RealParameter("Annual labour input increase for technological change Routine L", 0.0042, 0.015),
        RealParameter("Annual technological productivity growth Routine L", 0.006, 0.01),
      #Routine I:
        #RealParameter("Technological bottleneck period Routine I", 0, 12),
        RealParameter("Technological implementation period Routine I", 240, 241),
        RealParameter("Technological automation estimate Routine I", 0.09, 0.102),
        RealParameter("Automation probability Routine I", 0.999, 1),
        #RealParameter("Annual labour input increase for technological change Routine I", 0.0042, 0.015),
        RealParameter("Annual technological productivity growth Routine I", 0.006,0.01),
      #Manual L:
        #RealParameter("Technological bottleneck period Manual L", 0, 12),
        RealParameter("Technological implementation period Manual L", 240, 241),
        RealParameter("Technological automation estimate Manual L", 0.09, 0.102),
        RealParameter("Automation probability Manual L", 0.999, 1),
        #RealParameter("Annual labour input increase for technological change Manual L", 0.0042, 0.015),
        RealParameter("Annual technological productivity growth Manual L", 0.006, 0.01),
      #Manual I:
        #RealParameter("Technological bottleneck period Manual I", 0, 12),
        RealParameter("Technological implementation period Manual I", 240, 241),
        RealParameter("Technological automation estimate Manual I", 0.09, 0.102),
        RealParameter("Automation probability Manual I", 0.999, 1),
        #RealParameter("Annual labour input increase for technological change Manual I", 0.0042, 0.015),
        RealParameter("Annual technological productivity growth Manual I", 0.006, 0.01),

        RealParameter("Upper bound technological bottleneck proportion of tasks", 0.001, 0.01)
]

vensimModel.outcomes = [
    #POPULATION MODEL OUTCOMES
#           TimeSeriesOutcome('Total population'),
    #EDUCATION MODEL OUTCOMES
        TimeSeriesOutcome('ST HI m total reskill percentage'),
        TimeSeriesOutcome('ST MI m total reskill percentage'),
        TimeSeriesOutcome('ST LI m total reskill percentage'),
        TimeSeriesOutcome('ST ML m total upskill percentage'),
        TimeSeriesOutcome('ST MI m total upskill percentage'),
        TimeSeriesOutcome('ST LL m total upskill percentage'),
        TimeSeriesOutcome('ST LI m total upskill percentage'),
        TimeSeriesOutcome('ST HI f total reskill percentage'),
        TimeSeriesOutcome('ST MI f total reskill percentage'),
        TimeSeriesOutcome('ST LI f total reskill percentage'),
        TimeSeriesOutcome('ST ML f total upskill percentage'),
        TimeSeriesOutcome('ST MI f total upskill percentage'),
        TimeSeriesOutcome('ST LL f total upskill percentage'),
        TimeSeriesOutcome('ST LI f total upskill percentage'),
        TimeSeriesOutcome('LF HI m total reskill percentage'),
```

```
        TimeSeriesOutcome('LF MI m total reskill percentage'),
        TimeSeriesOutcome('LF LI m total reskill percentage'),
        TimeSeriesOutcome('LF ML m total upskill percentage'),
        TimeSeriesOutcome('LF MI m total upskill percentage'),
        TimeSeriesOutcome('LF LL m total upskill percentage'),
        TimeSeriesOutcome('LF LI m total upskill percentage'),
        TimeSeriesOutcome('LF HI f total reskill percentage'),
        TimeSeriesOutcome('LF MI f total reskill percentage'),
        TimeSeriesOutcome('LF LI f total reskill percentage'),
        TimeSeriesOutcome('LF ML f total upskill percentage'),
        TimeSeriesOutcome('LF MI f total upskill percentage'),
        TimeSeriesOutcome('LF LL f total upskill percentage'),
        TimeSeriesOutcome('LF LI f total upskill percentage'),
    #LABOUR MARKET OUTCOMES
        TimeSeriesOutcome('Labour force ft Index'),
        TimeSeriesOutcome('HL ft average wage index'),
        TimeSeriesOutcome('HI ft average wage index'),
        TimeSeriesOutcome('ML ft average wage index'),
        TimeSeriesOutcome('MI ft average wage index'),
        TimeSeriesOutcome('LL ft average wage index'),
        TimeSeriesOutcome('LI ft average wage index'),
        TimeSeriesOutcome('HL Avg ft Unemployment rate'),
        TimeSeriesOutcome('HI Avg ft Unemployment rate'),
        TimeSeriesOutcome('ML Avg ft Unemployment rate'),
        TimeSeriesOutcome('MI Avg ft Unemployment rate'),
        TimeSeriesOutcome('LL Avg ft Unemployment rate'),
        TimeSeriesOutcome('LI Avg ft Unemployment rate'),
#       TimeSeriesOutcome('Total Labour Force HL ft'),
#       TimeSeriesOutcome('Total Labour Force HI ft'),
#       TimeSeriesOutcome('Total Labour Force ML ft'),
#       TimeSeriesOutcome('Total Labour Force MI ft'),
#       TimeSeriesOutcome('Total Labour Force LL ft'),
#       TimeSeriesOutcome('Total Labour Force LI ft'),
#       TimeSeriesOutcome('LI to Manual I for employment ft'),
#       TimeSeriesOutcome('LL to Manual I for employment ft'),
        TimeSeriesOutcome('MI to Manual I for employment ft'),
        TimeSeriesOutcome('ML to Manual I for employment ft'),
        TimeSeriesOutcome('HI to Manual I for employment ft'),
        TimeSeriesOutcome('HL to Manual I for employment ft'),
#       TimeSeriesOutcome('LL to Manual L for employment ft'),
#       TimeSeriesOutcome('ML to Manual L for employment ft'),
        TimeSeriesOutcome('HL to Manual L for employment ft'),
#       TimeSeriesOutcome('LI to Routine I for employment ft'),
#       TimeSeriesOutcome('LL to Routine I for employment ft'),
#       TimeSeriesOutcome('MI to Routine I for employment ft'),
#       TimeSeriesOutcome('ML to Routine I for employment ft'),
        TimeSeriesOutcome('HI to Routine I for employment ft'),
        TimeSeriesOutcome('HL to Routine I for employment ft'),
#       TimeSeriesOutcome('LL to Routine L for employment ft'),
#       TimeSeriesOutcome('ML to Routine L for employment ft'),
        TimeSeriesOutcome('HL to Routine L for employment ft'),
#       TimeSeriesOutcome('HI to Abstract I for employment ft'),
#       TimeSeriesOutcome('HL to Abstract I for employment ft'),
```

```
#           TimeSeriesOutcome('HL to Abstract L for employment ft'),
    #PRODUCTION MODEL OUTCOMES
          TimeSeriesOutcome('Annual Macro Economic growth rate'),
          TimeSeriesOutcome('Total wage income index'),
          TimeSeriesOutcome('Aggregate annual TFP'),
          TimeSeriesOutcome('Average Labour share'),
#           TimeSeriesOutcome('Relative price development Abstract L'),
#           TimeSeriesOutcome('Relative price development Abstract I'),
#           TimeSeriesOutcome('Relative price development Routine L'),
#           TimeSeriesOutcome('Relative price development Routine I'),
#           TimeSeriesOutcome('Relative price development Manual L'),
#           TimeSeriesOutcome('Relative price development Manual I'),
    #TECHNOLOGY MODEL OUTCOMES
          TimeSeriesOutcome('Technological substitution Abstract L'),
          TimeSeriesOutcome('Technological substitution Abstract I'),
          TimeSeriesOutcome('Technological substitution Routine L'),
          TimeSeriesOutcome('Technological substitution Routine I'),
          TimeSeriesOutcome('Technological substitution Manual L'),
          TimeSeriesOutcome('Technological substitution Manual I'),
          TimeSeriesOutcome('Profit index Abstract L'),
          TimeSeriesOutcome('Profit index Abstract I'),
          TimeSeriesOutcome('Profit index Routine L'),
          TimeSeriesOutcome('Profit index Routine I'),
          TimeSeriesOutcome('Profit index Manual L'),
          TimeSeriesOutcome('Profit index Manual I')
#           TimeSeriesOutcome('Labour share index Abstract L'),
#           TimeSeriesOutcome('Labour share index Abstract I'),
#           TimeSeriesOutcome('Labour share index Routine L'),
#           TimeSeriesOutcome('Labour share index Routine I'),
#           TimeSeriesOutcome('Labour share index Manual L'),
#           TimeSeriesOutcome('Labour share index Manual I'),
#           TimeSeriesOutcome('Wage index Abstract L'),
#           TimeSeriesOutcome('Wage index Abstract I'),
#           TimeSeriesOutcome('Wage index Routine L'),
#           TimeSeriesOutcome('Wage index Routine I'),
#           TimeSeriesOutcome('Wage index Manual L'),
#           TimeSeriesOutcome('Wage index Manual I'),
]

policies = [
           Policy('Model_IV',

model_file=r"C:\Users\LocalAdmin\Documents\Koen\Final\Final_Models\Thesis_model_Final_IV.vpm")
          ]
```

```
# Model simulation

results = perform_experiments(vensimModel, 1000, policies= policies)
```

```
# Save results

results_name = './EMA_NED_Uncertainty_A_Results.tar.gz'
save_results(results, results_name)
```

For uncertainty C:

```
# Simulation configuration

import numpy as np
import matplotlib
import matplotlib.pyplot as plt
import pandas as pd
import SALib
import seaborn as sns
import mpl_toolkits.axisartist as AA
import scipy as sp
import copy
import matplotlib.ticker as ticker

from ema_workbench import (Model,
                    RealParameter,
                    IntegerParameter,
                    CategoricalParameter,
                    Constant,
                    TimeSeriesOutcome,
                    ScalarOutcome,
                    perform_experiments,
                    ema_logging,
                    save_results,
                    load_results)
from ema_workbench import (Policy)
from ema_workbench import (MultiprocessingEvaluator)
from ema_workbench.connectors import vensimDLLwrapper
from ema_workbench.connectors.vensim import VensimModel
from ema_workbench.em_framework.samplers import sample_levers, sample_uncertainties
from ema_workbench.util import load_results
from ema_workbench.util import ema_logging

from ema_workbench.analysis import prim
import matplotlib.pyplot as plt
from ema_workbench.analysis.plotting import lines, multiple_densities, kde_over_time
from ema_workbench.analysis.plotting_util import KDE
from ema_workbench.analysis.plotting_util import determine_time_dimension
from ema_workbench.analysis.pairs_plotting import pairs_scatter

from SALib.sample import saltelli
from SALib.analyze import sobol, morris
from SALib.test_functions import Ishigami

from mpl_toolkits.axes_grid1 import host_subplot

from scipy.stats import linregress
```

```
ema_logging.log_to_stderr(ema_logging.INFO)
```

```
vensimModel = VensimModel("ThesisModel", model_file=r"C:\Users\LocalAdmin\Documents\Koen\Final\Final_Models\Thesis_model_Final.vpm" )
```

```
# Uncertainty configuration Technological Substitution Dataset Arntz, Gregory, & Zierahn (2016) for the Netherlands

vensimModel.uncertainties = [
   #POPULATION MODEL UNCERTAINTIES
         RealParameter("Normal fertility rate per f", 1.58, 1.7),

   #EDUCATION MODEL UNCERTAINTIES
#        #CH Education
#            RealParameter("CH Edu performance Reskill equivalent", 25, 30),
#            RealParameter("CH Edu performance Upskill equivalent", 25, 30),
#          #Policy
#            #RealParameter("Time to introduction STEM program", 0, 300),
#            #RealParameter("Minimum fixed period CH Edu capacity expansion", 1, 36),
#            #RealParameter("Time to realise CH Edu capacity expansion", 1, 48),
#            #RealParameter("STEM educated vs STEM graduated ratio", 0.4, 1),
#            #RealParameter("MANUAL CH Edu performance overall improvement H", 0, 25),
#            #RealParameter("MANUAL CH Edu performance overall improvement M", 0, 25),
#            #RealParameter("MANUAL CH Edu performance overall improvement L", 0, 25),
#            #RealParameter("MANUAL CH Edu performance STEM improvement H", 0, 16.75),
#            #RealParameter("MANUAL CH Edu performance STEM improvement M", 0, 16.75),
#            #RealParameter("MANUAL CH Edu performance STEM improvement L", 0, 16.75),
#        #ST Education
          RealParameter("ST Labour market awareness and sensitivity", 0, 1),
          RealParameter("ST knowledge YA Unemployment delay", 12, 48),
#          #Policy
#            #RealParameter("ST STEM stimulation and awareness", 1, 2),
#            #RealParameter("ST High Edu stimulation and awareness", 1, 2),
#            #RealParameter("Time to realise ST Edu capacity expansion", 12, 60),
#            #RealParameter("Fixed period ST Edu capacity expansion", 1, 12),
#        #WA Education
          RealParameter("WAu reskill and upskill sensitivity", 0, 1),
          RealParameter("WAe reskill and upskill sensitivity", 0, 1),
#          #Policy
#            RealParameter("WA STEM stimulation and awareness", 1, 2),
#            RealParameter("WA High Edu stimulation and awareness", 1, 2),
#            RealParameter("Socioeconomic influence education and training H", 1, 2),
#            RealParameter("Socioeconomic influence education and training M", 0.895, 2),
#            RealParameter("Socioeconomic influence education and training L", 0.561, 2),

   #LABOUR MARKET MODEL UNCERTAINTIES
      #Labour reallocation
          RealParameter("Sensitivity Wage reallocation", 0, 0.999),
          RealParameter("Wage sacrifice ratio for employment", 0.01, 0.5),
          RealParameter("Sensitivity Unemployment reallocation", 0, 1),
         #Policy
          RealParameter("Labour reallocation delay", 12, 48),
         #Setting
          RealParameter("Error MINMAX corrector", 10000000000000000, 100000000000000000),

   #PRODUCTION MODEL UNCERTAINTIES
      #Labour input
#            RealParameter("Price elasticity of demand Abstract L", 0, 1),
```

```
#           RealParameter("Price elasticity of demand Abstract I", 0, 1),
#           RealParameter("Price elasticity of demand Routine L", 0, 1),
#           RealParameter("Price elasticity of demand Routine I", 0, 1),
#           RealParameter("Price elasticity of demand Manual L", 0, 1),
#           RealParameter("Price elasticity of demand Manual I", 0, 1),
        #GDP growth
            RealParameter("Long term economic growth error margin", 0, 0.05),
            RealParameter("Business cycle fluctuation amplitude", 0.001, 0.0033),
            RealParameter("Business cycle fluctuation period", 2, 3),
            RealParameter("Time to first recession", 2, 5),
            RealParameter("Business cycle recession amplitude", 0.0187, 0.0263),
            RealParameter("Business cycle recession duration", 3, 3.64),
            RealParameter("Busines cycle recession period", 8, 9.4),
            RealParameter("Severe recession timing", 1, 3),
            RealParameter("Severe recession duration", 4, 4.7),
            RealParameter("Severe recession amplitude", 0.0489, 0.0631),
            RealParameter("Severe recession occurance", 0, 1),
            RealParameter("Proportion of time in recession", 0.18, 0.21),
            RealParameter("Initial Labour share", 0.554, 0.714),
        #Others
#           RealParameter("Macro economic Technological TFP growth", 0.004, 0.0067),
            RealParameter("Task substitution elasticity", 0.66, 0.9),
        #Policy
            #RealParameter("Hours fulltime contracts", 32, 38),

    #TECHNOLOGY MODEL UNCERTAINTIES
            RealParameter("Proportion profit invested in innovation", 0.02, 1),
            RealParameter("Innovation allocation sensivitity to business cycle", 0, 0.1),
            RealParameter("Prior Substituted Labour demand", 8.9, 10.1),
            RealParameter("Time difference automation and substitution", 0.999, 1.001),
            RealParameter("TFP Wage allocation Abstract L", 0.1, 1),
            RealParameter("TFP Wage allocation Abstract I", 0.1, 1),
            RealParameter("TFP Wage allocation Routine L", 0.1, 1),
            RealParameter("TFP Wage allocation Routine I", 0.1, 1),
            RealParameter("TFP Wage allocation Manual L", 0.1, 1),
            RealParameter("TFP Wage allocation Manual I", 0.1, 1),
    #Substitution
        #Abstract L:
            #RealParameter("Technological bottleneck period Abstract L", 0, 12),
            RealParameter("Technological implementation period Abstract L", 216, 264),
            RealParameter("Technological automation estimate Abstract L", 0.001, 0.01),
            RealParameter("Automation probability Abstract L", 0.7, 1.0),
            #RealParameter("Annual labour input increase for technological change Abstract L", 0.0042, 0.015),
            RealParameter("Annual technological productivity growth Abstract L", 0.006, 0.01),
        #Abstract I:
            #RealParameter("Technological bottleneck period Abstract I", 0, 12),
            RealParameter("Technological implementation period Abstract I", 216, 264),
            RealParameter("Technological automation estimate Abstract I", 0.001, 0.01),
            RealParameter("Automation probability Abstract I", 0.7, 1.0),
            #RealParameter("Annual labour input increase for technological change Abstract I", 0.0042, 0.015),
            RealParameter("Annual technological productivity growth Abstract I", 0.006, 0.01),
        #Routine L:
            #RealParameter("Technological bottleneck period Routine L", 0, 12),
```

```
        RealParameter("Technological implementation period Routine L", 216, 264),
        RealParameter("Technological automation estimate Routine L", 0.06825, 0.07175),
        RealParameter("Automation probability Routine L", 0.7, 1.0),
        #RealParameter("Annual labour input increase for technological change Routine L", 0.0042, 0.015),
        RealParameter("Annual technological productivity growth Routine L", 0.006, 0.01),
      #Routine I:
        #RealParameter("Technological bottleneck period Routine I", 0, 12),
        RealParameter("Technological implementation period Routine I", 216, 264),
        RealParameter("Technological automation estimate Routine I", 0.06825, 0.07175),
        RealParameter("Automation probability Routine I", 0.7, 1.0),
        #RealParameter("Annual labour input increase for technological change Routine I", 0.0042, 0.015),
        RealParameter("Annual technological productivity growth Routine I", 0.006,0.01),
      #Manual L:
        #RealParameter("Technological bottleneck period Manual L", 0, 12),
        RealParameter("Technological implementation period Manual L", 216, 264),
        RealParameter("Technological automation estimate Manual L", 0.37, 0.51),
        RealParameter("Automation probability Manual L", 0.7, 1.0),
        #RealParameter("Annual labour input increase for technological change Manual L", 0.0042, 0.015),
        RealParameter("Annual technological productivity growth Manual L", 0.006, 0.01),
      #Manual I:
        #RealParameter("Technological bottleneck period Manual I", 0, 12),
        RealParameter("Technological implementation period Manual I", 216, 264),
        RealParameter("Technological automation estimate Manual I", 0.37, 0.51),
        RealParameter("Automation probability Manual I", 0.7, 1.0),
        #RealParameter("Annual labour input increase for technological change Manual I", 0.0042, 0.015),
        RealParameter("Annual technological productivity growth Manual I", 0.006, 0.01),

        RealParameter("Upper bound technological bottleneck proportion of tasks", 0.001, 0.01)
]

vensimModel.outcomes = [
    #POPULATION MODEL OUTCOMES
#          TimeSeriesOutcome('Total population'),
    #EDUCATION MODEL OUTCOMES
        TimeSeriesOutcome('ST HI m total reskill percentage'),
        TimeSeriesOutcome('ST MI m total reskill percentage'),
        TimeSeriesOutcome('ST LI m total reskill percentage'),
        TimeSeriesOutcome('ST ML m total upskill percentage'),
        TimeSeriesOutcome('ST MI m total upskill percentage'),
        TimeSeriesOutcome('ST LL m total upskill percentage'),
        TimeSeriesOutcome('ST LI m total upskill percentage'),
        TimeSeriesOutcome('ST HI f total reskill percentage'),
        TimeSeriesOutcome('ST MI f total reskill percentage'),
        TimeSeriesOutcome('ST LI f total reskill percentage'),
        TimeSeriesOutcome('ST ML f total upskill percentage'),
        TimeSeriesOutcome('ST MI f total upskill percentage'),
        TimeSeriesOutcome('ST LL f total upskill percentage'),
        TimeSeriesOutcome('ST LI f total upskill percentage'),
        TimeSeriesOutcome('LF HI m total reskill percentage'),
        TimeSeriesOutcome('LF MI m total reskill percentage'),
        TimeSeriesOutcome('LF LI m total reskill percentage'),
        TimeSeriesOutcome('LF ML m total upskill percentage'),
        TimeSeriesOutcome('LF MI m total upskill percentage'),
```

```
        TimeSeriesOutcome('LF LL m total upskill percentage'),
        TimeSeriesOutcome('LF LI m total upskill percentage'),
        TimeSeriesOutcome('LF HI f total reskill percentage'),
        TimeSeriesOutcome('LF MI f total reskill percentage'),
        TimeSeriesOutcome('LF LI f total reskill percentage'),
        TimeSeriesOutcome('LF ML f total upskill percentage'),
        TimeSeriesOutcome('LF MI f total upskill percentage'),
        TimeSeriesOutcome('LF LL f total upskill percentage'),
        TimeSeriesOutcome('LF LI f total upskill percentage'),
    #LABOUR MARKET OUTCOMES
        TimeSeriesOutcome('Labour force ft Index'),
        TimeSeriesOutcome('HL ft average wage index'),
        TimeSeriesOutcome('HI ft average wage index'),
        TimeSeriesOutcome('ML ft average wage index'),
        TimeSeriesOutcome('MI ft average wage index'),
        TimeSeriesOutcome('LL ft average wage index'),
        TimeSeriesOutcome('LI ft average wage index'),
        TimeSeriesOutcome('HL Avg ft Unemployment rate'),
        TimeSeriesOutcome('HI Avg ft Unemployment rate'),
        TimeSeriesOutcome('ML Avg ft Unemployment rate'),
        TimeSeriesOutcome('MI Avg ft Unemployment rate'),
        TimeSeriesOutcome('LL Avg ft Unemployment rate'),
        TimeSeriesOutcome('LI Avg ft Unemployment rate'),
#         TimeSeriesOutcome('Total Labour Force HL ft'),
#         TimeSeriesOutcome('Total Labour Force HI ft'),
#         TimeSeriesOutcome('Total Labour Force ML ft'),
#         TimeSeriesOutcome('Total Labour Force MI ft'),
#         TimeSeriesOutcome('Total Labour Force LL ft'),
#         TimeSeriesOutcome('Total Labour Force LI ft'),
#         TimeSeriesOutcome('LI to Manual I for employment ft'),
#         TimeSeriesOutcome('LL to Manual I for employment ft'),
        TimeSeriesOutcome('MI to Manual I for employment ft'),
        TimeSeriesOutcome('ML to Manual I for employment ft'),
        TimeSeriesOutcome('HI to Manual I for employment ft'),
        TimeSeriesOutcome('HL to Manual I for employment ft'),
#        TimeSeriesOutcome('LL to Manual L for employment ft'),
#        TimeSeriesOutcome('ML to Manual L for employment ft'),
        TimeSeriesOutcome('HL to Manual L for employment ft'),
#         TimeSeriesOutcome('LI to Routine I for employment ft'),
#         TimeSeriesOutcome('LL to Routine I for employment ft'),
#         TimeSeriesOutcome('MI to Routine I for employment ft'),
#         TimeSeriesOutcome('ML to Routine I for employment ft'),
        TimeSeriesOutcome('HI to Routine I for employment ft'),
        TimeSeriesOutcome('HL to Routine I for employment ft'),
#         TimeSeriesOutcome('LL to Routine L for employment ft'),
#         TimeSeriesOutcome('ML to Routine L for employment ft'),
        TimeSeriesOutcome('HL to Routine L for employment ft'),
#         TimeSeriesOutcome('HI to Abstract I for employment ft'),
#         TimeSeriesOutcome('HL to Abstract I for employment ft'),
#         TimeSeriesOutcome('HL to Abstract L for employment ft'),
    #PRODUCTION MODEL OUTCOMES
        TimeSeriesOutcome('Annual Macro Economic growth rate'),
        TimeSeriesOutcome('Total wage income index'),
```

```
          TimeSeriesOutcome('Aggregate annual TFP'),
          TimeSeriesOutcome('Average Labour share'),
#           TimeSeriesOutcome('Relative price development Abstract L'),
#           TimeSeriesOutcome('Relative price development Abstract I'),
#           TimeSeriesOutcome('Relative price development Routine L'),
#           TimeSeriesOutcome('Relative price development Routine I'),
#           TimeSeriesOutcome('Relative price development Manual L'),
#           TimeSeriesOutcome('Relative price development Manual I'),
    #TECHNOLOGY MODEL OUTCOMES
          TimeSeriesOutcome('Technological substitution Abstract L'),
          TimeSeriesOutcome('Technological substitution Abstract I'),
          TimeSeriesOutcome('Technological substitution Routine L'),
          TimeSeriesOutcome('Technological substitution Routine I'),
          TimeSeriesOutcome('Technological substitution Manual L'),
          TimeSeriesOutcome('Technological substitution Manual I'),
          TimeSeriesOutcome('Profit index Abstract L'),
          TimeSeriesOutcome('Profit index Abstract I'),
          TimeSeriesOutcome('Profit index Routine L'),
          TimeSeriesOutcome('Profit index Routine I'),
          TimeSeriesOutcome('Profit index Manual L'),
          TimeSeriesOutcome('Profit index Manual I')
#           TimeSeriesOutcome('Labour share index Abstract L'),
#           TimeSeriesOutcome('Labour share index Abstract I'),
#           TimeSeriesOutcome('Labour share index Routine L'),
#           TimeSeriesOutcome('Labour share index Routine I'),
#           TimeSeriesOutcome('Labour share index Manual L'),
#           TimeSeriesOutcome('Labour share index Manual I'),
#           TimeSeriesOutcome('Wage index Abstract L'),
#           TimeSeriesOutcome('Wage index Abstract I'),
#           TimeSeriesOutcome('Wage index Routine L'),
#           TimeSeriesOutcome('Wage index Routine I'),
#           TimeSeriesOutcome('Wage index Manual L'),
#           TimeSeriesOutcome('Wage index Manual I'),
]

policies = [
           Policy('Model_IV',

model_file=r"C:\Users\LocalAdmin\Documents\Koen\Final\Final_Models\Thesis_model_Final_IV.vpm")
          ]
```

```
# Model simulation

results = perform_experiments(vensimModel, 1000, policies= policies)
```

```
# Save results

results_name = './EMA_NED_Uncertainty_C_Results.tar.gz'
save_results(results, results_name)
```

For uncertainty D:

```
# Simulation configuration

import numpy as np
import matplotlib
import matplotlib.pyplot as plt
import pandas as pd
import SALib
import seaborn as sns
import mpl_toolkits.axisartist as AA
import scipy as sp
import copy
import matplotlib.ticker as ticker

from ema_workbench import (Model,
                    RealParameter,
                    IntegerParameter,
                    CategoricalParameter,
                    Constant,
                    TimeSeriesOutcome,
                    ScalarOutcome,
                    perform_experiments,
                    ema_logging,
                    save_results,
                    load_results)
from ema_workbench import (Policy)
from ema_workbench import (MultiprocessingEvaluator)
from ema_workbench.connectors import vensimDLLwrapper
from ema_workbench.connectors.vensim import VensimModel
from ema_workbench.em_framework.samplers import sample_levers, sample_uncertainties
from ema_workbench.util import load_results
from ema_workbench.util import ema_logging

from ema_workbench.analysis import prim
import matplotlib.pyplot as plt
from ema_workbench.analysis.plotting import lines, multiple_densities, kde_over_time
from ema_workbench.analysis.plotting_util import KDE
from ema_workbench.analysis.plotting_util import determine_time_dimension
from ema_workbench.analysis.pairs_plotting import pairs_scatter

from SALib.sample import saltelli
from SALib.analyze import sobol, morris
from SALib.test_functions import Ishigami

from mpl_toolkits.axes_grid1 import host_subplot

from scipy.stats import linregress
```

```
ema_logging.log_to_stderr(ema_logging.INFO)
```

```
vensimModel = VensimModel("ThesisModel",
model_file=r"C:\Users\LocalAdmin\Documents\Koen\Final\Final_Models\Thesis_model_Final.vpm" )
```

```
# Uncertainty configuration Technological Substitution Dataset Nedelkoska & Quintini (2018) for the Netherlands

vensimModel.uncertainties = [
   #POPULATION MODEL UNCERTAINTIES
          RealParameter("Normal fertility rate per f", 1.58, 1.7),

   #EDUCATION MODEL UNCERTAINTIES
#        #CH Education
#           RealParameter("CH Edu performance Reskill equivalent", 25, 30),
#           RealParameter("CH Edu performance Upskill equivalent", 25, 30),
#          #Policy
#           #RealParameter("Time to introduction STEM program", 0, 300),
#           #RealParameter("Minimum fixed period CH Edu capacity expansion", 1, 36),
#           #RealParameter("Time to realise CH Edu capacity expansion", 1, 48),
#           #RealParameter("STEM educated vs STEM graduated ratio", 0.4, 1),
#           #RealParameter("MANUAL CH Edu performance overall improvement H", 0, 25),
#           #RealParameter("MANUAL CH Edu performance overall improvement M", 0, 25),
#           #RealParameter("MANUAL CH Edu performance overall improvement L", 0, 25),
#           #RealParameter("MANUAL CH Edu performance STEM improvement H", 0, 16.75),
#           #RealParameter("MANUAL CH Edu performance STEM improvement M", 0, 16.75),
#           #RealParameter("MANUAL CH Edu performance STEM improvement L", 0, 16.75),
#        #ST Education
          RealParameter("ST Labour market awareness and sensitivity", 0, 1),
          RealParameter("ST knowledge YA Unemployment delay", 12, 48),
#          #Policy
#           #RealParameter("ST STEM stimulation and awareness", 1, 2),
#           #RealParameter("ST High Edu stimulation and awareness", 1, 2),
#           #RealParameter("Time to realise ST Edu capacity expansion", 12, 60),
#           #RealParameter("Fixed period ST Edu capacity expansion", 1, 12),
#        #WA Education
          RealParameter("WAu reskill and upskill sensitivity", 0, 1),
          RealParameter("WAe reskill and upskill sensitivity", 0, 1),
#          #Policy
#           RealParameter("WA STEM stimulation and awareness", 1, 2),
#           RealParameter("WA High Edu stimulation and awareness", 1, 2),
#           RealParameter("Socioeconomic influence education and training H", 1, 2),
#           RealParameter("Socioeconomic influence education and training M", 0.895, 2),
#           RealParameter("Socioeconomic influence education and training L", 0.561, 2),

   #LABOUR MARKET MODEL UNCERTAINTIES
      #Labour reallocation
          RealParameter("Sensitivity Wage reallocation", 0, 0.999),
          RealParameter("Wage sacrifice ratio for employment", 0.01, 0.5),
          RealParameter("Sensitivity Unemployment reallocation", 0, 1),
         #Policy
          RealParameter("Labour reallocation delay", 12, 48),
         #Setting
          RealParameter("Error MINMAX corrector", 10000000000000000, 100000000000000000),

   #PRODUCTION MODEL UNCERTAINTIES
      #Labour input
#           RealParameter("Price elasticity of demand Abstract L", 0, 1),
```

```
#           RealParameter("Price elasticity of demand Abstract I", 0, 1),
#           RealParameter("Price elasticity of demand Routine L", 0, 1),
#           RealParameter("Price elasticity of demand Routine I", 0, 1),
#           RealParameter("Price elasticity of demand Manual L", 0, 1),
#           RealParameter("Price elasticity of demand Manual I", 0, 1),
        #GDP growth
            RealParameter("Long term economic growth error margin", 0, 0.05),
            RealParameter("Business cycle fluctuation amplitude", 0.001, 0.0033),
            RealParameter("Business cycle fluctuation period", 2, 3),
            RealParameter("Time to first recession", 2, 5),
            RealParameter("Business cycle recession amplitude", 0.0187, 0.0263),
            RealParameter("Business cycle recession duration", 3, 3.64),
            RealParameter("Busines cycle recession period", 8, 9.4),
            RealParameter("Severe recession timing", 1, 3),
            RealParameter("Severe recession duration", 4, 4.7),
            RealParameter("Severe recession amplitude", 0.0489, 0.0631),
            RealParameter("Severe recession occurance", 0, 1),
            RealParameter("Proportion of time in recession", 0.18, 0.21),
            RealParameter("Initial Labour share", 0.554, 0.714),
        #Others
#           RealParameter("Macro economic Technological TFP growth", 0.004, 0.0067),
            RealParameter("Task substitution elasticity", 0.66, 0.9),
        #Policy
            #RealParameter("Hours fulltime contracts", 32, 38),

    #TECHNOLOGY MODEL UNCERTAINTIES
            RealParameter("Proportion profit invested in innovation", 0.02, 1),
            RealParameter("Innovation allocation sensivitity to business cycle", 0, 0.1),
            RealParameter("Prior Substituted Labour demand", 8.9, 10.1),
            RealParameter("Time difference automation and substitution", 0.999, 1.001),
            RealParameter("TFP Wage allocation Abstract L", 0.1, 1),
            RealParameter("TFP Wage allocation Abstract I", 0.1, 1),
            RealParameter("TFP Wage allocation Routine L", 0.1, 1),
            RealParameter("TFP Wage allocation Routine I", 0.1, 1),
            RealParameter("TFP Wage allocation Manual L", 0.1, 1),
            RealParameter("TFP Wage allocation Manual I", 0.1, 1),
    #Substitution
         #Abstract L:
             #RealParameter("Technological bottleneck period Abstract L", 0, 12),
             RealParameter("Technological implementation period Abstract L", 216, 264),
             RealParameter("Technological automation estimate Abstract L", 0.001, 0.01),
             RealParameter("Automation probability Abstract L", 0.27, 0.85),
             #RealParameter("Annual labour input increase for technological change Abstract L", 0.0042, 0.015),
             RealParameter("Annual technological productivity growth Abstract L", 0.006, 0.01),
        #Abstract I:
            #RealParameter("Technological bottleneck period Abstract I", 0, 12),
            RealParameter("Technological implementation period Abstract I", 216, 264),
            RealParameter("Technological automation estimate Abstract I", 0.001, 0.01),
            RealParameter("Automation probability Abstract I", 0.27, 0.85),
            #RealParameter("Annual labour input increase for technological change Abstract I", 0.0042, 0.015),
            RealParameter("Annual technological productivity growth Abstract I", 0.006, 0.01),
        #Routine L:
            #RealParameter("Technological bottleneck period Routine L", 0, 12),
```

```
        RealParameter("Technological implementation period Routine L", 216, 264),
        RealParameter("Technological automation estimate Routine L", 0.289, 0.326),
        RealParameter("Automation probability Routine L", 0.59, 0.94),
        #RealParameter("Annual labour input increase for technological change Routine L", 0.0042, 0.015),
        RealParameter("Annual technological productivity growth Routine L", 0.006, 0.01),
    #Routine I:
        #RealParameter("Technological bottleneck period Routine I", 0, 12),
        RealParameter("Technological implementation period Routine I", 216, 264),
        RealParameter("Technological automation estimate Routine I", 0.289, 0.326),
        RealParameter("Automation probability Routine I", 0.59, 0.94),
        #RealParameter("Annual labour input increase for technological change Routine I", 0.0042, 0.015),
        RealParameter("Annual technological productivity growth Routine I", 0.006,0.01),
    #Manual L:
        #RealParameter("Technological bottleneck period Manual L", 0, 12),
        RealParameter("Technological implementation period Manual L", 216, 264),
        RealParameter("Technological automation estimate Manual L", 0.289, 0.326),
        RealParameter("Automation probability Manual L", 0.59, 0.94),
        #RealParameter("Annual labour input increase for technological change Manual L", 0.0042, 0.015),
        RealParameter("Annual technological productivity growth Manual L", 0.006, 0.01),
    #Manual I:
        #RealParameter("Technological bottleneck period Manual I", 0, 12),
        RealParameter("Technological implementation period Manual I", 216, 264),
        RealParameter("Technological automation estimate Manual I", 0.245, 0.422),
        RealParameter("Automation probability Manual I", 0.7, 1.0),
        #RealParameter("Annual labour input increase for technological change Manual I", 0.0042, 0.015),
        RealParameter("Annual technological productivity growth Manual I", 0.006, 0.01),

        RealParameter("Upper bound technological bottleneck proportion of tasks", 0.001, 0.01)
]

vensimModel.outcomes = [
  #POPULATION MODEL OUTCOMES
#       TimeSeriesOutcome('Total population'),
  #EDUCATION MODEL OUTCOMES
        TimeSeriesOutcome('ST HI m total reskill percentage'),
        TimeSeriesOutcome('ST MI m total reskill percentage'),
        TimeSeriesOutcome('ST LI m total reskill percentage'),
        TimeSeriesOutcome('ST ML m total upskill percentage'),
        TimeSeriesOutcome('ST MI m total upskill percentage'),
        TimeSeriesOutcome('ST LL m total upskill percentage'),
        TimeSeriesOutcome('ST LI m total upskill percentage'),
        TimeSeriesOutcome('ST HI f total reskill percentage'),
        TimeSeriesOutcome('ST MI f total reskill percentage'),
        TimeSeriesOutcome('ST LI f total reskill percentage'),
        TimeSeriesOutcome('ST ML f total upskill percentage'),
        TimeSeriesOutcome('ST MI f total upskill percentage'),
        TimeSeriesOutcome('ST LL f total upskill percentage'),
        TimeSeriesOutcome('ST LI f total upskill percentage'),
        TimeSeriesOutcome('LF HI m total reskill percentage'),
        TimeSeriesOutcome('LF MI m total reskill percentage'),
        TimeSeriesOutcome('LF LI m total reskill percentage'),
        TimeSeriesOutcome('LF ML m total upskill percentage'),
        TimeSeriesOutcome('LF MI m total upskill percentage'),
```

```
        TimeSeriesOutcome('LF LL m total upskill percentage'),
        TimeSeriesOutcome('LF LI m total upskill percentage'),
        TimeSeriesOutcome('LF HI f total reskill percentage'),
        TimeSeriesOutcome('LF MI f total reskill percentage'),
        TimeSeriesOutcome('LF LI f total reskill percentage'),
        TimeSeriesOutcome('LF ML f total upskill percentage'),
        TimeSeriesOutcome('LF MI f total upskill percentage'),
        TimeSeriesOutcome('LF LL f total upskill percentage'),
        TimeSeriesOutcome('LF LI f total upskill percentage'),
    #LABOUR MARKET OUTCOMES
        TimeSeriesOutcome('Labour force ft Index'),
        TimeSeriesOutcome('HL ft average wage index'),
        TimeSeriesOutcome('HI ft average wage index'),
        TimeSeriesOutcome('ML ft average wage index'),
        TimeSeriesOutcome('MI ft average wage index'),
        TimeSeriesOutcome('LL ft average wage index'),
        TimeSeriesOutcome('LI ft average wage index'),
        TimeSeriesOutcome('HL Avg ft Unemployment rate'),
        TimeSeriesOutcome('HI Avg ft Unemployment rate'),
        TimeSeriesOutcome('ML Avg ft Unemployment rate'),
        TimeSeriesOutcome('MI Avg ft Unemployment rate'),
        TimeSeriesOutcome('LL Avg ft Unemployment rate'),
        TimeSeriesOutcome('LI Avg ft Unemployment rate'),
#         TimeSeriesOutcome('Total Labour Force HL ft'),
#         TimeSeriesOutcome('Total Labour Force HI ft'),
#         TimeSeriesOutcome('Total Labour Force ML ft'),
#         TimeSeriesOutcome('Total Labour Force MI ft'),
#         TimeSeriesOutcome('Total Labour Force LL ft'),
#         TimeSeriesOutcome('Total Labour Force LI ft'),
#         TimeSeriesOutcome('LI to Manual I for employment ft'),
#         TimeSeriesOutcome('LL to Manual I for employment ft'),
        TimeSeriesOutcome('MI to Manual I for employment ft'),
        TimeSeriesOutcome('ML to Manual I for employment ft'),
        TimeSeriesOutcome('HI to Manual I for employment ft'),
        TimeSeriesOutcome('HL to Manual I for employment ft'),
#        TimeSeriesOutcome('LL to Manual L for employment ft'),
#        TimeSeriesOutcome('ML to Manual L for employment ft'),
        TimeSeriesOutcome('HL to Manual L for employment ft'),
#         TimeSeriesOutcome('LI to Routine I for employment ft'),
#         TimeSeriesOutcome('LL to Routine I for employment ft'),
#         TimeSeriesOutcome('MI to Routine I for employment ft'),
#         TimeSeriesOutcome('ML to Routine I for employment ft'),
        TimeSeriesOutcome('HI to Routine I for employment ft'),
        TimeSeriesOutcome('HL to Routine I for employment ft'),
#         TimeSeriesOutcome('LL to Routine L for employment ft'),
#         TimeSeriesOutcome('ML to Routine L for employment ft'),
        TimeSeriesOutcome('HL to Routine L for employment ft'),
#         TimeSeriesOutcome('HI to Abstract I for employment ft'),
#         TimeSeriesOutcome('HL to Abstract I for employment ft'),
#         TimeSeriesOutcome('HL to Abstract L for employment ft'),
    #PRODUCTION MODEL OUTCOMES
        TimeSeriesOutcome('Annual Macro Economic growth rate'),
        TimeSeriesOutcome('Total wage income index'),
```

```
          TimeSeriesOutcome('Aggregate annual TFP'),
          TimeSeriesOutcome('Average Labour share'),
#           TimeSeriesOutcome('Relative price development Abstract L'),
#           TimeSeriesOutcome('Relative price development Abstract I'),
#           TimeSeriesOutcome('Relative price development Routine L'),
#           TimeSeriesOutcome('Relative price development Routine I'),
#           TimeSeriesOutcome('Relative price development Manual L'),
#           TimeSeriesOutcome('Relative price development Manual I'),
   #TECHNOLOGY MODEL OUTCOMES
          TimeSeriesOutcome('Technological substitution Abstract L'),
          TimeSeriesOutcome('Technological substitution Abstract I'),
          TimeSeriesOutcome('Technological substitution Routine L'),
          TimeSeriesOutcome('Technological substitution Routine I'),
          TimeSeriesOutcome('Technological substitution Manual L'),
          TimeSeriesOutcome('Technological substitution Manual I'),
          TimeSeriesOutcome('Profit index Abstract L'),
          TimeSeriesOutcome('Profit index Abstract I'),
          TimeSeriesOutcome('Profit index Routine L'),
          TimeSeriesOutcome('Profit index Routine I'),
          TimeSeriesOutcome('Profit index Manual L'),
          TimeSeriesOutcome('Profit index Manual I')
#           TimeSeriesOutcome('Labour share index Abstract L'),
#           TimeSeriesOutcome('Labour share index Abstract I'),
#           TimeSeriesOutcome('Labour share index Routine L'),
#           TimeSeriesOutcome('Labour share index Routine I'),
#           TimeSeriesOutcome('Labour share index Manual L'),
#           TimeSeriesOutcome('Labour share index Manual I'),
#           TimeSeriesOutcome('Wage index Abstract L'),
#           TimeSeriesOutcome('Wage index Abstract I'),
#           TimeSeriesOutcome('Wage index Routine L'),
#           TimeSeriesOutcome('Wage index Routine I'),
#           TimeSeriesOutcome('Wage index Manual L'),
#           TimeSeriesOutcome('Wage index Manual I'),
]

policies = [
           Policy('Model_IV',

model_file=r"C:\Users\LocalAdmin\Documents\Koen\Final\Final_Models\Thesis_model_Final_IV.vpm"),
          ]
```

```
# Model simulation

results = perform_experiments(vensimModel, 1000, policies= policies)
```

```
# Save results

results_name = './EMA_NED_Uncertainty_D_Results.tar.gz'
save_results(results, results_name)
```

For uncertainty G:

```
# Simulation configuration

import numpy as np
import matplotlib
import matplotlib.pyplot as plt
import pandas as pd
import SALib
import seaborn as sns
import mpl_toolkits.axisartist as AA
import scipy as sp
import copy
import matplotlib.ticker as ticker

from ema_workbench import (Model,
                        RealParameter,
                        IntegerParameter,
                        CategoricalParameter,
                        Constant,
                        TimeSeriesOutcome,
                        ScalarOutcome,
                        perform_experiments,
                        ema_logging,
                        save_results,
                        load_results)
from ema_workbench import (Policy)
from ema_workbench import (MultiprocessingEvaluator)
from ema_workbench.connectors import vensimDLLwrapper
from ema_workbench.connectors.vensim import VensimModel
from ema_workbench.em_framework.samplers import sample_levers, sample_uncertainties
from ema_workbench.util import load_results
from ema_workbench.util import ema_logging

from ema_workbench.analysis import prim
import matplotlib.pyplot as plt
from ema_workbench.analysis.plotting import lines, multiple_densities, kde_over_time
from ema_workbench.analysis.plotting_util import KDE
from ema_workbench.analysis.plotting_util import determine_time_dimension
from ema_workbench.analysis.pairs_plotting import pairs_scatter

from SALib.sample import saltelli
from SALib.analyze import sobol, morris
from SALib.test_functions import Ishigami

from mpl_toolkits.axes_grid1 import host_subplot

from scipy.stats import linregress
```

```
ema_logging.log_to_stderr(ema_logging.INFO)
```

```
vensimModel = VensimModel("ThesisModel",
model_file=r"C:\Users\LocalAdmin\Documents\Koen\Final\Final_Models\Thesis_model_Final.vpm" )
```

```
# Uncertainty configuration Dataset Deloitte (2016) for the Netherlands

vensimModel.uncertainties = [
    #POPULATION MODEL UNCERTAINTIES
            RealParameter("Normal fertility rate per f", 1.58, 1.7),

    #EDUCATION MODEL UNCERTAINTIES
#        #CH Education
#            RealParameter("CH Edu performance Reskill equivalent", 25, 30),
#            RealParameter("CH Edu performance Upskill equivalent", 25, 30),
#          #Policy
#            #RealParameter("Time to introduction STEM program", 0, 300),
#            #RealParameter("Minimum fixed period CH Edu capacity expansion", 1, 36),
#            #RealParameter("Time to realise CH Edu capacity expansion", 1, 48),
#            #RealParameter("STEM educated vs STEM graduated ratio", 0.4, 1),
#            #RealParameter("MANUAL CH Edu performance overall improvement H", 0, 25),
#            #RealParameter("MANUAL CH Edu performance overall improvement M", 0, 25),
#            #RealParameter("MANUAL CH Edu performance overall improvement L", 0, 25),
#            #RealParameter("MANUAL CH Edu performance STEM improvement H", 0, 16.75),
#            #RealParameter("MANUAL CH Edu performance STEM improvement M", 0, 16.75),
#            #RealParameter("MANUAL CH Edu performance STEM improvement L", 0, 16.75),
#        #ST Education
            RealParameter("ST Labour market awareness and sensitivity", 0, 1),
            RealParameter("ST knowledge YA Unemployment delay", 12, 48),
#          #Policy
#            #RealParameter("ST STEM stimulation and awareness", 1, 2),
#            #RealParameter("ST High Edu stimulation and awareness", 1, 2),
#            #RealParameter("Time to realise ST Edu capacity expansion", 12, 60),
#            #RealParameter("Fixed period ST Edu capacity expansion", 1, 12),
#        #WA Education
            RealParameter("WAu reskill and upskill sensitivity", 0, 1),
            RealParameter("WAe reskill and upskill sensitivity", 0, 1),
#          #Policy
#            RealParameter("WA STEM stimulation and awareness", 1, 2),
#            RealParameter("WA High Edu stimulation and awareness", 1, 2),
#            RealParameter("Socioeconomic influence education and training H", 1, 2),
#            RealParameter("Socioeconomic influence education and training M", 0.895, 2),
#            RealParameter("Socioeconomic influence education and training L", 0.561, 2),

    #LABOUR MARKET MODEL UNCERTAINTIES
        #Labour reallocation
            RealParameter("Sensitivity Wage reallocation", 0, 0.999),
            RealParameter("Wage sacrifice ratio for employment", 0.01, 0.5),
            RealParameter("Sensitivity Unemployment reallocation", 0, 1),
           #Policy
            RealParameter("Labour reallocation delay", 12, 48),
           #Setting
            RealParameter("Error MINMAX corrector", 10000000000000000, 100000000000000000),

    #PRODUCTION MODEL UNCERTAINTIES
        #Labour input
#            RealParameter("Price elasticity of demand Abstract L", 0, 1),
#            RealParameter("Price elasticity of demand Abstract I", 0, 1),
```

```
#           RealParameter("Price elasticity of demand Routine L", 0, 1),
#           RealParameter("Price elasticity of demand Routine I", 0, 1),
#           RealParameter("Price elasticity of demand Manual L", 0, 1),
#           RealParameter("Price elasticity of demand Manual I", 0, 1),
        #GDP growth
            RealParameter("Long term economic growth error margin", 0, 0.05),
            RealParameter("Business cycle fluctuation amplitude", 0.001, 0.0033),
            RealParameter("Business cycle fluctuation period", 2, 3),
            RealParameter("Time to first recession", 2, 5),
            RealParameter("Business cycle recession amplitude", 0.0187, 0.0263),
            RealParameter("Business cycle recession duration", 3, 3.64),
            RealParameter("Busines cycle recession period", 8, 9.4),
            RealParameter("Severe recession timing", 1, 3),
            RealParameter("Severe recession duration", 4, 4.7),
            RealParameter("Severe recession amplitude", 0.0489, 0.0631),
            RealParameter("Severe recession occurance", 0, 1),
            RealParameter("Proportion of time in recession", 0.18, 0.21),
            RealParameter("Initial Labour share", 0.554, 0.714),
        #Others
#           RealParameter("Macro economic Technological TFP growth", 0.004, 0.0067),
            RealParameter("Task substitution elasticity", 0.66, 0.9),
        #Policy
            #RealParameter("Hours fulltime contracts", 32, 38),

    #TECHNOLOGY MODEL UNCERTAINTIES
            RealParameter("Proportion profit invested in innovation", 0.02, 1),
            RealParameter("Innovation allocation sensivitity to business cycle", 0, 0.1),
            RealParameter("Prior Substituted Labour demand", 8.9, 10.1),
            RealParameter("Time difference automation and substitution", 0.999, 1.001),
            RealParameter("TFP Wage allocation Abstract L", 0.1, 1),
            RealParameter("TFP Wage allocation Abstract I", 0.1, 1),
            RealParameter("TFP Wage allocation Routine L", 0.1, 1),
            RealParameter("TFP Wage allocation Routine I", 0.1, 1),
            RealParameter("TFP Wage allocation Manual L", 0.1, 1),
            RealParameter("TFP Wage allocation Manual I", 0.1, 1),
    #Substitution
         #Abstract L:
             #RealParameter("Technological bottleneck period Abstract L", 0, 12),
             RealParameter("Technological implementation period Abstract L", 216, 264),
             RealParameter("Technological automation estimate Abstract L", 0.104, 0.193),
             RealParameter("Automation probability Abstract L", 0.7, 1.0),
             #RealParameter("Annual labour input increase for technological change Abstract L", 0.0042, 0.015),
             RealParameter("Annual technological productivity growth Abstract L", 0.006, 0.01),
        #Abstract I:
            #RealParameter("Technological bottleneck period Abstract I", 0, 12),
            RealParameter("Technological implementation period Abstract I", 216, 264),
            RealParameter("Technological automation estimate Abstract I", 0.104, 0.193),
            RealParameter("Automation probability Abstract I", 0.7, 1.0),
            #RealParameter("Annual labour input increase for technological change Abstract I", 0.0042, 0.015),
            RealParameter("Annual technological productivity growth Abstract I", 0.006, 0.01),
        #Routine L:
            #RealParameter("Technological bottleneck period Routine L", 0, 12),
            RealParameter("Technological implementation period Routine L", 216, 264),
```

```
        RealParameter("Technological automation estimate Routine L", 0.412425, 0.433575),
        RealParameter("Automation probability Routine L", 0.7, 1.0),
        #RealParameter("Annual labour input increase for technological change Routine L", 0.0042, 0.015),
        RealParameter("Annual technological productivity growth Routine L", 0.006, 0.01),
      #Routine I:
        #RealParameter("Technological bottleneck period Routine I", 0, 12),
        RealParameter("Technological implementation period Routine I", 216, 264),
        RealParameter("Technological automation estimate Routine I", 0.412425, 0.433575),
        RealParameter("Automation probability Routine I", 0.7, 1.0),
        #RealParameter("Annual labour input increase for technological change Routine I", 0.0042, 0.015),
        RealParameter("Annual technological productivity growth Routine I", 0.006,0.01),
      #Manual L:
        #RealParameter("Technological bottleneck period Manual L", 0, 12),
        RealParameter("Technological implementation period Manual L", 216, 264),
        RealParameter("Technological automation estimate Manual L", 0.412425, 0.433575),
        RealParameter("Automation probability Manual L", 0.7, 1.0),
        #RealParameter("Annual labour input increase for technological change Manual L", 0.0042, 0.015),
        RealParameter("Annual technological productivity growth Manual L", 0.006, 0.01),
      #Manual I:
        #RealParameter("Technological bottleneck period Manual I", 0, 12),
        RealParameter("Technological implementation period Manual I", 216, 264),
        RealParameter("Technological automation estimate Manual I", 0.412425, 0.433575),
        RealParameter("Automation probability Manual I", 0.7, 1.0),
        #RealParameter("Annual labour input increase for technological change Manual I", 0.0042, 0.015),
        RealParameter("Annual technological productivity growth Manual I", 0.006, 0.01),

        RealParameter("Upper bound technological bottleneck proportion of tasks", 0.001, 0.01)
]

vensimModel.outcomes = [
   #POPULATION MODEL OUTCOMES
#       TimeSeriesOutcome('Total population'),
   #EDUCATION MODEL OUTCOMES
        TimeSeriesOutcome('ST HI m total reskill percentage'),
        TimeSeriesOutcome('ST MI m total reskill percentage'),
        TimeSeriesOutcome('ST LI m total reskill percentage'),
        TimeSeriesOutcome('ST ML m total upskill percentage'),
        TimeSeriesOutcome('ST MI m total upskill percentage'),
        TimeSeriesOutcome('ST LL m total upskill percentage'),
        TimeSeriesOutcome('ST LI m total upskill percentage'),
        TimeSeriesOutcome('ST HI f total reskill percentage'),
        TimeSeriesOutcome('ST MI f total reskill percentage'),
        TimeSeriesOutcome('ST LI f total reskill percentage'),
        TimeSeriesOutcome('ST ML f total upskill percentage'),
        TimeSeriesOutcome('ST MI f total upskill percentage'),
        TimeSeriesOutcome('ST LL f total upskill percentage'),
        TimeSeriesOutcome('ST LI f total upskill percentage'),
        TimeSeriesOutcome('LF HI m total reskill percentage'),
        TimeSeriesOutcome('LF MI m total reskill percentage'),
        TimeSeriesOutcome('LF LI m total reskill percentage'),
        TimeSeriesOutcome('LF ML m total upskill percentage'),
        TimeSeriesOutcome('LF MI m total upskill percentage'),
        TimeSeriesOutcome('LF LL m total upskill percentage'),
```

```
        TimeSeriesOutcome('LF LI m total upskill percentage'),
        TimeSeriesOutcome('LF HI f total reskill percentage'),
        TimeSeriesOutcome('LF MI f total reskill percentage'),
        TimeSeriesOutcome('LF LI f total reskill percentage'),
        TimeSeriesOutcome('LF ML f total upskill percentage'),
        TimeSeriesOutcome('LF MI f total upskill percentage'),
        TimeSeriesOutcome('LF LL f total upskill percentage'),
        TimeSeriesOutcome('LF LI f total upskill percentage'),
    #LABOUR MARKET OUTCOMES
        TimeSeriesOutcome('Labour force ft Index'),
        TimeSeriesOutcome('HL ft average wage index'),
        TimeSeriesOutcome('HI ft average wage index'),
        TimeSeriesOutcome('ML ft average wage index'),
        TimeSeriesOutcome('MI ft average wage index'),
        TimeSeriesOutcome('LL ft average wage index'),
        TimeSeriesOutcome('LI ft average wage index'),
        TimeSeriesOutcome('HL Avg ft Unemployment rate'),
        TimeSeriesOutcome('HI Avg ft Unemployment rate'),
        TimeSeriesOutcome('ML Avg ft Unemployment rate'),
        TimeSeriesOutcome('MI Avg ft Unemployment rate'),
        TimeSeriesOutcome('LL Avg ft Unemployment rate'),
        TimeSeriesOutcome('LI Avg ft Unemployment rate'),
#       TimeSeriesOutcome('Total Labour Force HL ft'),
#       TimeSeriesOutcome('Total Labour Force HI ft'),
#       TimeSeriesOutcome('Total Labour Force ML ft'),
#       TimeSeriesOutcome('Total Labour Force MI ft'),
#       TimeSeriesOutcome('Total Labour Force LL ft'),
#       TimeSeriesOutcome('Total Labour Force LI ft'),
#       TimeSeriesOutcome('LI to Manual I for employment ft'),
#       TimeSeriesOutcome('LL to Manual I for employment ft'),
        TimeSeriesOutcome('MI to Manual I for employment ft'),
        TimeSeriesOutcome('ML to Manual I for employment ft'),
        TimeSeriesOutcome('HI to Manual I for employment ft'),
        TimeSeriesOutcome('HL to Manual I for employment ft'),
#       TimeSeriesOutcome('LL to Manual L for employment ft'),
#       TimeSeriesOutcome('ML to Manual L for employment ft'),
        TimeSeriesOutcome('HL to Manual L for employment ft'),
#       TimeSeriesOutcome('LI to Routine I for employment ft'),
#       TimeSeriesOutcome('LL to Routine I for employment ft'),
#       TimeSeriesOutcome('MI to Routine I for employment ft'),
#       TimeSeriesOutcome('ML to Routine I for employment ft'),
        TimeSeriesOutcome('HI to Routine I for employment ft'),
        TimeSeriesOutcome('HL to Routine I for employment ft'),
#       TimeSeriesOutcome('LL to Routine L for employment ft'),
#       TimeSeriesOutcome('ML to Routine L for employment ft'),
        TimeSeriesOutcome('HL to Routine L for employment ft'),
#       TimeSeriesOutcome('HI to Abstract I for employment ft'),
#       TimeSeriesOutcome('HL to Abstract I for employment ft'),
#       TimeSeriesOutcome('HL to Abstract L for employment ft'),
    #PRODUCTION MODEL OUTCOMES
        TimeSeriesOutcome('Annual Macro Economic growth rate'),
        TimeSeriesOutcome('Total wage income index'),
        TimeSeriesOutcome('Aggregate annual TFP'),
```

```
        TimeSeriesOutcome('Average Labour share'),
#           TimeSeriesOutcome('Relative price development Abstract L'),
#           TimeSeriesOutcome('Relative price development Abstract I'),
#           TimeSeriesOutcome('Relative price development Routine L'),
#           TimeSeriesOutcome('Relative price development Routine I'),
#           TimeSeriesOutcome('Relative price development Manual L'),
#           TimeSeriesOutcome('Relative price development Manual I'),
   #TECHNOLOGY MODEL OUTCOMES
        TimeSeriesOutcome('Technological substitution Abstract L'),
        TimeSeriesOutcome('Technological substitution Abstract I'),
        TimeSeriesOutcome('Technological substitution Routine L'),
        TimeSeriesOutcome('Technological substitution Routine I'),
        TimeSeriesOutcome('Technological substitution Manual L'),
        TimeSeriesOutcome('Technological substitution Manual I'),
        TimeSeriesOutcome('Profit index Abstract L'),
        TimeSeriesOutcome('Profit index Abstract I'),
        TimeSeriesOutcome('Profit index Routine L'),
        TimeSeriesOutcome('Profit index Routine I'),
        TimeSeriesOutcome('Profit index Manual L'),
        TimeSeriesOutcome('Profit index Manual I')
#           TimeSeriesOutcome('Labour share index Abstract L'),
#           TimeSeriesOutcome('Labour share index Abstract I'),
#           TimeSeriesOutcome('Labour share index Routine L'),
#           TimeSeriesOutcome('Labour share index Routine I'),
#           TimeSeriesOutcome('Labour share index Manual L'),
#           TimeSeriesOutcome('Labour share index Manual I'),
#           TimeSeriesOutcome('Wage index Abstract L'),
#           TimeSeriesOutcome('Wage index Abstract I'),
#           TimeSeriesOutcome('Wage index Routine L'),
#           TimeSeriesOutcome('Wage index Routine I'),
#           TimeSeriesOutcome('Wage index Manual L'),
#           TimeSeriesOutcome('Wage index Manual I'),
]

policies = [
         Policy('Model_IV',

model_file=r"C:\Users\LocalAdmin\Documents\Koen\Final\Final_Models\Thesis_model_Final_IV.vpm"),
        ]
```

```
# Model simulation

results = perform_experiments(vensimModel, 1000, policies= policies)
```

```
# Save results

results_name = './EMA_NED_Uncertainty_G_Results.tar.gz'
save_results(results, results_name)
```

XIII Unemployment projections

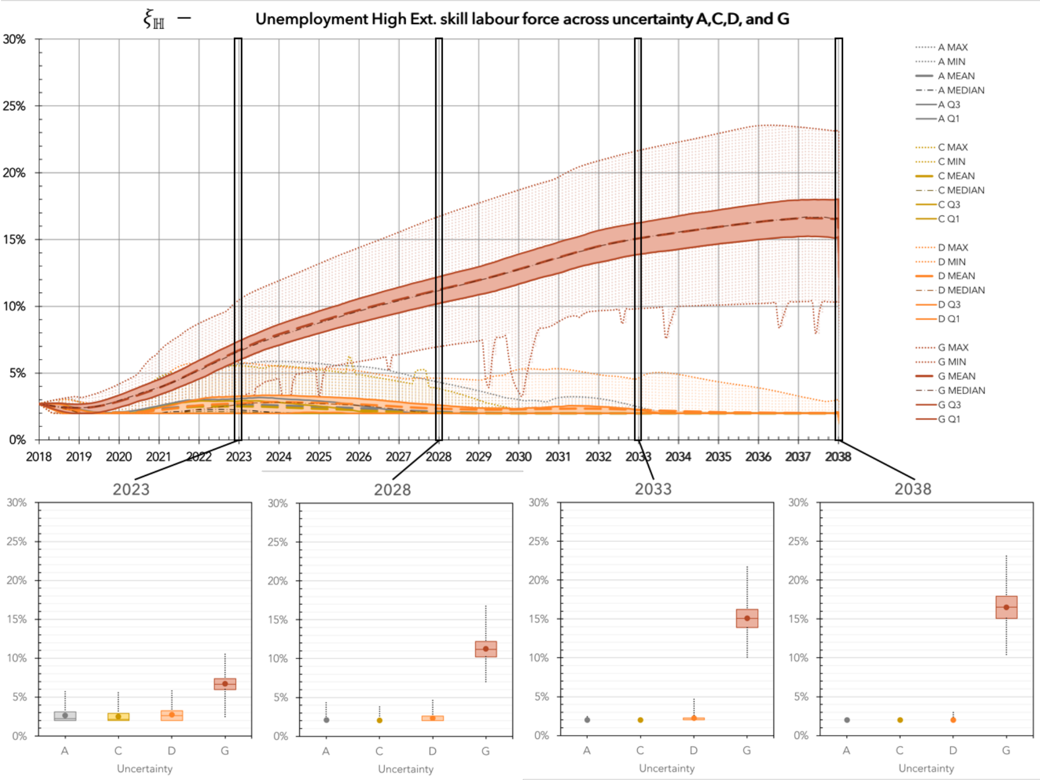


Figure 75 Unemployment projections $\xi_{\mathbb{H}}$ for the Netherlands across uncertainty A, C, D, and G (Table 4)

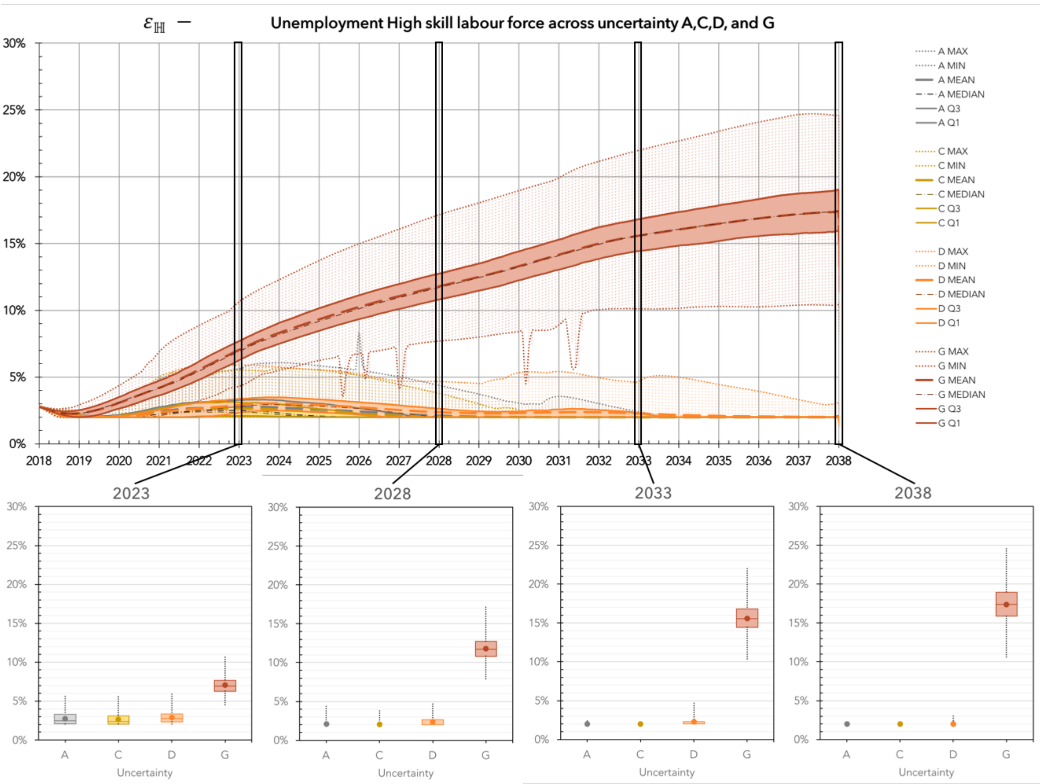


Figure 76 Unemployment projections $\varepsilon_{\mathbb{H}}$ for the Netherlands across uncertainty A, C, D, and G (Table 4)

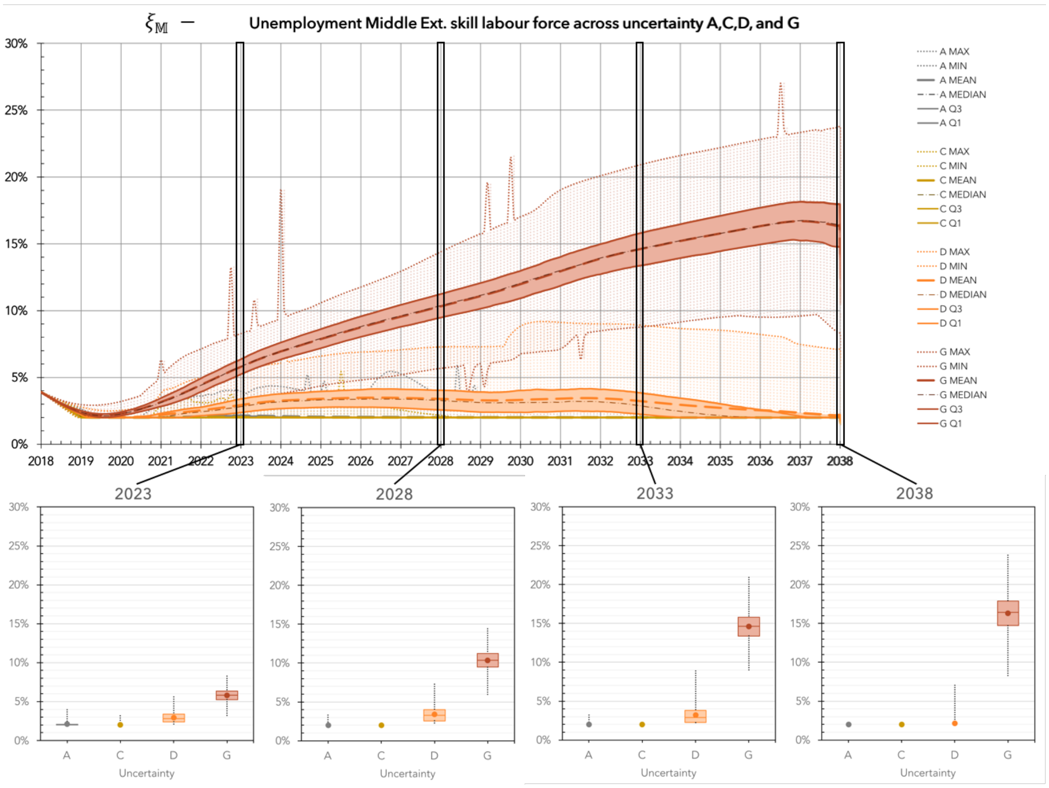


Figure 77 Unemployment projections $\xi_{\mathbb{M}}$ for the Netherlands across uncertainty A, C, D, and G (Table 4)

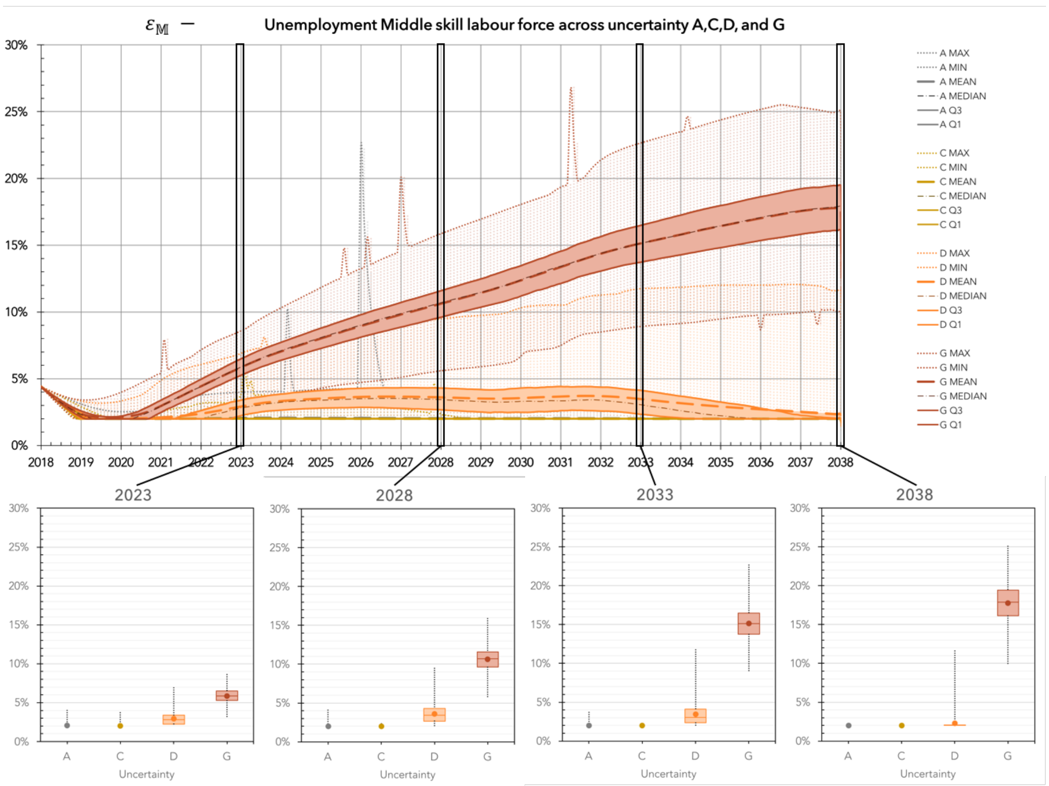


Figure 78 Unemployment projections $\varepsilon_{\mathbb{M}}$ for the Netherlands across uncertainty A, C, D, and G (Table 4)

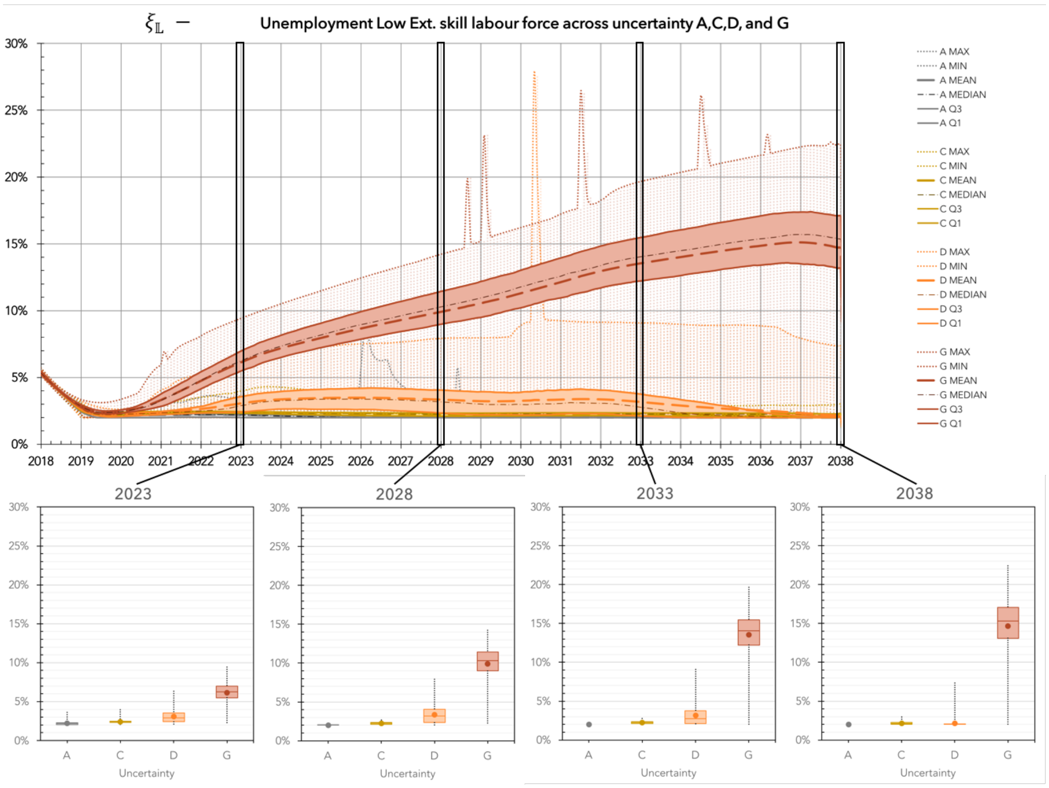


Figure 79 Unemployment projections $\xi_{\mathbb{L}}$ for the Netherlands across uncertainty A, C, D, and G (Table 4)

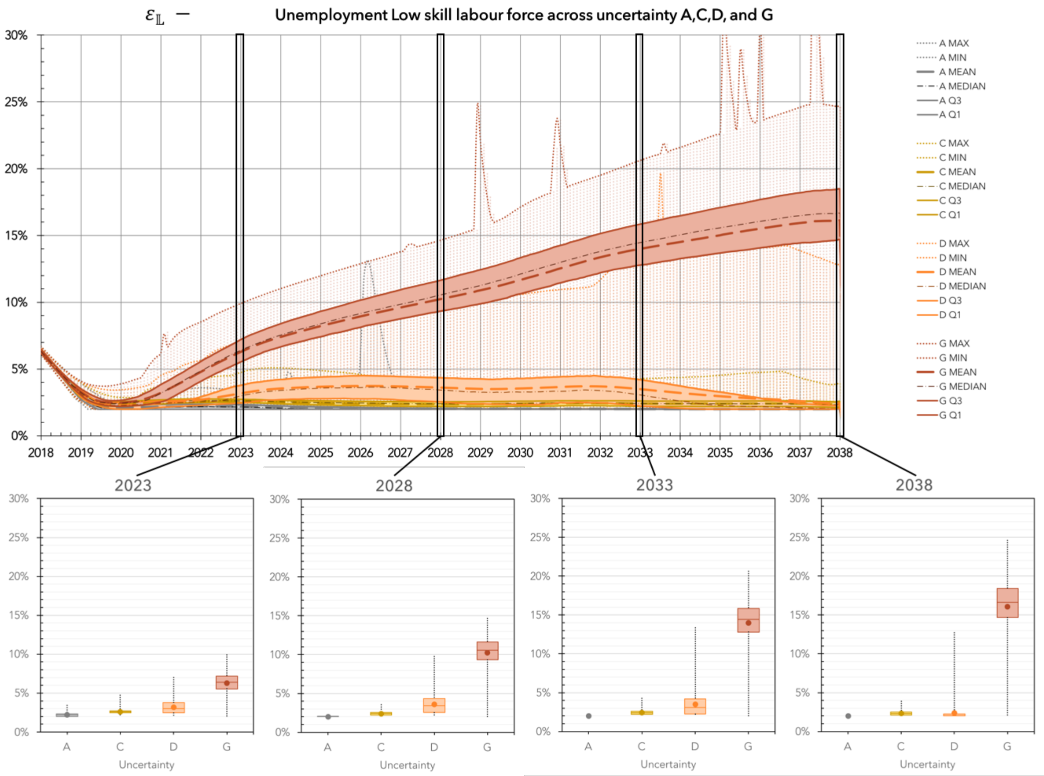


Figure 80 Unemployment projections $\varepsilon_{\mathbb{L}}$ for the Netherlands across uncertainty A, C, D, and G (Table 4)

XIV EMA Python script Solow Paradox

```
# Simulation configuration

import numpy as np
import matplotlib
import matplotlib.pyplot as plt
import pandas as pd
import SALib
import seaborn as sns
import mpl_toolkits.axisartist as AA
import scipy as sp
import copy
import matplotlib.ticker as ticker

from ema_workbench import (Model,
                           RealParameter,
                           IntegerParameter,
                           CategoricalParameter,
                           Constant,
                           TimeSeriesOutcome,
                           ScalarOutcome,
                           perform_experiments,
                           ema_logging,
                           save_results,
                           load_results)
from ema_workbench import (Policy)
from ema_workbench import (MultiprocessingEvaluator)
from ema_workbench.connectors import vensimDLLwrapper
from ema_workbench.connectors.vensim import VensimModel
from ema_workbench.em_framework.samplers import sample_levers, sample_uncertainties
from ema_workbench.util import load_results
from ema_workbench.util import ema_logging

from ema_workbench.analysis import prim
import matplotlib.pyplot as plt
from ema_workbench.analysis.plotting import lines, multiple_densities, kde_over_time
from ema_workbench.analysis.plotting_util import KDE
from ema_workbench.analysis.plotting_util import determine_time_dimension
from ema_workbench.analysis.pairs_plotting import pairs_scatter

from SALib.sample import saltelli
from SALib.analyze import sobol, morris
from SALib.test_functions import Ishigami

from mpl_toolkits.axes_grid1 import host_subplot

from scipy.stats import linregress
```

```
ema_logging.log_to_stderr(ema_logging.INFO)
```

```
vensimModel = VensimModel("ThesisModel",
```

```
model_file=r"C:\Users\LocalAdmin\Documents\Koen\Final\Final_Models\Thesis_model_Final.vpm" )
```

```
# Uncertainty configuration Dataset Deloitte (2016) for the Netherlands

vensimModel.uncertainties = [
    #POPULATION MODEL UNCERTAINTIES
            RealParameter("Normal fertility rate per f", 1.58, 1.7),

    #EDUCATION MODEL UNCERTAINTIES
#         #CH Education
#             RealParameter("CH Edu performance Reskill equivalent", 25, 30),
#             RealParameter("CH Edu performance Upskill equivalent", 25, 30),
#           #Policy
#             #RealParameter("Time to introduction STEM program", 0, 300),
#             #RealParameter("Minimum fixed period CH Edu capacity expansion", 1, 36),
#             #RealParameter("Time to realise CH Edu capacity expansion", 1, 48),
#             #RealParameter("STEM educated vs STEM graduated ratio", 0.4, 1),
#             #RealParameter("MANUAL CH Edu performance overall improvement H", 0, 25),
#             #RealParameter("MANUAL CH Edu performance overall improvement M", 0, 25),
#             #RealParameter("MANUAL CH Edu performance overall improvement L", 0, 25),
#             #RealParameter("MANUAL CH Edu performance STEM improvement H", 0, 16.75),
#             #RealParameter("MANUAL CH Edu performance STEM improvement M", 0, 16.75),
#             #RealParameter("MANUAL CH Edu performance STEM improvement L", 0, 16.75),
#         #ST Education
            RealParameter("ST Labour market awareness and sensitivity", 0, 1),
            RealParameter("ST knowledge YA Unemployment delay", 12, 48),
#           #Policy
#             #RealParameter("ST STEM stimulation and awareness", 1, 2),
#             #RealParameter("ST High Edu stimulation and awareness", 1, 2),
#             #RealParameter("Time to realise ST Edu capacity expansion", 12, 60),
#             #RealParameter("Fixed period ST Edu capacity expansion", 1, 12),
#         #WA Education
            RealParameter("WAu reskill and upskill sensitivity", 0, 1),
            RealParameter("WAe reskill and upskill sensitivity", 0, 1),
#           #Policy
#             RealParameter("WA STEM stimulation and awareness", 1, 2),
#             RealParameter("WA High Edu stimulation and awareness", 1, 2),
#             RealParameter("Socioeconomic influence education and training H", 1, 2),
#             RealParameter("Socioeconomic influence education and training M", 0.895, 2),
#             RealParameter("Socioeconomic influence education and training L", 0.561, 2),

    #LABOUR MARKET MODEL UNCERTAINTIES
        #Labour reallocation
            RealParameter("Sensitivity Wage reallocation", 0, 0.999),
            RealParameter("Wage sacrifice ratio for employment", 0.01, 0.5),
            RealParameter("Sensitivity Unemployment reallocation", 0, 1),
           #Policy
            RealParameter("Labour reallocation delay", 12, 48),
           #Setting
            RealParameter("Error MINMAX corrector", 10000000000000000, 100000000000000000),

    #PRODUCTION MODEL UNCERTAINTIES
        #Labour input
```

```
#           RealParameter("Price elasticity of demand Abstract L", 0, 1),
#           RealParameter("Price elasticity of demand Abstract I", 0, 1),
#           RealParameter("Price elasticity of demand Routine L", 0, 1),
#           RealParameter("Price elasticity of demand Routine I", 0, 1),
#           RealParameter("Price elasticity of demand Manual L", 0, 1),
#           RealParameter("Price elasticity of demand Manual I", 0, 1),
        #GDP growth
          RealParameter("Long term economic growth error margin", 0, 0.05),
          RealParameter("Business cycle fluctuation amplitude", 0.001, 0.0033),
          RealParameter("Business cycle fluctuation period", 2, 3),
          RealParameter("Time to first recession", 2, 5),
          RealParameter("Business cycle recession amplitude", 0.0187, 0.0263),
          RealParameter("Business cycle recession duration", 3, 3.64),
          RealParameter("Busines cycle recession period", 8, 9.4),
          RealParameter("Severe recession timing", 1, 3),
          RealParameter("Severe recession duration", 4, 4.7),
          RealParameter("Severe recession amplitude", 0.0489, 0.0631),
          RealParameter("Severe recession occurance", 0, 1),
          RealParameter("Proportion of time in recession", 0.18, 0.21),
          RealParameter("Initial Labour share", 0.554, 0.714),
        #Others
#          RealParameter("Macro economic Technological TFP growth", 0.004, 0.0067),
          RealParameter("Task substitution elasticity", 0.66, 0.9),
        #Policy
          #RealParameter("Hours fulltime contracts", 32, 38),

    #TECHNOLOGY MODEL UNCERTAINTIES
          RealParameter("Proportion profit invested in innovation", 0.02, 1),
          RealParameter("Innovation allocation sensivitity to business cycle", 0, 0.1),
          RealParameter("Prior Substituted Labour demand", 8.9, 10.1),
          RealParameter("Solow Paradox multiplier", 0.5, 1.0),
          RealParameter("Time difference automation and substitution", 0.999, 1.001),
          RealParameter("TFP Wage allocation Abstract L", 0.1, 1),
          RealParameter("TFP Wage allocation Abstract I", 0.1, 1),
          RealParameter("TFP Wage allocation Routine L", 0.1, 1),
          RealParameter("TFP Wage allocation Routine I", 0.1, 1),
          RealParameter("TFP Wage allocation Manual L", 0.1, 1),
          RealParameter("TFP Wage allocation Manual I", 0.1, 1),
    #Substitution
        #Abstract L:
           #RealParameter("Technological bottleneck period Abstract L", 0, 12),
           RealParameter("Technological implementation period Abstract L", 216, 264),
           RealParameter("Technological automation estimate Abstract L", 0.104, 0.193),
           RealParameter("Automation probability Abstract L", 0.7, 1.0),
           #RealParameter("Annual labour input increase for technological change Abstract L", 0.0042, 0.015),
           RealParameter("Annual technological productivity growth Abstract L", 0.006, 0.01),
        #Abstract I:
          #RealParameter("Technological bottleneck period Abstract I", 0, 12),
          RealParameter("Technological implementation period Abstract I", 216, 264),
          RealParameter("Technological automation estimate Abstract I", 0.104, 0.193),
          RealParameter("Automation probability Abstract I", 0.7, 1.0),
          #RealParameter("Annual labour input increase for technological change Abstract I", 0.0042, 0.015),
          RealParameter("Annual technological productivity growth Abstract I", 0.006, 0.01),
```

```
        #Routine L:
            #RealParameter("Technological bottleneck period Routine L", 0, 12),
            RealParameter("Technological implementation period Routine L", 216, 264),
            RealParameter("Technological automation estimate Routine L", 0.412425, 0.433575),
            RealParameter("Automation probability Routine L", 0.7, 1.0),
            #RealParameter("Annual labour input increase for technological change Routine L", 0.0042, 0.015),
            RealParameter("Annual technological productivity growth Routine L", 0.006, 0.01),
        #Routine I:
            #RealParameter("Technological bottleneck period Routine I", 0, 12),
            RealParameter("Technological implementation period Routine I", 216, 264),
            RealParameter("Technological automation estimate Routine I", 0.412425, 0.433575),
            RealParameter("Automation probability Routine I", 0.7, 1.0),
            #RealParameter("Annual labour input increase for technological change Routine I", 0.0042, 0.015),
            RealParameter("Annual technological productivity growth Routine I", 0.006,0.01),
        #Manual L:
            #RealParameter("Technological bottleneck period Manual L", 0, 12),
            RealParameter("Technological implementation period Manual L", 216, 264),
            RealParameter("Technological automation estimate Manual L", 0.412425, 0.433575),
            RealParameter("Automation probability Manual L", 0.7, 1.0),
            #RealParameter("Annual labour input increase for technological change Manual L", 0.0042, 0.015),
            RealParameter("Annual technological productivity growth Manual L", 0.006, 0.01),
        #Manual I:
            #RealParameter("Technological bottleneck period Manual I", 0, 12),
            RealParameter("Technological implementation period Manual I", 216, 264),
            RealParameter("Technological automation estimate Manual I", 0.412425, 0.433575),
            RealParameter("Automation probability Manual I", 0.7, 1.0),
            #RealParameter("Annual labour input increase for technological change Manual I", 0.0042, 0.015),
            RealParameter("Annual technological productivity growth Manual I", 0.006, 0.01),

            RealParameter("Upper bound technological bottleneck proportion of tasks", 0.001, 0.01)
]

vensimModel.outcomes = [
    #POPULATION MODEL OUTCOMES
#           TimeSeriesOutcome('Total population'),
    #EDUCATION MODEL OUTCOMES
            TimeSeriesOutcome('ST HI m total reskill percentage'),
            TimeSeriesOutcome('ST MI m total reskill percentage'),
            TimeSeriesOutcome('ST LI m total reskill percentage'),
            TimeSeriesOutcome('ST ML m total upskill percentage'),
            TimeSeriesOutcome('ST MI m total upskill percentage'),
            TimeSeriesOutcome('ST LL m total upskill percentage'),
            TimeSeriesOutcome('ST LI m total upskill percentage'),
            TimeSeriesOutcome('ST HI f total reskill percentage'),
            TimeSeriesOutcome('ST MI f total reskill percentage'),
            TimeSeriesOutcome('ST LI f total reskill percentage'),
            TimeSeriesOutcome('ST ML f total upskill percentage'),
            TimeSeriesOutcome('ST MI f total upskill percentage'),
            TimeSeriesOutcome('ST LL f total upskill percentage'),
            TimeSeriesOutcome('ST LI f total upskill percentage'),
            TimeSeriesOutcome('LF HI m total reskill percentage'),
            TimeSeriesOutcome('LF MI m total reskill percentage'),
            TimeSeriesOutcome('LF LI m total reskill percentage'),
```

```
        TimeSeriesOutcome('LF ML m total upskill percentage'),
        TimeSeriesOutcome('LF MI m total upskill percentage'),
        TimeSeriesOutcome('LF LL m total upskill percentage'),
        TimeSeriesOutcome('LF LI m total upskill percentage'),
        TimeSeriesOutcome('LF HI f total reskill percentage'),
        TimeSeriesOutcome('LF MI f total reskill percentage'),
        TimeSeriesOutcome('LF LI f total reskill percentage'),
        TimeSeriesOutcome('LF ML f total upskill percentage'),
        TimeSeriesOutcome('LF MI f total upskill percentage'),
        TimeSeriesOutcome('LF LL f total upskill percentage'),
        TimeSeriesOutcome('LF LI f total upskill percentage'),
    #LABOUR MARKET OUTCOMES
        TimeSeriesOutcome('Labour force ft Index'),
        TimeSeriesOutcome('HL ft average wage index'),
        TimeSeriesOutcome('HI ft average wage index'),
        TimeSeriesOutcome('ML ft average wage index'),
        TimeSeriesOutcome('MI ft average wage index'),
        TimeSeriesOutcome('LL ft average wage index'),
        TimeSeriesOutcome('LI ft average wage index'),
        TimeSeriesOutcome('HL Avg ft Unemployment rate'),
        TimeSeriesOutcome('HI Avg ft Unemployment rate'),
        TimeSeriesOutcome('ML Avg ft Unemployment rate'),
        TimeSeriesOutcome('MI Avg ft Unemployment rate'),
        TimeSeriesOutcome('LL Avg ft Unemployment rate'),
        TimeSeriesOutcome('LI Avg ft Unemployment rate'),
#         TimeSeriesOutcome('Total Labour Force HL ft'),
#         TimeSeriesOutcome('Total Labour Force HI ft'),
#         TimeSeriesOutcome('Total Labour Force ML ft'),
#         TimeSeriesOutcome('Total Labour Force MI ft'),
#         TimeSeriesOutcome('Total Labour Force LL ft'),
#         TimeSeriesOutcome('Total Labour Force LI ft'),
#         TimeSeriesOutcome('LI to Manual I for employment ft'),
#         TimeSeriesOutcome('LL to Manual I for employment ft'),
        TimeSeriesOutcome('MI to Manual I for employment ft'),
        TimeSeriesOutcome('ML to Manual I for employment ft'),
        TimeSeriesOutcome('HI to Manual I for employment ft'),
        TimeSeriesOutcome('HL to Manual I for employment ft'),
#        TimeSeriesOutcome('LL to Manual L for employment ft'),
#        TimeSeriesOutcome('ML to Manual L for employment ft'),
        TimeSeriesOutcome('HL to Manual L for employment ft'),
#         TimeSeriesOutcome('LI to Routine I for employment ft'),
#         TimeSeriesOutcome('LL to Routine I for employment ft'),
#         TimeSeriesOutcome('MI to Routine I for employment ft'),
#         TimeSeriesOutcome('ML to Routine I for employment ft'),
        TimeSeriesOutcome('HI to Routine I for employment ft'),
        TimeSeriesOutcome('HL to Routine I for employment ft'),
#         TimeSeriesOutcome('LL to Routine L for employment ft'),
#         TimeSeriesOutcome('ML to Routine L for employment ft'),
        TimeSeriesOutcome('HL to Routine L for employment ft'),
#         TimeSeriesOutcome('HI to Abstract I for employment ft'),
#         TimeSeriesOutcome('HL to Abstract I for employment ft'),
#         TimeSeriesOutcome('HL to Abstract L for employment ft'),
    #PRODUCTION MODEL OUTCOMES
```

```
        TimeSeriesOutcome('Annual Macro Economic growth rate'),
        TimeSeriesOutcome('Total wage income index'),
        TimeSeriesOutcome('Aggregate annual TFP'),
        TimeSeriesOutcome('Average Labour share'),
#         TimeSeriesOutcome('Relative price development Abstract L'),
#         TimeSeriesOutcome('Relative price development Abstract I'),
#         TimeSeriesOutcome('Relative price development Routine L'),
#         TimeSeriesOutcome('Relative price development Routine I'),
#         TimeSeriesOutcome('Relative price development Manual L'),
#         TimeSeriesOutcome('Relative price development Manual I'),
    #TECHNOLOGY MODEL OUTCOMES
        TimeSeriesOutcome('Technological substitution Abstract L'),
        TimeSeriesOutcome('Technological substitution Abstract I'),
        TimeSeriesOutcome('Technological substitution Routine L'),
        TimeSeriesOutcome('Technological substitution Routine I'),
        TimeSeriesOutcome('Technological substitution Manual L'),
        TimeSeriesOutcome('Technological substitution Manual I'),
        TimeSeriesOutcome('Profit index Abstract L'),
        TimeSeriesOutcome('Profit index Abstract I'),
        TimeSeriesOutcome('Profit index Routine L'),
        TimeSeriesOutcome('Profit index Routine I'),
        TimeSeriesOutcome('Profit index Manual L'),
        TimeSeriesOutcome('Profit index Manual I')
#         TimeSeriesOutcome('Labour share index Abstract L'),
#         TimeSeriesOutcome('Labour share index Abstract I'),
#         TimeSeriesOutcome('Labour share index Routine L'),
#         TimeSeriesOutcome('Labour share index Routine I'),
#         TimeSeriesOutcome('Labour share index Manual L'),
#         TimeSeriesOutcome('Labour share index Manual I'),
#         TimeSeriesOutcome('Wage index Abstract L'),
#         TimeSeriesOutcome('Wage index Abstract I'),
#         TimeSeriesOutcome('Wage index Routine L'),
#         TimeSeriesOutcome('Wage index Routine I'),
#         TimeSeriesOutcome('Wage index Manual L'),
#         TimeSeriesOutcome('Wage index Manual I'),
]

policies = [
         Policy('Model_V',

model_file=r"C:\Users\LocalAdmin\Documents\Koen\Final\Final_Models\Thesis_model_Final_V.vpm")
        ]
```

```
# Model simulation

results = perform_experiments(vensimModel, 1000, policies= policies)
```

```
# Save results

results_name = './EMA_NED_Uncertainty_G_Results_Solow.tar.gz'
save_results(results, results_name)
```

XV Solow paradox projections

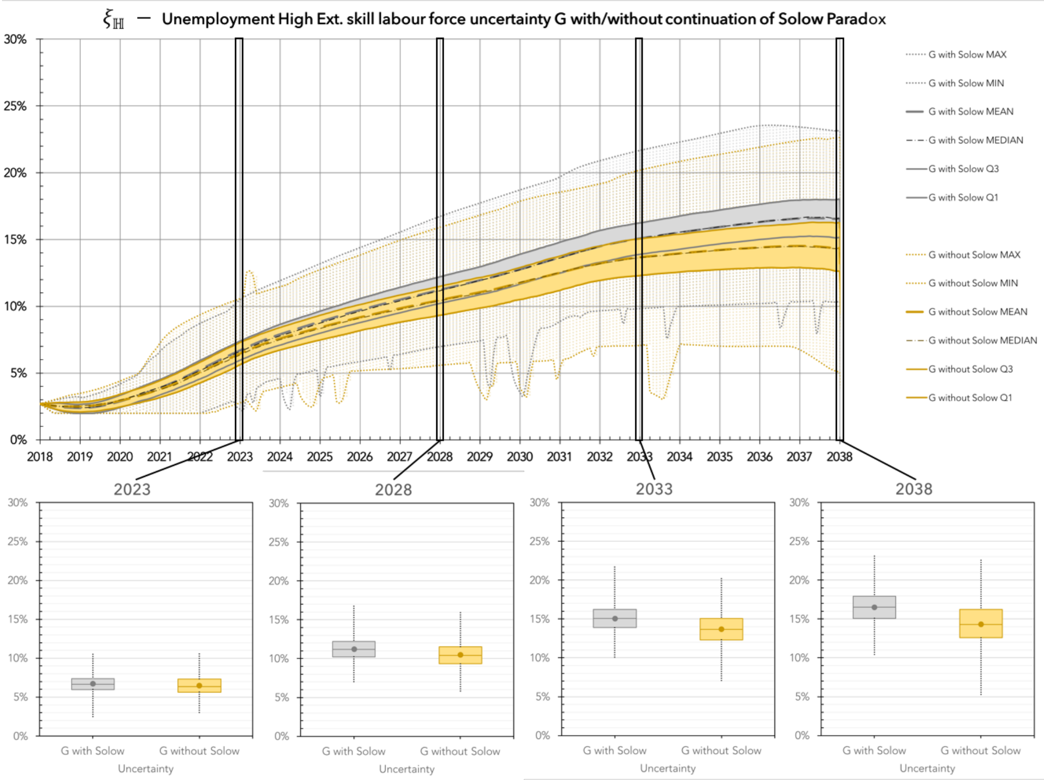


Figure 81 Unemployment projections $\xi_{\mathbb{H}}$ for uncertainties G with and without continuation of the Solow paradox (Table 4)

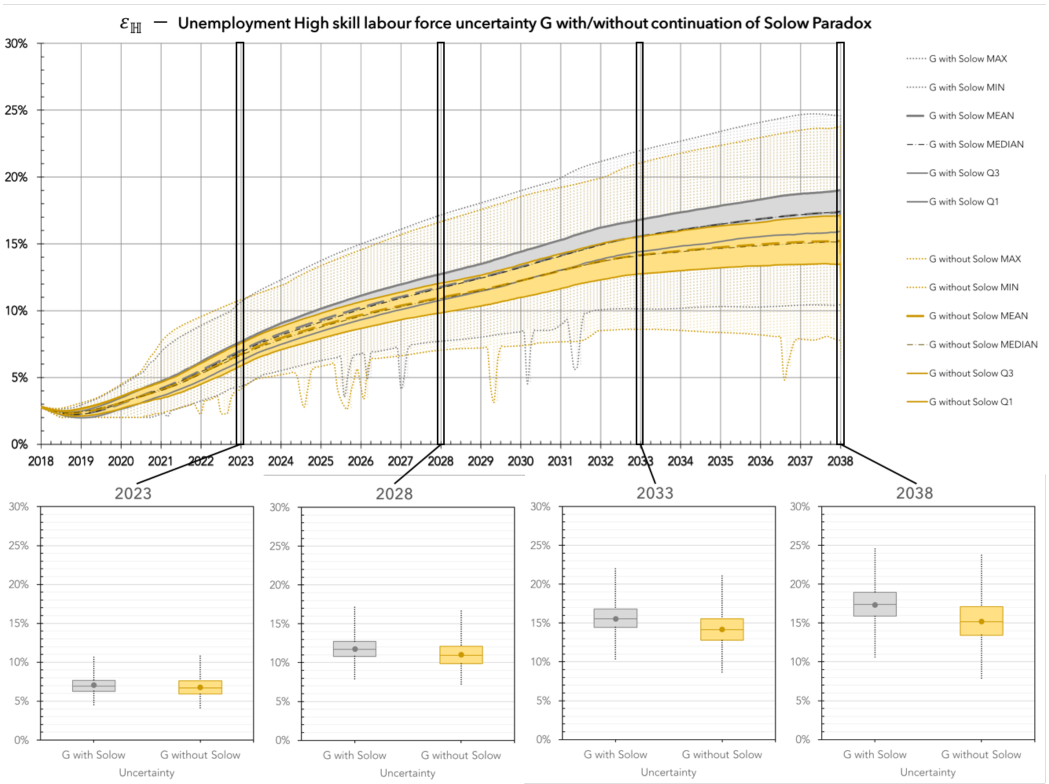


Figure 82 Unemployment projections $\varepsilon_{\mathbb{H}}$ for uncertainties G with and without continuation of the Solow paradox (Table 4)

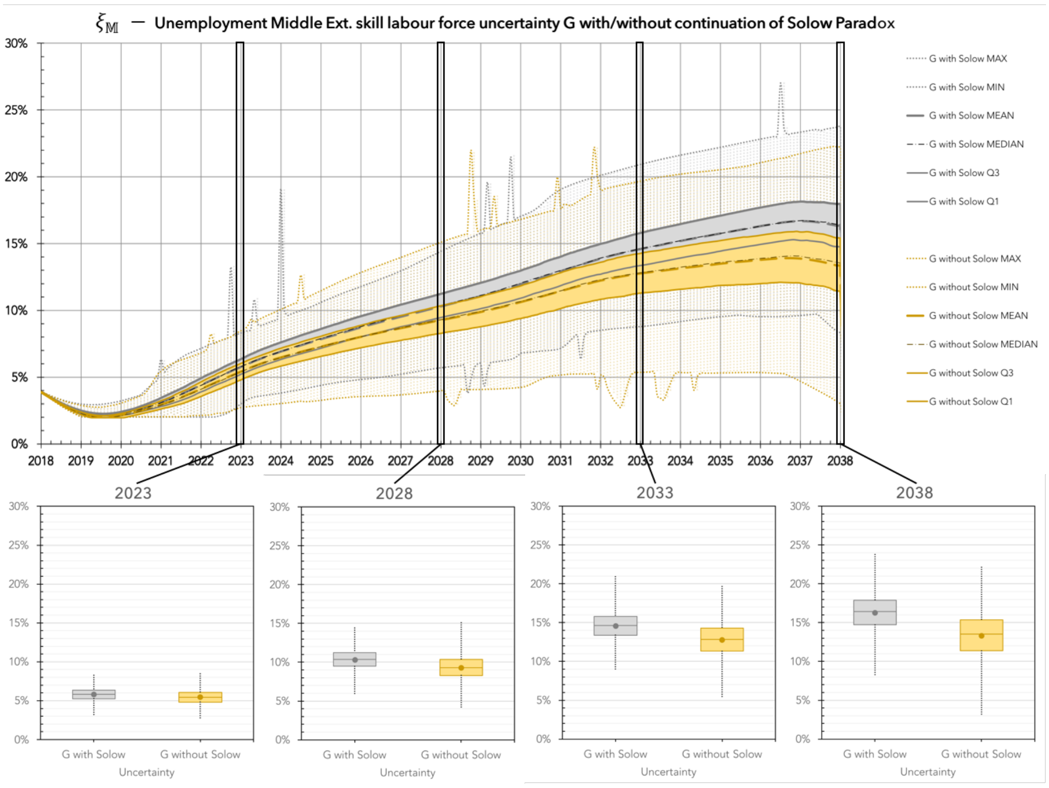


Figure 83 Unemployment projections $\xi_{\mathbb{M}}$ for uncertainties G with and without continuation of the Solow paradox (Table 4)

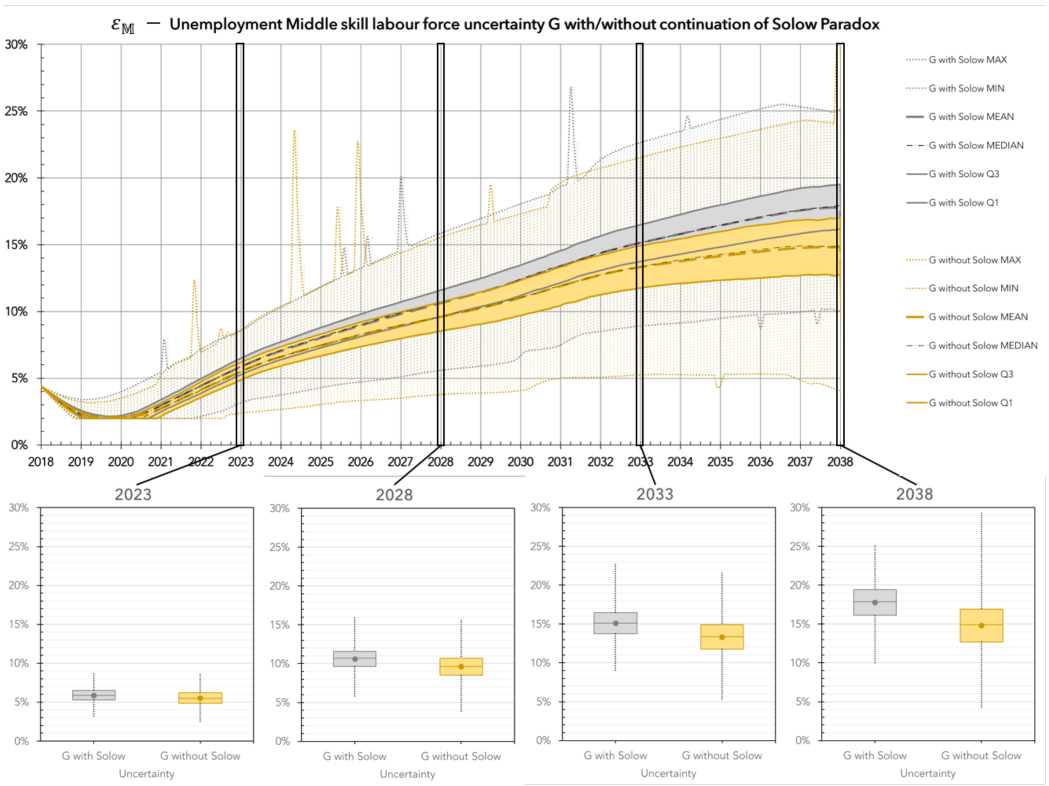


Figure 84 Unemployment projections $\varepsilon_{\mathbb{M}}$ for uncertainties G with and without continuation of the Solow paradox (Table 4)

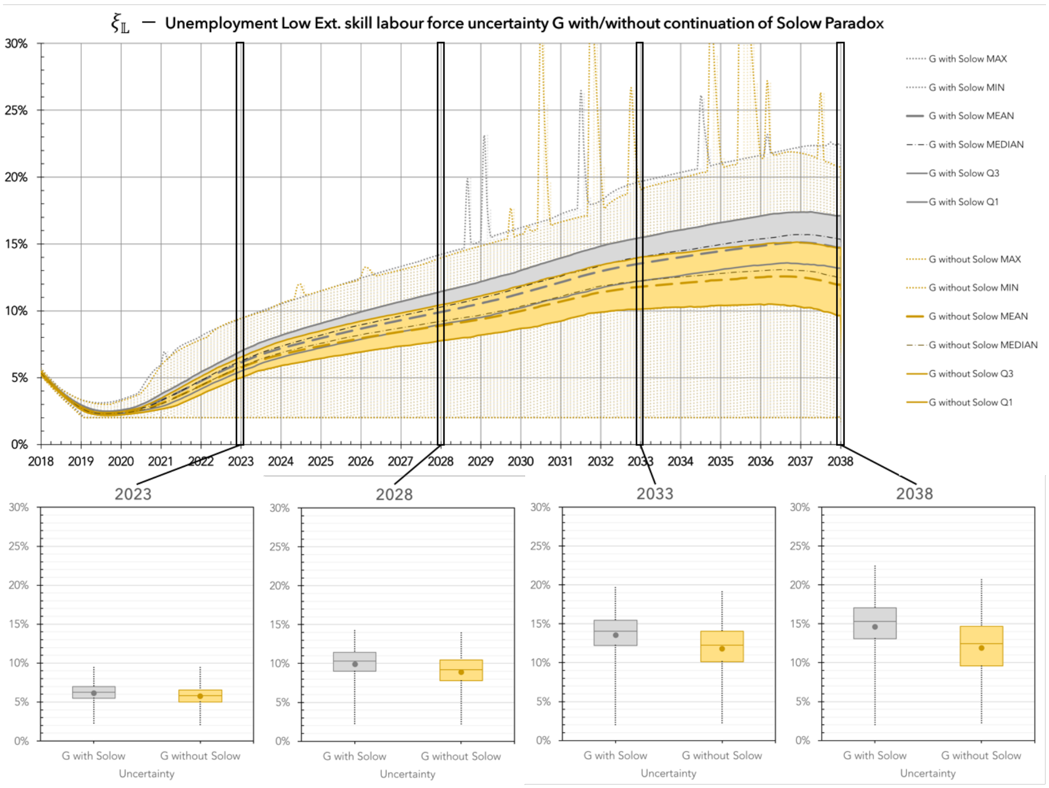


Figure 85 Unemployment projections $\xi_{\mathbb{L}}$ for uncertainties G with and without continuation of the Solow paradox (Table 4)

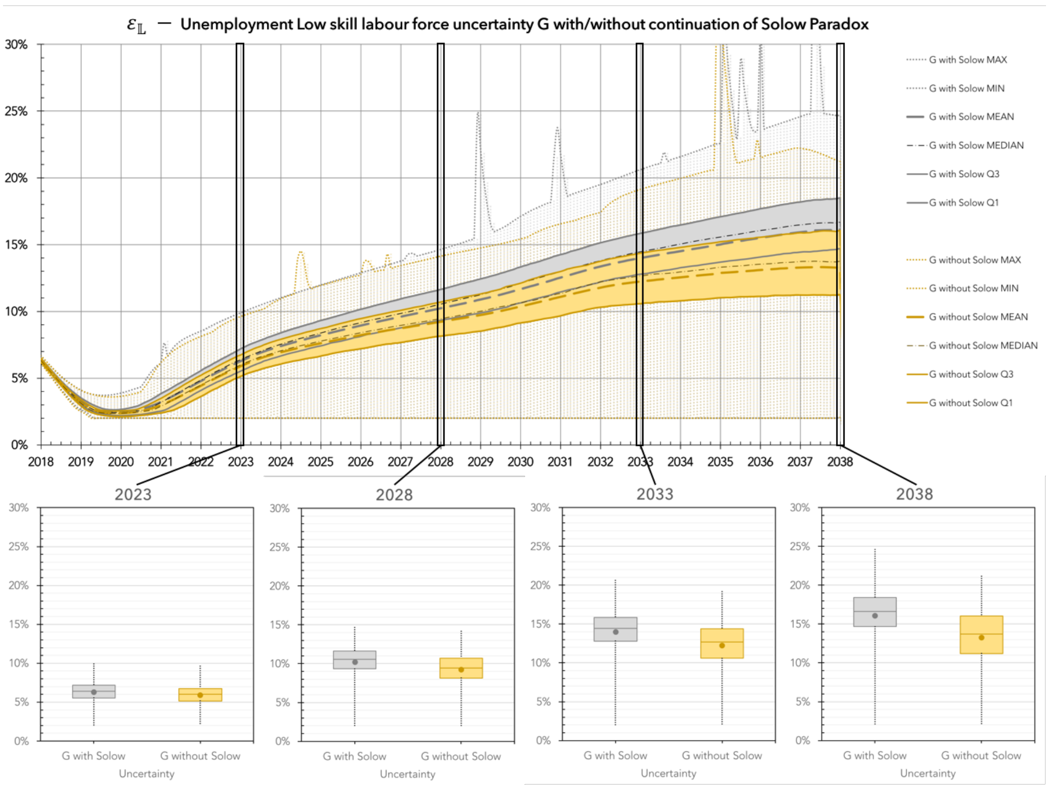


Figure 86 Unemployment projections $\varepsilon_{\mathbb{L}}$ for uncertainties G with and without continuation of the Solow paradox (Table 4)

XVI EMA Python script difference

```
# Simulation configuration

import numpy as np
import matplotlib
import matplotlib.pyplot as plt
import pandas as pd
import SALib
import seaborn as sns
import mpl_toolkits.axisartist as AA
import scipy as sp
import copy
import matplotlib.ticker as ticker

from ema_workbench import (Model,
                           RealParameter,
                           IntegerParameter,
                           CategoricalParameter,
                           Constant,
                           TimeSeriesOutcome,
                           ScalarOutcome,
                           perform_experiments,
                           ema_logging,
                           save_results,
                           load_results)
from ema_workbench import (Policy)
from ema_workbench import (MultiprocessingEvaluator)
from ema_workbench.connectors import vensimDLLwrapper
from ema_workbench.connectors.vensim import VensimModel
from ema_workbench.em_framework.samplers import sample_levers, sample_uncertainties
from ema_workbench.util import load_results
from ema_workbench.util import ema_logging

from ema_workbench.analysis import prim
import matplotlib.pyplot as plt
from ema_workbench.analysis.plotting import lines, multiple_densities, kde_over_time
from ema_workbench.analysis.plotting_util import KDE
from ema_workbench.analysis.plotting_util import determine_time_dimension
from ema_workbench.analysis.pairs_plotting import pairs_scatter

from SALib.sample import saltelli
from SALib.analyze import sobol, morris
from SALib.test_functions import Ishigami

from mpl_toolkits.axes_grid1 import host_subplot

from scipy.stats import linregress
```

```
ema_logging.log_to_stderr(ema_logging.INFO)
```

```
vensimModel                        =                        VensimModel("ThesisModel",
```

```
model_file=r"C:\Users\LocalAdmin\Documents\Koen\Final\Final_Models\Thesis_model_Final.vpm" )
```

```
# Uncertainty configuration Dataset Deloitte (2016) for the Netherlands

vensimModel.uncertainties = [
    #POPULATION MODEL UNCERTAINTIES
            RealParameter("Normal fertility rate per f", 1.58, 1.7),

    #EDUCATION MODEL UNCERTAINTIES
#        #CH Education
#            RealParameter("CH Edu performance Reskill equivalent", 25, 30),
#            RealParameter("CH Edu performance Upskill equivalent", 25, 30),
#          #Policy
#            #RealParameter("Time to introduction STEM program", 0, 300),
#            #RealParameter("Minimum fixed period CH Edu capacity expansion", 1, 36),
#            #RealParameter("Time to realise CH Edu capacity expansion", 1, 48),
#            #RealParameter("STEM educated vs STEM graduated ratio", 0.4, 1),
#            #RealParameter("MANUAL CH Edu performance overall improvement H", 0, 25),
#            #RealParameter("MANUAL CH Edu performance overall improvement M", 0, 25),
#            #RealParameter("MANUAL CH Edu performance overall improvement L", 0, 25),
#            #RealParameter("MANUAL CH Edu performance STEM improvement H", 0, 16.75),
#            #RealParameter("MANUAL CH Edu performance STEM improvement M", 0, 16.75),
#            #RealParameter("MANUAL CH Edu performance STEM improvement L", 0, 16.75),
#        #ST Education
          RealParameter("ST Labour market awareness and sensitivity", 0, 1),
          RealParameter("ST knowledge YA Unemployment delay", 12, 48),
#          #Policy
#            #RealParameter("ST STEM stimulation and awareness", 1, 2),
#            #RealParameter("ST High Edu stimulation and awareness", 1, 2),
#            #RealParameter("Time to realise ST Edu capacity expansion", 12, 60),
#            #RealParameter("Fixed period ST Edu capacity expansion", 1, 12),
#        #WA Education
          RealParameter("WAu reskill and upskill sensitivity", 0, 1),
          RealParameter("WAe reskill and upskill sensitivity", 0, 1),
#          #Policy
#            RealParameter("WA STEM stimulation and awareness", 1, 2),
#            RealParameter("WA High Edu stimulation and awareness", 1, 2),
#            RealParameter("Socioeconomic influence education and training H", 1, 2),
#            RealParameter("Socioeconomic influence education and training M", 0.895, 2),
#            RealParameter("Socioeconomic influence education and training L", 0.561, 2),

    #LABOUR MARKET MODEL UNCERTAINTIES
        #Labour reallocation
          RealParameter("Sensitivity Wage reallocation", 0, 0.999),
          RealParameter("Wage sacrifice ratio for employment", 0.01, 0.5),
          RealParameter("Sensitivity Unemployment reallocation", 0, 1),
         #Policy
          RealParameter("Labour reallocation delay", 12, 48),
         #Setting
          RealParameter("Error MINMAX corrector", 10000000000000000, 100000000000000000),

    #PRODUCTION MODEL UNCERTAINTIES
        #Labour input
```

```
#           RealParameter("Price elasticity of demand Abstract L", 0, 1),
#           RealParameter("Price elasticity of demand Abstract I", 0, 1),
#           RealParameter("Price elasticity of demand Routine L", 0, 1),
#           RealParameter("Price elasticity of demand Routine I", 0, 1),
#           RealParameter("Price elasticity of demand Manual L", 0, 1),
#           RealParameter("Price elasticity of demand Manual I", 0, 1),
        #GDP growth
            RealParameter("Long term economic growth error margin", 0, 0.05),
            RealParameter("Business cycle fluctuation amplitude", 0.001, 0.0033),
            RealParameter("Business cycle fluctuation period", 2, 3),
            RealParameter("Time to first recession", 2, 5),
            RealParameter("Business cycle recession amplitude", 0.0187, 0.0263),
            RealParameter("Business cycle recession duration", 3, 3.64),
            RealParameter("Busines cycle recession period", 8, 9.4),
            RealParameter("Severe recession timing", 1, 3),
            RealParameter("Severe recession duration", 4, 4.7),
            RealParameter("Severe recession amplitude", 0.0489, 0.0631),
            RealParameter("Severe recession occurance", 0, 1),
            RealParameter("Proportion of time in recession", 0.18, 0.21),
            RealParameter("Initial Labour share", 0.554, 0.714),
        #Others
#          RealParameter("Macro economic Technological TFP growth", 0.004, 0.0067),
            RealParameter("Task substitution elasticity", 0.66, 0.9),
        #Policy
            #RealParameter("Hours fulltime contracts", 32, 38),

    #TECHNOLOGY MODEL UNCERTAINTIES
            RealParameter("Proportion profit invested in innovation", 0.02, 1),
            RealParameter("Innovation allocation sensivitity to business cycle", 0, 0.1),
            RealParameter("Prior Substituted Labour demand", 8.9, 10.1),
            RealParameter("Time difference automation and substitution", 1.000, 2.903),
            RealParameter("TFP Wage allocation Abstract L", 0.1, 1),
            RealParameter("TFP Wage allocation Abstract I", 0.1, 1),
            RealParameter("TFP Wage allocation Routine L", 0.1, 1),
            RealParameter("TFP Wage allocation Routine I", 0.1, 1),
            RealParameter("TFP Wage allocation Manual L", 0.1, 1),
            RealParameter("TFP Wage allocation Manual I", 0.1, 1),
    #Substitution
        #Abstract L:
            #RealParameter("Technological bottleneck period Abstract L", 0, 12),
            RealParameter("Technological implementation period Abstract L", 216, 264),
            RealParameter("Technological automation estimate Abstract L", 0.104, 0.193),
            RealParameter("Automation probability Abstract L", 0.7, 1.0),
            #RealParameter("Annual labour input increase for technological change Abstract L", 0.0042, 0.015),
            RealParameter("Annual technological productivity growth Abstract L", 0.006, 0.01),
        #Abstract I:
            #RealParameter("Technological bottleneck period Abstract I", 0, 12),
            RealParameter("Technological implementation period Abstract I", 216, 264),
            RealParameter("Technological automation estimate Abstract I", 0.104, 0.193),
            RealParameter("Automation probability Abstract I", 0.7, 1.0),
            #RealParameter("Annual labour input increase for technological change Abstract I", 0.0042, 0.015),
            RealParameter("Annual technological productivity growth Abstract I", 0.006, 0.01),
        #Routine L:
```

```
        #RealParameter("Technological bottleneck period Routine L", 0, 12),
        RealParameter("Technological implementation period Routine L", 216, 264),
        RealParameter("Technological automation estimate Routine L", 0.412425, 0.433575),
        RealParameter("Automation probability Routine L", 0.7, 1.0),
        #RealParameter("Annual labour input increase for technological change Routine L", 0.0042, 0.015),
        RealParameter("Annual technological productivity growth Routine L", 0.006, 0.01),
    #Routine I:
        #RealParameter("Technological bottleneck period Routine I", 0, 12),
        RealParameter("Technological implementation period Routine I", 216, 264),
        RealParameter("Technological automation estimate Routine I", 0.412425, 0.433575),
        RealParameter("Automation probability Routine I", 0.7, 1.0),
        #RealParameter("Annual labour input increase for technological change Routine I", 0.0042, 0.015),
        RealParameter("Annual technological productivity growth Routine I", 0.006,0.01),
    #Manual L:
        #RealParameter("Technological bottleneck period Manual L", 0, 12),
        RealParameter("Technological implementation period Manual L", 216, 264),
        RealParameter("Technological automation estimate Manual L", 0.412425, 0.433575),
        RealParameter("Automation probability Manual L", 0.7, 1.0),
        #RealParameter("Annual labour input increase for technological change Manual L", 0.0042, 0.015),
        RealParameter("Annual technological productivity growth Manual L", 0.006, 0.01),
    #Manual I:
        #RealParameter("Technological bottleneck period Manual I", 0, 12),
        RealParameter("Technological implementation period Manual I", 216, 264),
        RealParameter("Technological automation estimate Manual I", 0.412425, 0.433575),
        RealParameter("Automation probability Manual I", 0.7, 1.0),
        #RealParameter("Annual labour input increase for technological change Manual I", 0.0042, 0.015),
        RealParameter("Annual technological productivity growth Manual I", 0.006, 0.01),

        RealParameter("Upper bound technological bottleneck proportion of tasks", 0.001, 0.01)
]

vensimModel.outcomes = [
  #POPULATION MODEL OUTCOMES
#       TimeSeriesOutcome('Total population'),
  #EDUCATION MODEL OUTCOMES
        TimeSeriesOutcome('ST HI m total reskill percentage'),
        TimeSeriesOutcome('ST MI m total reskill percentage'),
        TimeSeriesOutcome('ST LI m total reskill percentage'),
        TimeSeriesOutcome('ST ML m total upskill percentage'),
        TimeSeriesOutcome('ST MI m total upskill percentage'),
        TimeSeriesOutcome('ST LL m total upskill percentage'),
        TimeSeriesOutcome('ST LI m total upskill percentage'),
        TimeSeriesOutcome('ST HI f total reskill percentage'),
        TimeSeriesOutcome('ST MI f total reskill percentage'),
        TimeSeriesOutcome('ST LI f total reskill percentage'),
        TimeSeriesOutcome('ST ML f total upskill percentage'),
        TimeSeriesOutcome('ST MI f total upskill percentage'),
        TimeSeriesOutcome('ST LL f total upskill percentage'),
        TimeSeriesOutcome('ST LI f total upskill percentage'),
        TimeSeriesOutcome('LF HI m total reskill percentage'),
        TimeSeriesOutcome('LF MI m total reskill percentage'),
        TimeSeriesOutcome('LF LI m total reskill percentage'),
        TimeSeriesOutcome('LF ML m total upskill percentage'),
```

```
        TimeSeriesOutcome('LF MI m total upskill percentage'),
        TimeSeriesOutcome('LF LL m total upskill percentage'),
        TimeSeriesOutcome('LF LI m total upskill percentage'),
        TimeSeriesOutcome('LF HI f total reskill percentage'),
        TimeSeriesOutcome('LF MI f total reskill percentage'),
        TimeSeriesOutcome('LF LI f total reskill percentage'),
        TimeSeriesOutcome('LF ML f total upskill percentage'),
        TimeSeriesOutcome('LF MI f total upskill percentage'),
        TimeSeriesOutcome('LF LL f total upskill percentage'),
        TimeSeriesOutcome('LF LI f total upskill percentage'),
    #LABOUR MARKET OUTCOMES
        TimeSeriesOutcome('Labour force ft Index'),
        TimeSeriesOutcome('HL ft average wage index'),
        TimeSeriesOutcome('HI ft average wage index'),
        TimeSeriesOutcome('ML ft average wage index'),
        TimeSeriesOutcome('MI ft average wage index'),
        TimeSeriesOutcome('LL ft average wage index'),
        TimeSeriesOutcome('LI ft average wage index'),
        TimeSeriesOutcome('HL Avg ft Unemployment rate'),
        TimeSeriesOutcome('HI Avg ft Unemployment rate'),
        TimeSeriesOutcome('ML Avg ft Unemployment rate'),
        TimeSeriesOutcome('MI Avg ft Unemployment rate'),
        TimeSeriesOutcome('LL Avg ft Unemployment rate'),
        TimeSeriesOutcome('LI Avg ft Unemployment rate'),
#       TimeSeriesOutcome('Total Labour Force HL ft'),
#       TimeSeriesOutcome('Total Labour Force HI ft'),
#       TimeSeriesOutcome('Total Labour Force ML ft'),
#       TimeSeriesOutcome('Total Labour Force MI ft'),
#       TimeSeriesOutcome('Total Labour Force LL ft'),
#       TimeSeriesOutcome('Total Labour Force LI ft'),
#       TimeSeriesOutcome('LI to Manual I for employment ft'),
#       TimeSeriesOutcome('LL to Manual I for employment ft'),
        TimeSeriesOutcome('MI to Manual I for employment ft'),
        TimeSeriesOutcome('ML to Manual I for employment ft'),
        TimeSeriesOutcome('HI to Manual I for employment ft'),
        TimeSeriesOutcome('HL to Manual I for employment ft'),
#       TimeSeriesOutcome('LL to Manual L for employment ft'),
#       TimeSeriesOutcome('ML to Manual L for employment ft'),
        TimeSeriesOutcome('HL to Manual L for employment ft'),
#       TimeSeriesOutcome('LI to Routine I for employment ft'),
#       TimeSeriesOutcome('LL to Routine I for employment ft'),
#       TimeSeriesOutcome('MI to Routine I for employment ft'),
#       TimeSeriesOutcome('ML to Routine I for employment ft'),
        TimeSeriesOutcome('HI to Routine I for employment ft'),
        TimeSeriesOutcome('HL to Routine I for employment ft'),
#       TimeSeriesOutcome('LL to Routine L for employment ft'),
#       TimeSeriesOutcome('ML to Routine L for employment ft'),
        TimeSeriesOutcome('HL to Routine L for employment ft'),
#       TimeSeriesOutcome('HI to Abstract I for employment ft'),
#       TimeSeriesOutcome('HL to Abstract I for employment ft'),
#       TimeSeriesOutcome('HL to Abstract L for employment ft'),
    #PRODUCTION MODEL OUTCOMES
        TimeSeriesOutcome('Annual Macro Economic growth rate'),
```

```
          TimeSeriesOutcome('Total wage income index'),
          TimeSeriesOutcome('Aggregate annual TFP'),
          TimeSeriesOutcome('Average Labour share'),
#           TimeSeriesOutcome('Relative price development Abstract L'),
#           TimeSeriesOutcome('Relative price development Abstract I'),
#           TimeSeriesOutcome('Relative price development Routine L'),
#           TimeSeriesOutcome('Relative price development Routine I'),
#           TimeSeriesOutcome('Relative price development Manual L'),
#           TimeSeriesOutcome('Relative price development Manual I'),
   #TECHNOLOGY MODEL OUTCOMES
          TimeSeriesOutcome('Technological substitution Abstract L'),
          TimeSeriesOutcome('Technological substitution Abstract I'),
          TimeSeriesOutcome('Technological substitution Routine L'),
          TimeSeriesOutcome('Technological substitution Routine I'),
          TimeSeriesOutcome('Technological substitution Manual L'),
          TimeSeriesOutcome('Technological substitution Manual I'),
          TimeSeriesOutcome('Profit index Abstract L'),
          TimeSeriesOutcome('Profit index Abstract I'),
          TimeSeriesOutcome('Profit index Routine L'),
          TimeSeriesOutcome('Profit index Routine I'),
          TimeSeriesOutcome('Profit index Manual L'),
          TimeSeriesOutcome('Profit index Manual I')
#           TimeSeriesOutcome('Labour share index Abstract L'),
#           TimeSeriesOutcome('Labour share index Abstract I'),
#           TimeSeriesOutcome('Labour share index Routine L'),
#           TimeSeriesOutcome('Labour share index Routine I'),
#           TimeSeriesOutcome('Labour share index Manual L'),
#           TimeSeriesOutcome('Labour share index Manual I'),
#           TimeSeriesOutcome('Wage index Abstract L'),
#           TimeSeriesOutcome('Wage index Abstract I'),
#           TimeSeriesOutcome('Wage index Routine L'),
#           TimeSeriesOutcome('Wage index Routine I'),
#           TimeSeriesOutcome('Wage index Manual L'),
#           TimeSeriesOutcome('Wage index Manual I'),
]

policies = [
Policy('Model_IV_D',

model_file=r"C:\Users\LocalAdmin\Documents\Koen\Final\Final_Models\Thesis_model_Final_IV.vpm"),
           Policy('Model_IV_D',

model_file=r"C:\Users\LocalAdmin\Documents\Koen\Final\Final_Models\Thesis_model_Final_IV_D.vpm")
          ]
```

```
# Model simulation

results = perform_experiments(vensimModel, 1000, policies= policies)
```

```
# Save results

results_name = './EMA_NED_Uncertainty_G_ Results_Delay.tar.gz'
save_results(results, results_name)
```

XVII Substitution difference projections

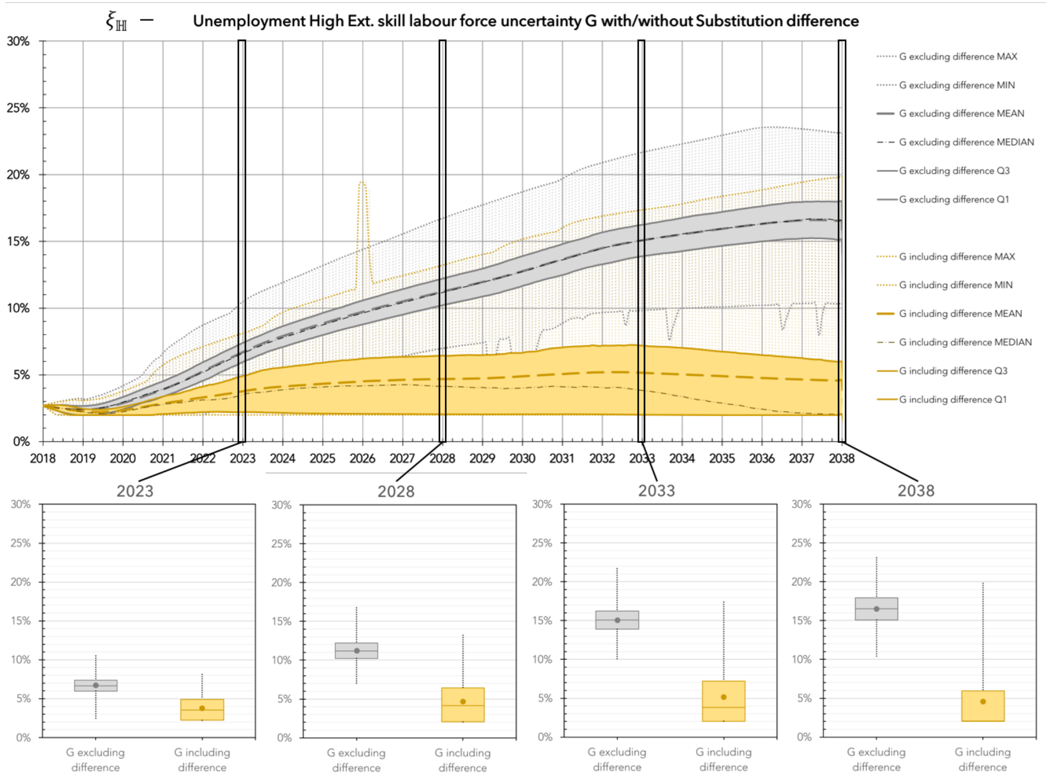


Figure 87 Unemployment projections $\xi_{\mathbb{H}}$ for uncertainties G with and without time difference between automatibility and substitution

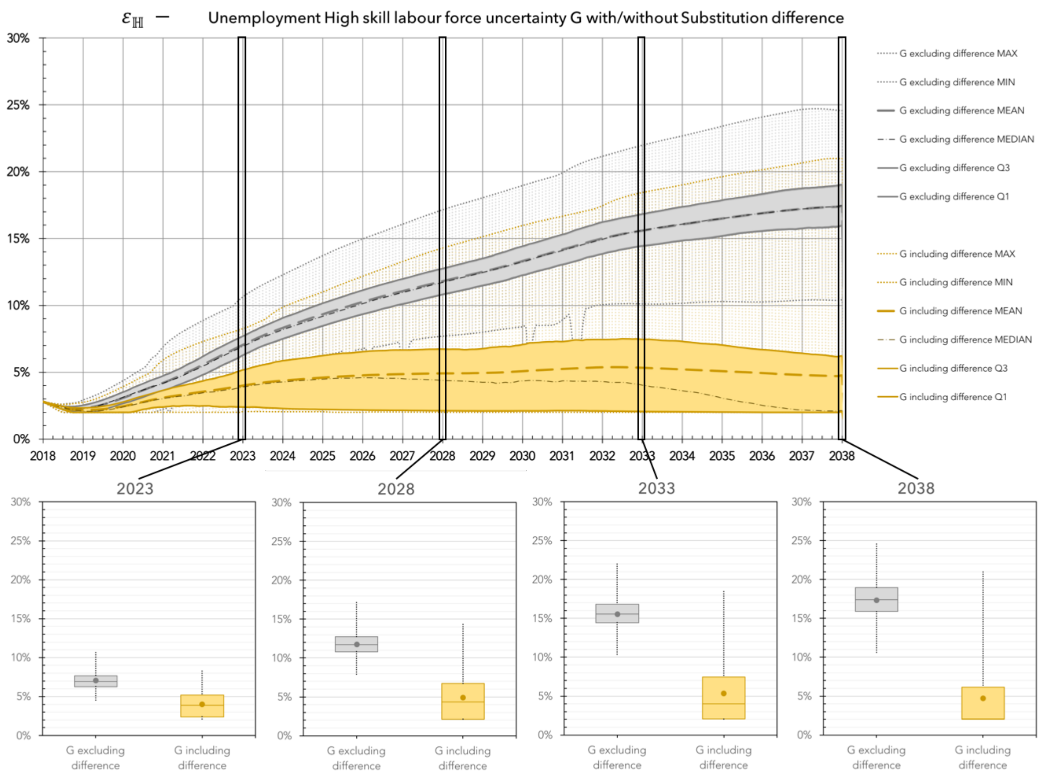


Figure 88 Unemployment projections $\varepsilon_{\mathbb{H}}$ for uncertainties G with and without time difference between automatibility and substitution

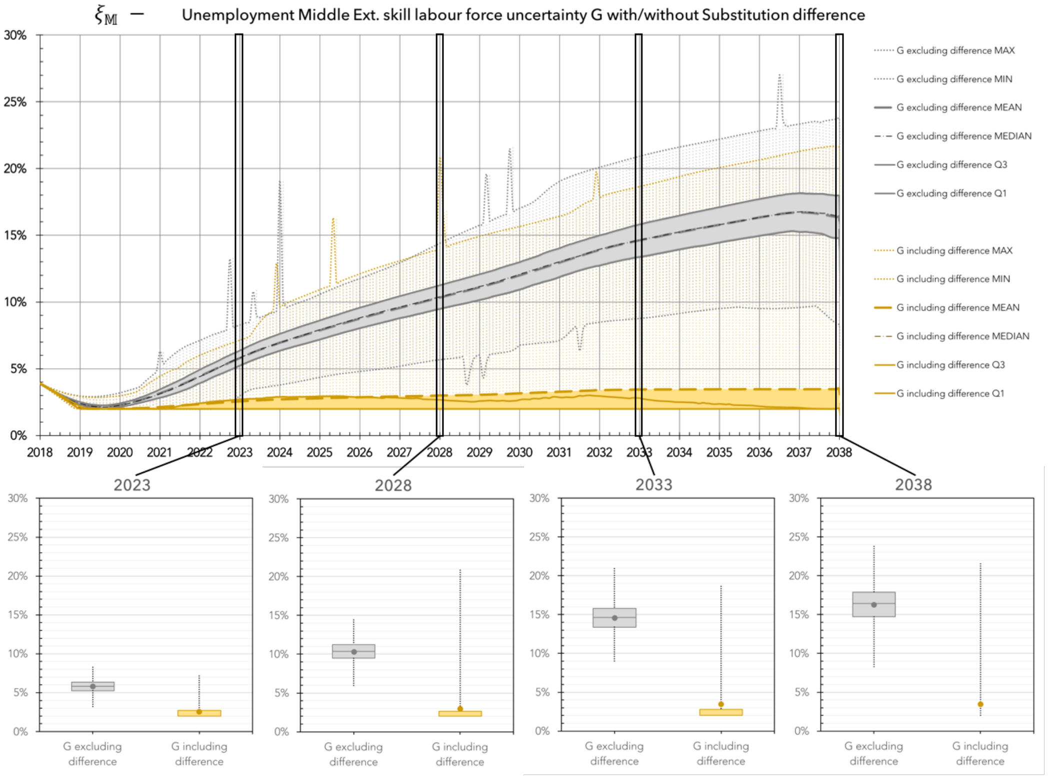


Figure 89 Unemployment projections $\xi_{\mathbb{M}}$ for uncertainties G with and without time difference between automatibility and substitution

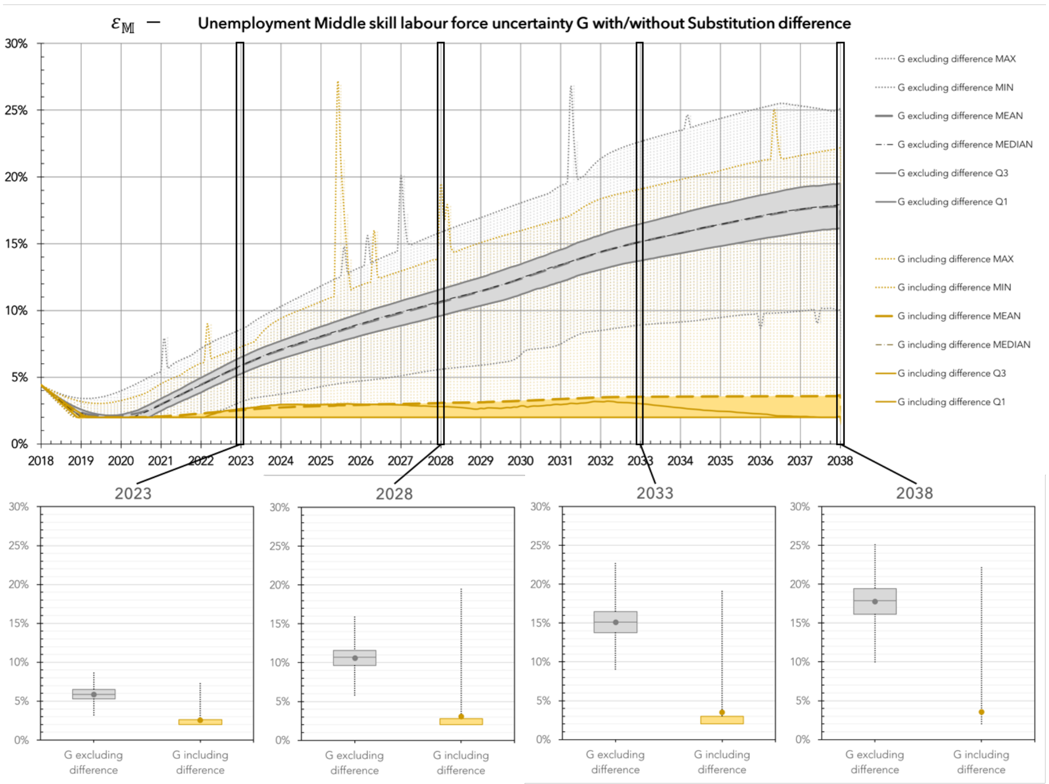


Figure 90 Unemployment projections $\varepsilon_{\mathbb{M}}$ for uncertainties G with and without time difference between automatibility and substitution

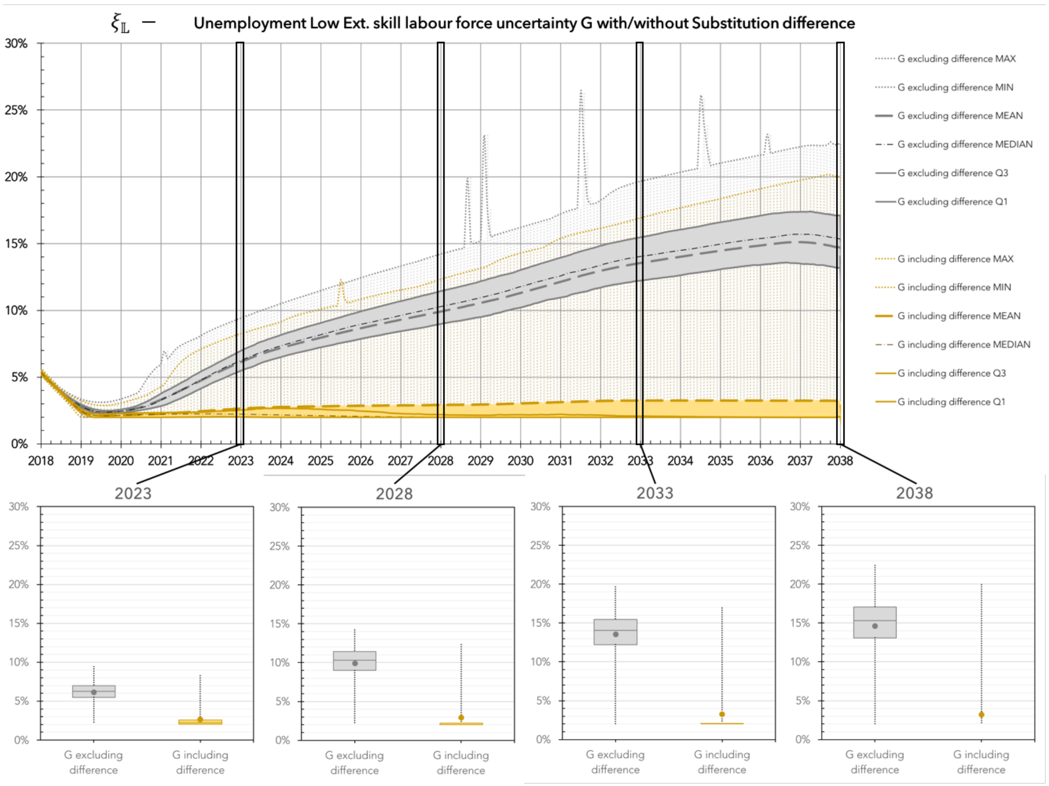


Figure 91 Unemployment projections $\xi_{\mathbb{L}}$ for uncertainties G with and without time difference between automatibility and substitution

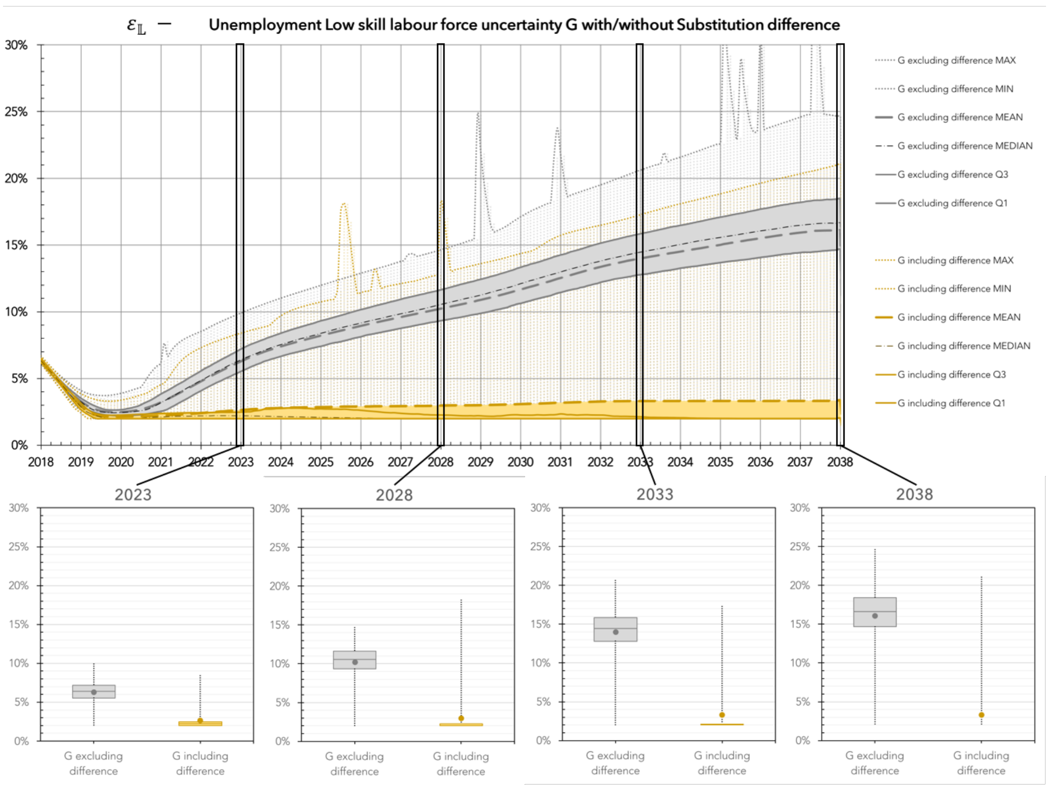


Figure 92 Unemployment projections $\varepsilon_{\mathbb{L}}$ for uncertainties G with and without time difference between automatibility and substitution

XVIII Substitution difference analysis using PRIM

Unemployment projection $\xi_{\mathbb{H}}$ upper quartile:

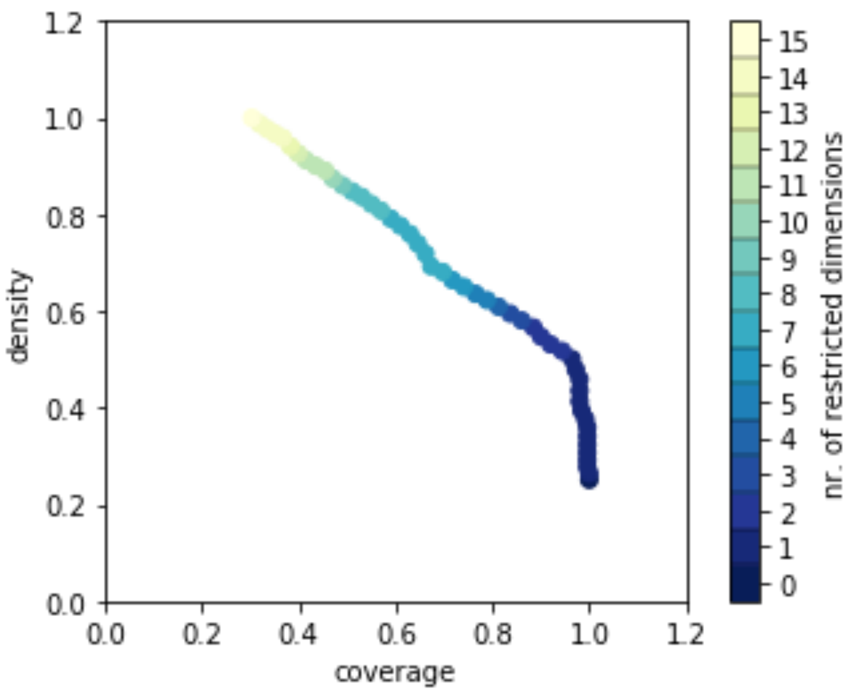
```
def classifyHLQiii(data):
    ooi = 'HL Avg ft Unemployment rate'
    outcome = np.mean(outcomes[ooi], axis=1)
    classes = np.zeros(outcome.shape[0])
    classes[outcome>0.0555] = 1
    return classes

prim_obj = prim.setup_prim(results, classifyHLQiii, threshold=0.8)
box_13 = prim_obj.find_box()
```

```
[MainProcess/INFO] 1000 points remaining, containing 251 cases of interest
[MainProcess/INFO] mean: 1.0, mass: 0.076, coverage: 0.30278884462151395, density: 1.0 re
stricted_dimensions: 15

coverage     0.76494
density     0.635762
mass           0.302
mean        0.635762
res dim            5
Name: 23, dtype: object

                                                box 23
                                                   min       max     qp values
Time difference automation and substitution   1.000615  1.734512  1.760703e-34
Wage sacrifice ratio for employment           0.010489  0.446382  1.854510e-01
Technological automation estimate Abstract I  0.109387  0.192952  2.668717e-01
WAe reskill and upskill sensitivity           0.052462  0.999285  3.167792e-01
Initial Labour share                          0.554158  0.704576  3.523170e
```



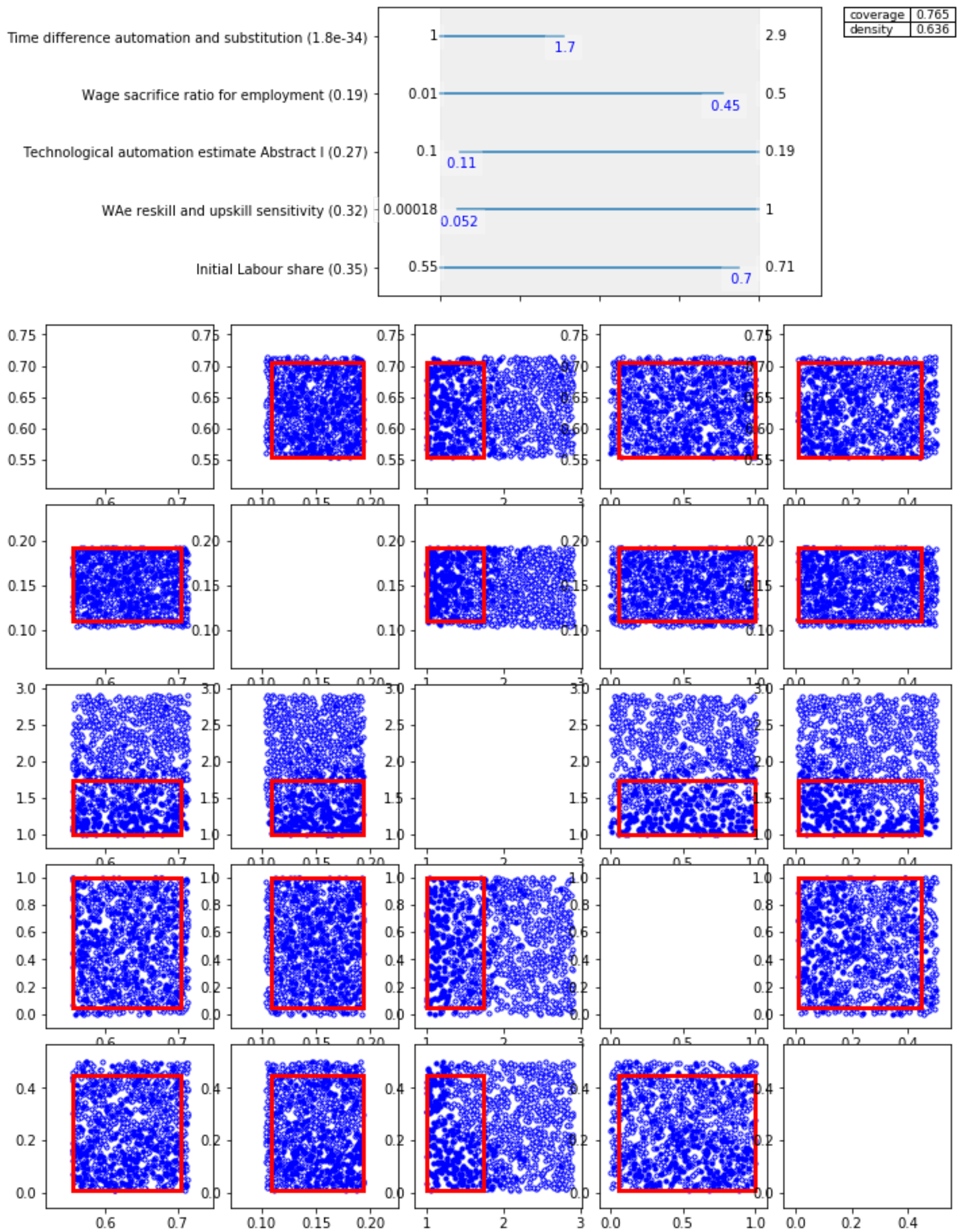


Figure 93 PRIM analysis $\xi_{\mathbb{H}}$ difference automatibility and substitution

Unemployment projection $\varepsilon_{\mathbb{H}}$ upper quartile:

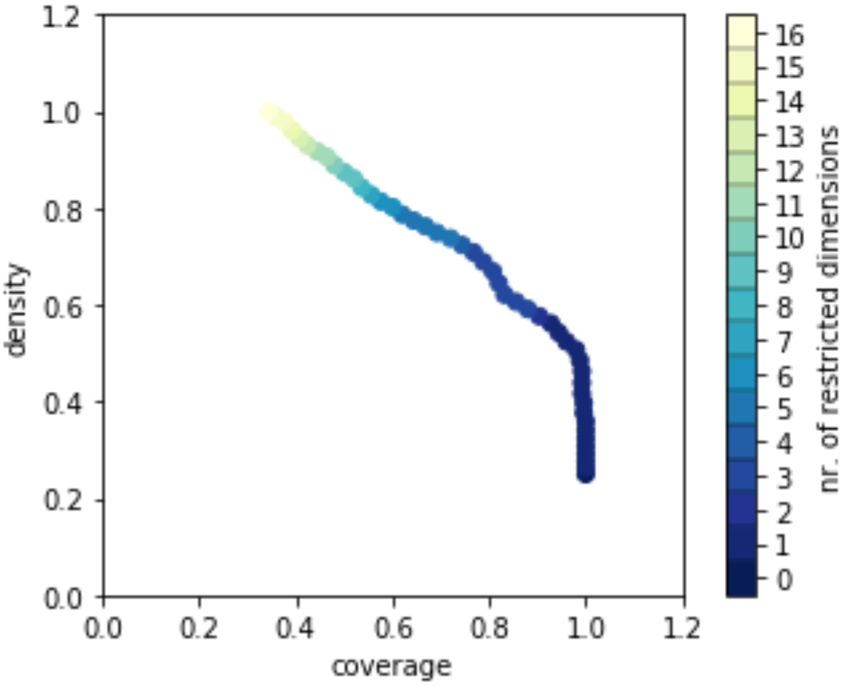
```
def classifyHIQiii(data):
    ooi = 'HI Avg ft Unemployment rate'
    outcome = np.mean(outcomes[ooi], axis=1)
    classes = np.zeros(outcome.shape[0])
    classes[outcome>0.0582] = 1
    return classes

prim_obj = prim.setup_prim(results, classifyHIQiii, threshold=0.8)
box_14 = prim_obj.find_box()
```

```
[MainProcess/INFO] 1000 points remaining, containing 250 cases of interest
[MainProcess/INFO]   mean:   1.0,   mass:   0.086,   coverage:   0.344,   density:   1.0
restricted_dimensions: 16

coverage       0.808
density     0.668874
mass           0.302
mean        0.668874
res dim            3
Name: 23, dtype: object

                                                  box 23
                                                     min       max     qp values
Time difference automation and substitution     1.000615  1.629914  8.604036e-48
Initial Labour share                            0.554158  0.704576  3.302435e-01
Technological automation estimate Abstract I    0.109627  0.192952  3.434054e-01
```



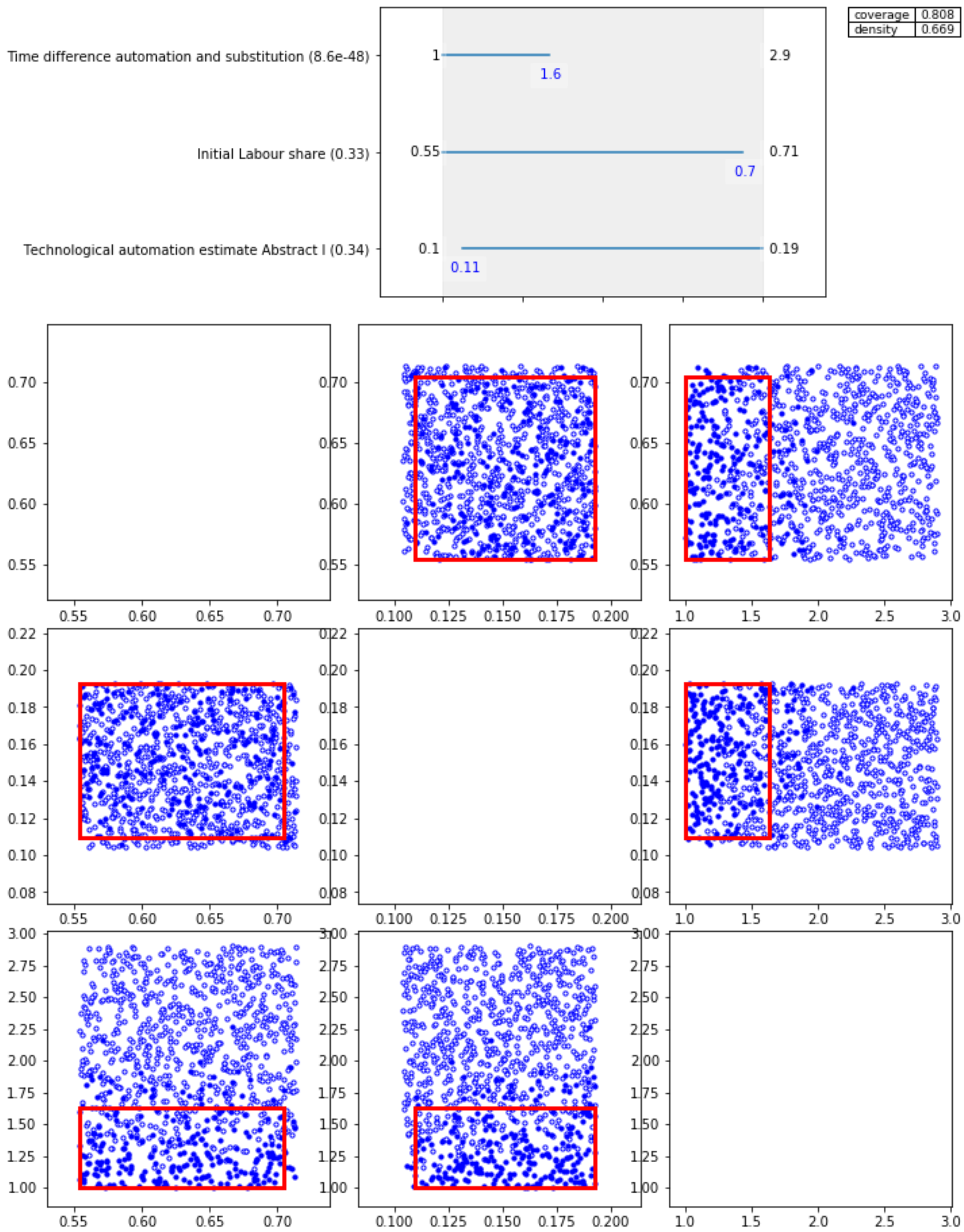


Figure 94 PRIM analysis $\varepsilon_{\mathbb{H}}$ difference automatibility and substitution

Unemployment projection $\xi_{\mathbb{M}}$ upper quartile:

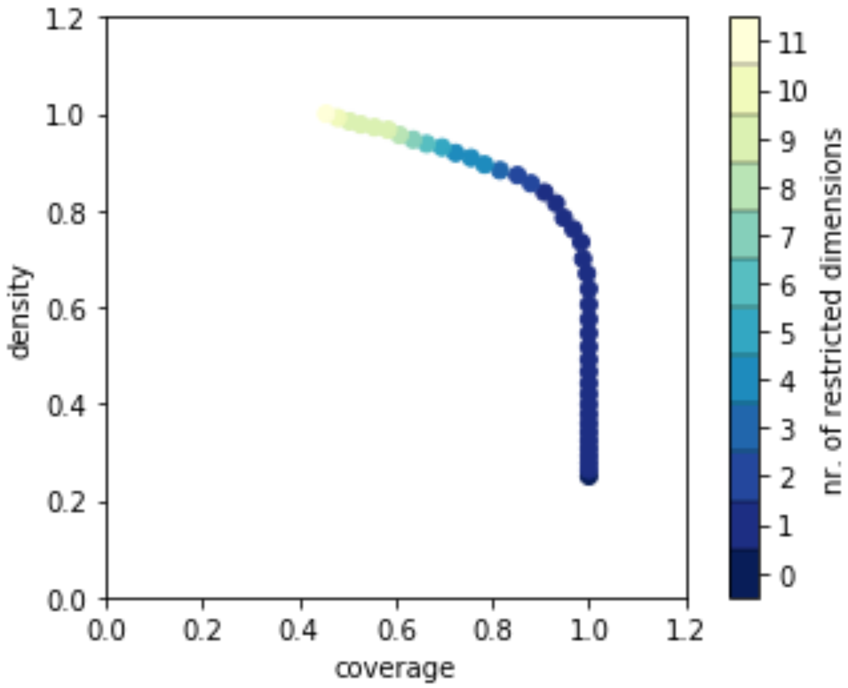
```
def classifyMLQiii(data):
    ooi = 'ML Avg ft Unemployment rate'
    outcome = np.mean(outcomes[ooi], axis=1)
    classes = np.zeros(outcome.shape[0])
    classes[outcome>0.0252] = 1
    return classes

prim_obj = prim.setup_prim(results, classifyMLQiii, threshold=0.8)
box_15 = prim_obj.find_box()
```

```
[MainProcess/INFO] 1000 points remaining, containing 250 cases of interest
[MainProcess/INFO] mean: 1.0, mass: 0.114, coverage: 0.456, density: 1.0 restricted_dimen
sions: 11

coverage        0.88
density     0.856031
mass           0.257
mean        0.856031
res dim            2
Name: 26, dtype: object

                                                 box 26
                                                    min       max     qp values
Time difference automation and substitution    1.000615  1.516424  9.364789e-91
Wage sacrifice ratio for employment            0.039033  0.499736  2.402312e-01
```



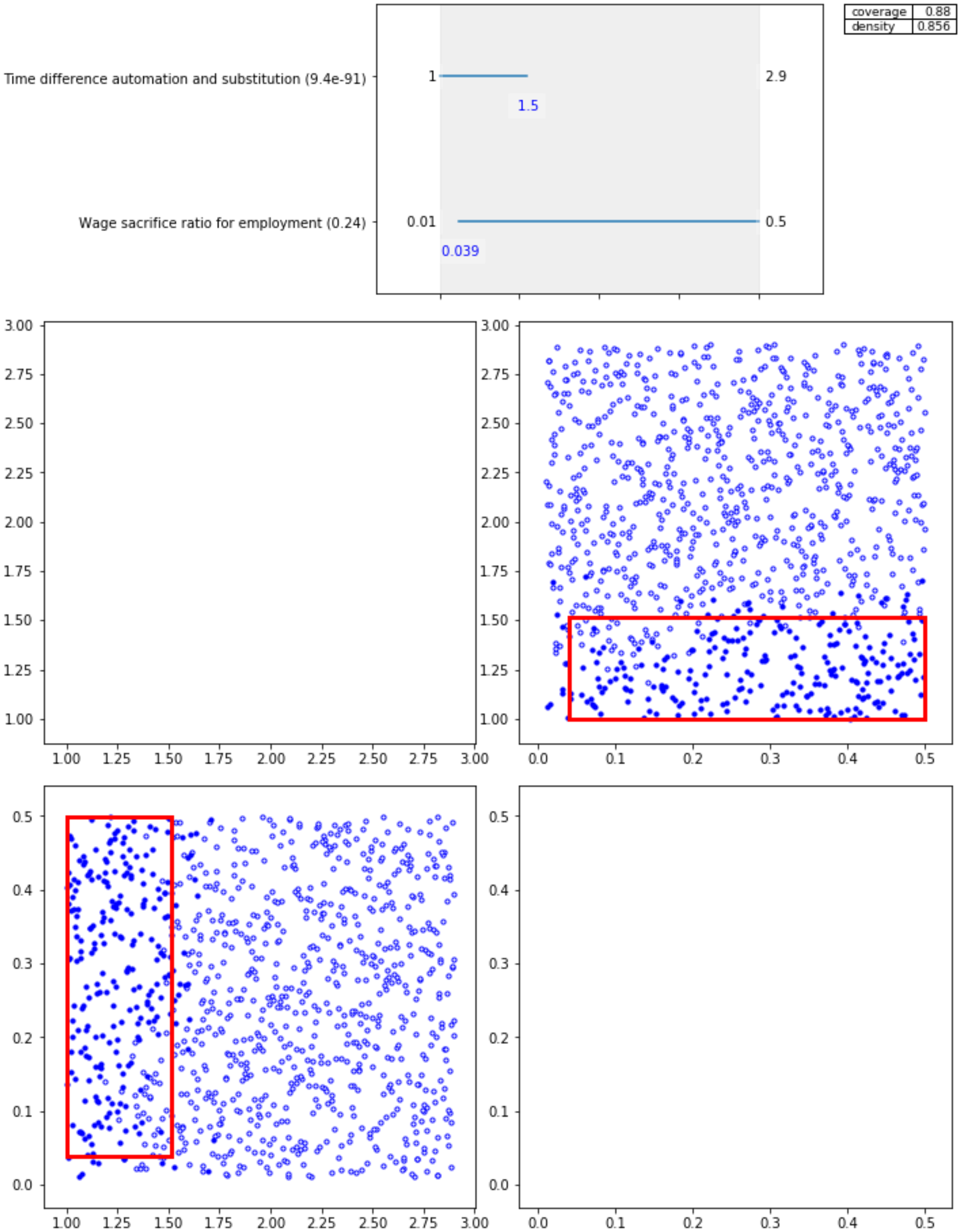


Figure 95 PRIM analysis $\xi_{\mathbb{M}}$ difference automatibility and substitution

Unemployment projection $\varepsilon_{\mathbb{M}}$ upper quartile:

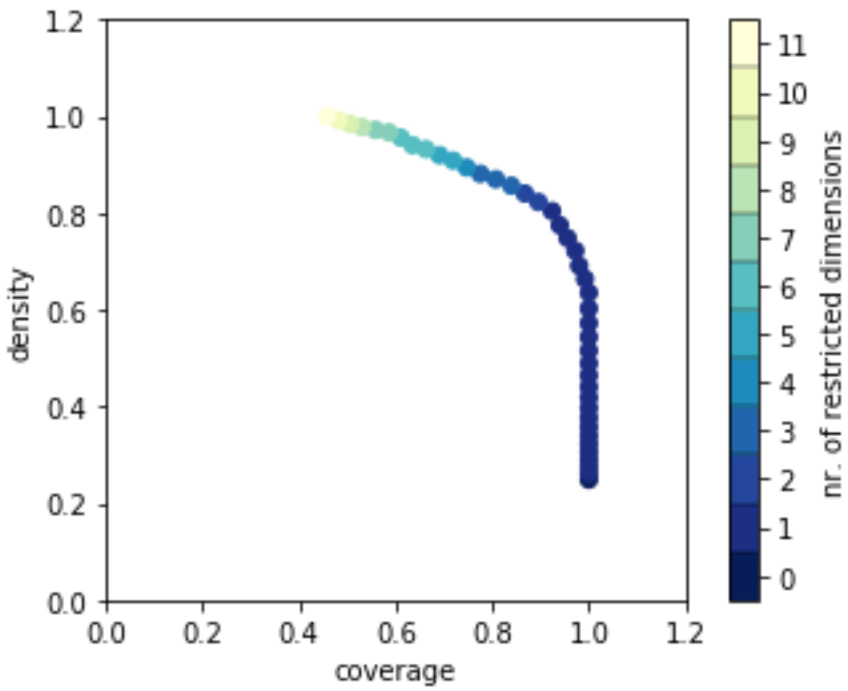
```
def classifyMIQiii(data):
    ooi = 'MI Avg ft Unemployment rate'
    outcome = np.mean(outcomes[ooi], axis=1)
    classes = np.zeros(outcome.shape[0])
    classes[outcome>0.0258] = 1
    return classes

prim_obj = prim.setup_prim(results, classifyMIQiii, threshold=0.8)
box_16 = prim_obj.find_box()
```

```
[MainProcess/INFO] 1000 points remaining, containing 249 cases of interest
[MainProcess/INFO] mean: 1.0, mass: 0.114, coverage: 0.4578313253012048, density: 1.0 res
tricted_dimensions: 11

coverage    0.839357
density     0.856557
mass           0.244
mean        0.856557
res dim            3
Name: 27, dtype: object

                                             box 27
                                                min       max     qp values
Time difference automation and substitution  1.000615  1.518316  6.045846e-86
ST Labour market awareness and sensitivity   0.000917  0.957313  1.956924e-01
Wage sacrifice ratio for employment          0.037620  0.499736  2.789291e-01
```



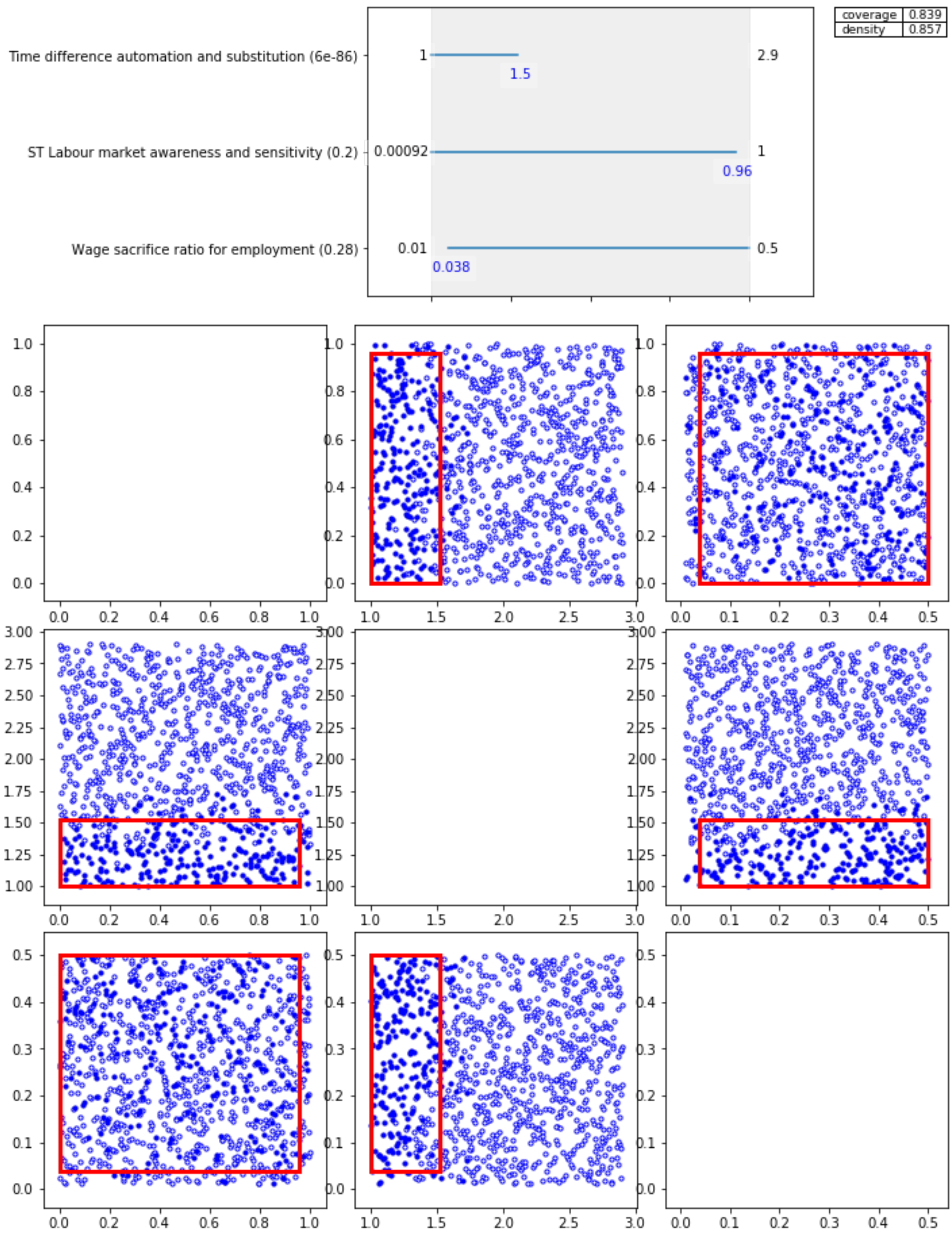


Figure 96 PRIM analysis $\varepsilon_{\mathbb{M}}$ difference automatibility and substitution

Unemployment projection $\xi_{\mathbb{L}}$ upper quartile:

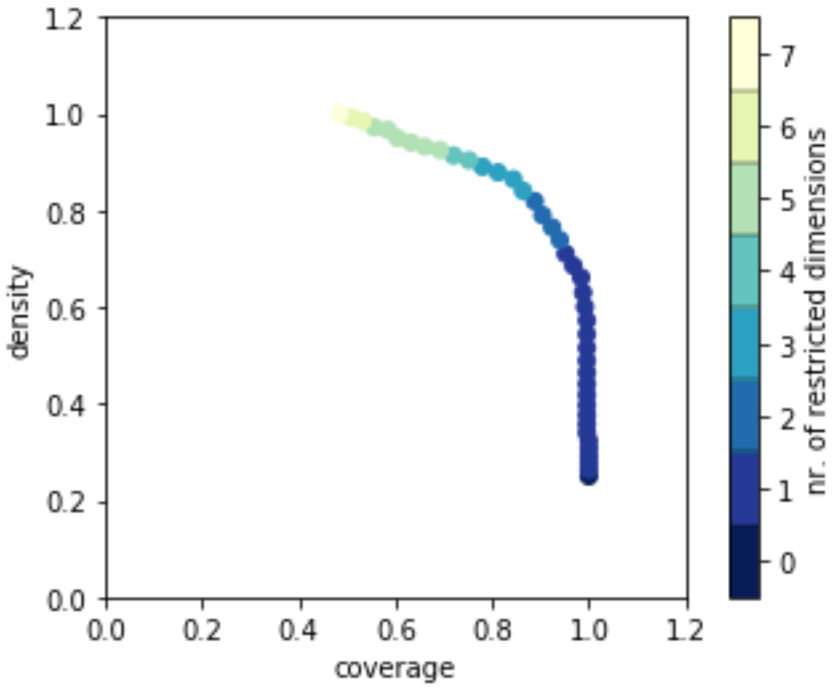
```
def classifyLLQiii(data):
    ooi = 'LL Avg ft Unemployment rate'
    outcome = np.mean(outcomes[ooi], axis=1)
    classes = np.zeros(outcome.shape[0])
    classes[outcome>0.0238] = 1
    return classes

prim_obj = prim.setup_prim(results, classifyLLQiii, threshold=0.8)
box_17 = prim_obj.find_box()
```

```
[MainProcess/INFO] 1000 points remaining, containing 250 cases of interest
[MainProcess/INFO] mean: 1.0, mass: 0.121, coverage: 0.484, density: 1.0 restricted_dimen
sions: 7

coverage       0.888
density     0.819188
mass           0.271
mean        0.819188
res dim            2
Name: 25, dtype: object

                                              box 25
                                                 min       max     qp values
Time difference automation and substitution 1.000615  1.543996  1.410008e-83
Sensitivity Unemployment reallocation       0.039109  0.999680  1.076388e-01
```



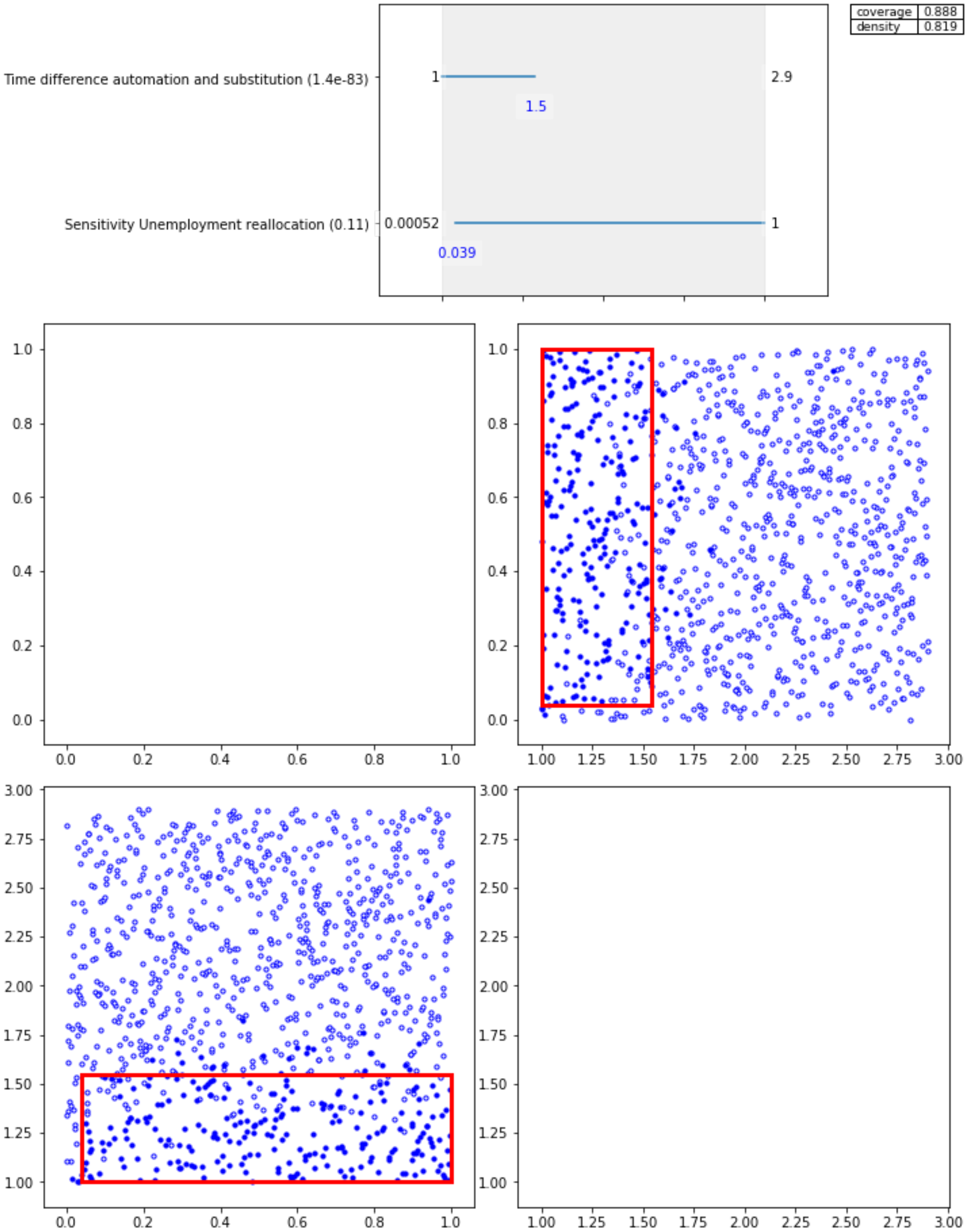


Figure 97 PRIM analysis $\xi_{\mathbb{L}}$ difference automatibility and substitution

Unemployment projection $\boldsymbol{\varepsilon}_{\mathbb{L}}$ upper quartile:

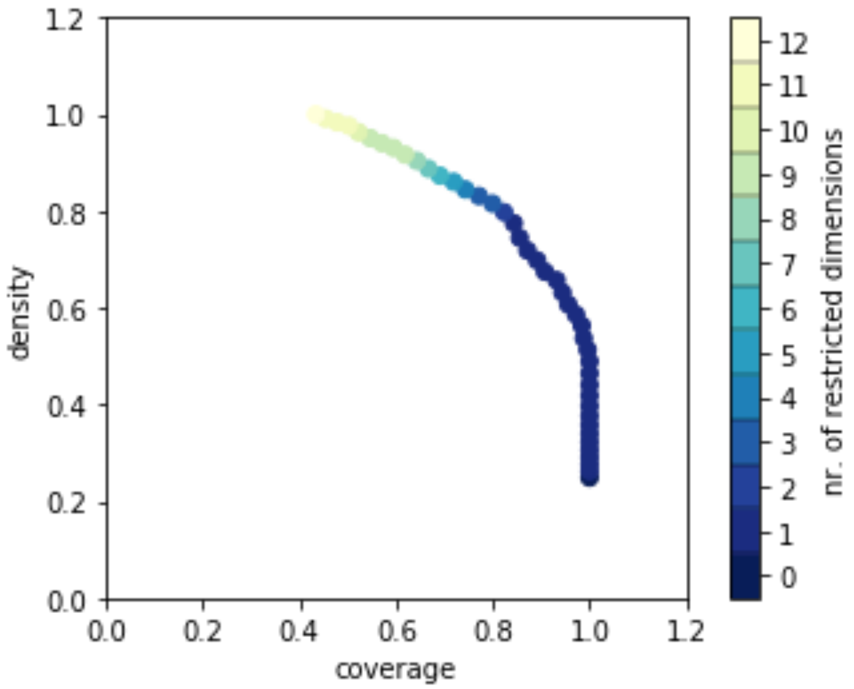
```
def classifyLIQiii(data):
    ooi = 'LI Avg ft Unemployment rate'
    outcome = np.mean(outcomes[ooi], axis=1)
    classes = np.zeros(outcome.shape[0])
    classes[outcome>0.0245] = 1
    return classes

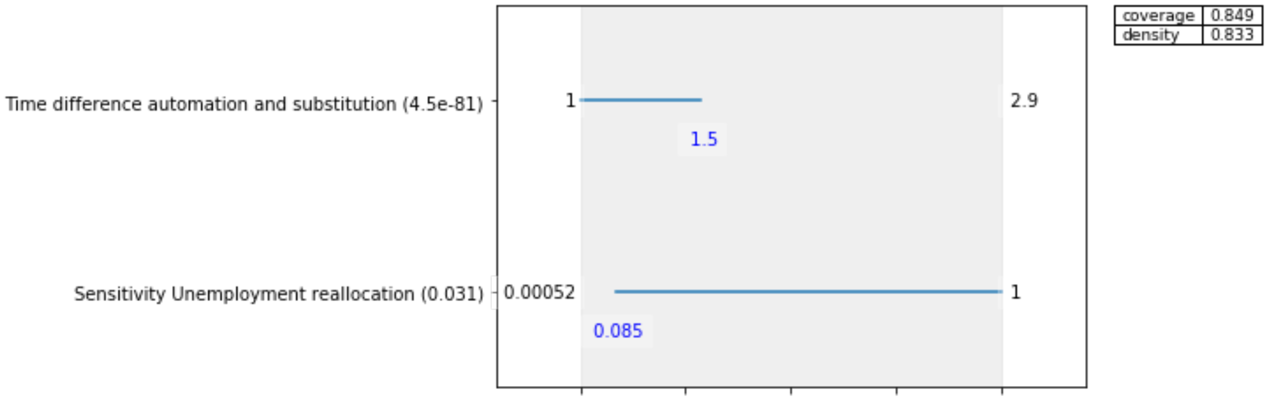
prim_obj = prim.setup_prim(results, classifyLIQiii, threshold=0.8)
box_18 = prim_obj.find_box()
```

```
[MainProcess/INFO] 1000 points remaining, containing 252 cases of interest
[MainProcess/INFO] mean: 1.0, mass: 0.108, coverage: 0.42857142857142855, density: 1.0 re
stricted_dimensions: 11

coverage    0.849206
density     0.832685
mass           0.257
mean        0.832685
res dim            2
Name: 26, dtype: object

                                            box 26
                                               min      max     qp values
Time difference automation and substitution 1.000615  1.54616  4.503108e-81
Sensitivity Unemployment reallocation       0.085413  0.99968  3.146181e-02
```





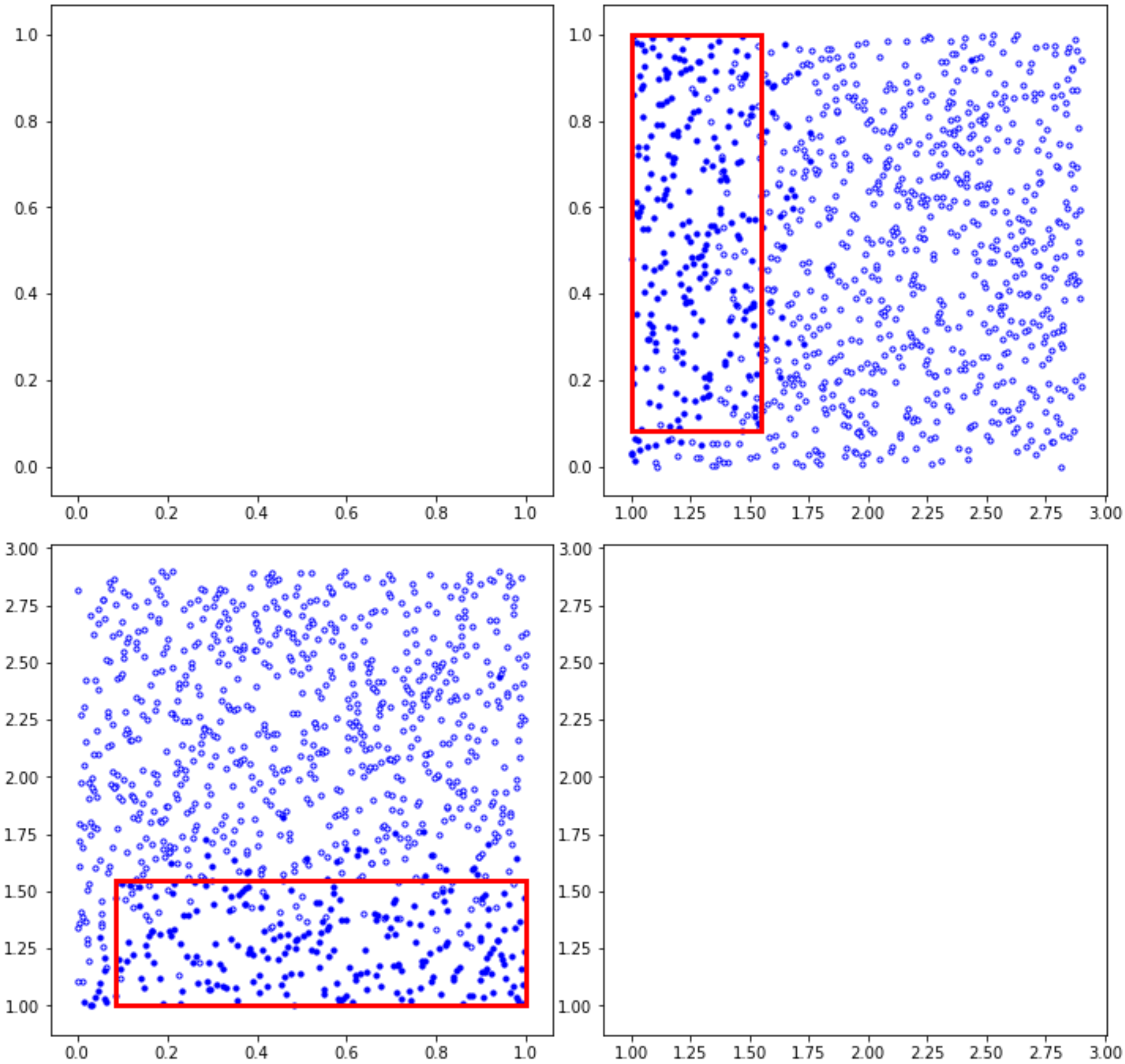


Figure 98 PRIM analysis $\varepsilon_{\mathbb{L}}$ difference automatibility and substitution

XIX Policy identification using PRIM

```
# Load data from prior simulation D
results = load_results('./EMA_NED_Uncertainty_D_Results.tar.gz')
experiments, outcomes= results
```

Unemployment projection $\xi_{\mathbb{H}}$ above current unemployment rate:

```
def classifyHLQiii(data):
    ooi = 'HL Avg ft Unemployment rate'
    outcome = np.mean(outcomes[ooi], axis=1)
    classes = np.zeros(outcome.shape[0])
    classes[outcome>0.03] = 1
    return classes

prim_obj = prim.setup_prim(results, classifyHLQiii, threshold=0.8)
box_13 = prim_obj.find_box()
```

```
[MainProcess/INFO] 1000 points remaining, containing 56 cases of interest
[MainProcess/INFO] box does not meet threshold criteria, value is 0.6981132075471698,
returning dump box
```

Unemployment projection $\varepsilon_{\mathbb{H}}$ above current unemployment rate:

```
def classifyHIQiii(data):
    ooi = 'HI Avg ft Unemployment rate'
    outcome = np.mean(outcomes[ooi], axis=1)
    classes = np.zeros(outcome.shape[0])
    classes[outcome>0.031] = 1
    return classes

prim_obj = prim.setup_prim(results, classifyHIQiii, threshold=0.8)
box_14 = prim_obj.find_box()
```

```
[MainProcess/INFO] 1000 points remaining, containing 49 cases of interest
[MainProcess/INFO] box does not meet threshold criteria, value is 0.5882352941176471,
returning dump box
```

Unemployment projection $\xi_{\mathbb{M}}$ above current unemployment rate:

```
def classifyMLQiii(data):
    ooi = 'ML Avg ft Unemployment rate'
    outcome = np.mean(outcomes[ooi], axis=1)
    classes = np.zeros(outcome.shape[0])
    classes[outcome>0.04] = 1
    return classes

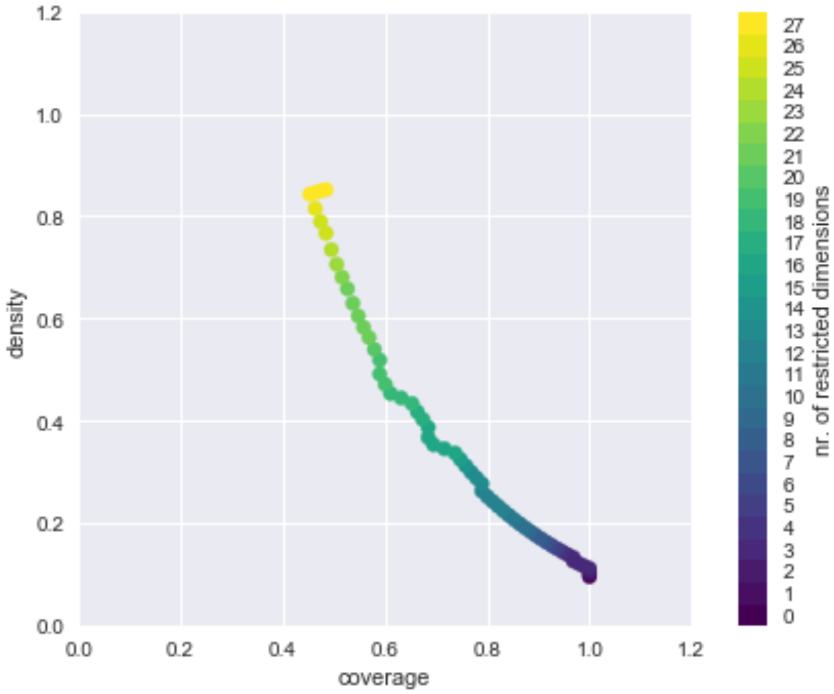
prim_obj = prim.setup_prim(results, classifyMLQiii, threshold=0.8)
box_15 = prim_obj.find_box()
```

```
[MainProcess/INFO] 1000 points remaining, containing 95 cases of interest
[MainProcess/INFO] mean: 0.8518518518518519, mass: 0.054, coverage: 0.4842105263157895, d
ensity: 0.8518518518518519 restricted_dimensions: 27.0

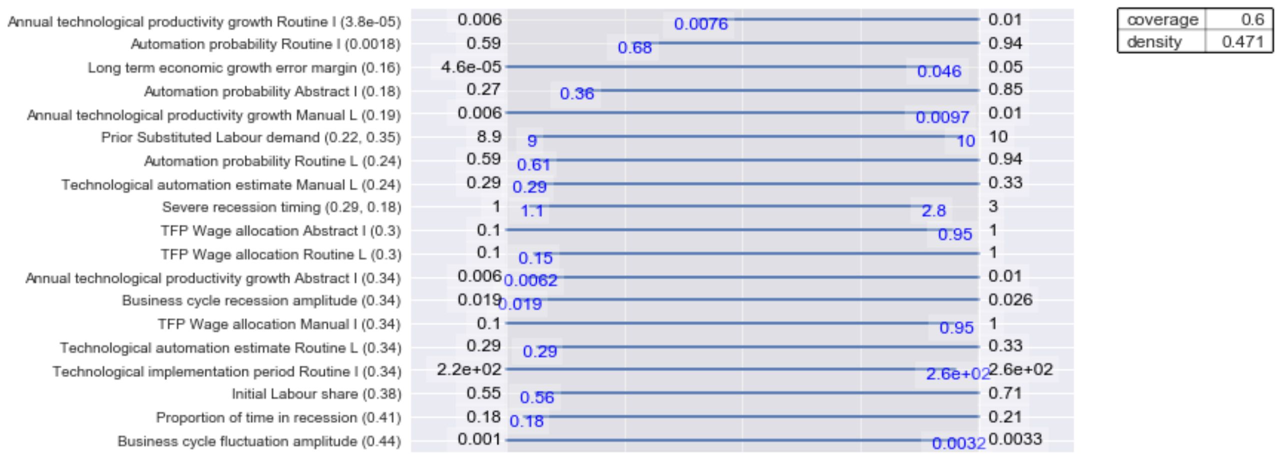
coverage     0.600000
density      0.471074
mass         0.121000
mean         0.471074
res dim     19.000000
Name: 40, dtype: float64
```

```
                                                         box 40             \
                                                            min         max
Annual technological productivity growth Routine I     0.007632    0.009996
Automation probability Routine I                       0.683871    0.939861
Long term economic growth error margin                 0.000046    0.045611
Automation probability Abstract I                      0.355404    0.849482
Annual technological productivity growth Manual L      0.006001    0.009678
Prior Substituted Labour demand                        8.959936   10.060589
Automation probability Routine L                       0.608982    0.939907
Technological automation estimate Manual L             0.290718    0.325997
Severe recession timing                                1.097678    2.801948
TFP Wage allocation Abstract I                         0.100633    0.950687
TFP Wage allocation Routine L                          0.152643    0.999727
Annual technological productivity growth Abstra...     0.006189    0.009997
Business cycle recession amplitude                     0.018881    0.026293
TFP Wage allocation Manual I                           0.100637    0.953010
Technological automation estimate Routine L            0.291463    0.325968
Technological implementation period Routine I        216.002765  261.598700
Initial Labour share                                   0.564019    0.713908
Proportion of time in recession                        0.181135    0.209988
Business cycle fluctuation amplitude                   0.001000    0.003194
```

```
                                                                             qp values
Annual technological productivity growth Routine I             [3.8050142979486015e-05]
Automation probability Routine I                                [0.0018069208436560914]
Long term economic growth error margin                            [0.15961805259070991]
Automation probability Abstract I                                 [0.17828506742856626]
Annual technological productivity growth Manual L                 [0.19021802605700544]
Prior Substituted Labour demand                 [0.21726847233185781, 0.34989446791197931]
Automation probability Routine L                                  [0.23949258065277512]
Technological automation estimate Manual L                        [0.23949258065277512]
Severe recession timing                         [0.28850355120341353, 0.17735991841584384]
TFP Wage allocation Abstract I                                    [0.29527888503483612]
TFP Wage allocation Routine L                                     [0.29527888503483612]
Annual technological productivity growth Abstra...                [0.34339715484332167]
Business cycle recession amplitude                                [0.34339715484332167]
TFP Wage allocation Manual I                                      [0.34339715484332167]
Technological automation estimate Routine L                       [0.34339715484332167]
Technological implementation period Routine I                     [0.34339715484332167]
Initial Labour share                                              [0.37914563133256918]
Proportion of time in recession                                   [0.40955403711056176]
Business cycle fluctuation amplitude                              [0.43540311297147538]
```



density
coverage
nr. of restricted dimensions



Annual technological productivity growth Routine I (3.8e-05) 0.006 0.0076 0.01
Automation probability Routine I (0.0018) 0.59 0.68 0.94
Long term economic growth error margin (0.16) 4.6e-05 0.046 0.05
Automation probability Abstract I (0.18) 0.27 0.36 0.85
Annual technological productivity growth Manual L (0.19) 0.006 0.0097 0.01
Prior Substituted Labour demand (0.22, 0.35) 8.9 9 10 10
Automation probability Routine L (0.24) 0.59 0.61 0.94
Technological automation estimate Manual L (0.24) 0.29 0.29 0.33
Severe recession timing (0.29, 0.18) 1 1.1 2.8 3
TFP Wage allocation Abstract I (0.3) 0.1 0.95 1
TFP Wage allocation Routine L (0.3) 0.1 0.15 1
Annual technological productivity growth Abstract I (0.34) 0.006 0.0062 0.01
Business cycle recession amplitude (0.34) 0.019 0.019 0.026
TFP Wage allocation Manual I (0.34) 0.1 0.95 1
Technological automation estimate Routine L (0.34) 0.29 0.29 0.33
Technological implementation period Routine I (0.34) 2.2e+02 2.6e+02 2.6e+02
Initial Labour share (0.38) 0.55 0.56 0.71
Proportion of time in recession (0.41) 0.18 0.18 0.21
Business cycle fluctuation amplitude (0.44) 0.001 0.0032 0.0033
coverage 0.6
density 0.471

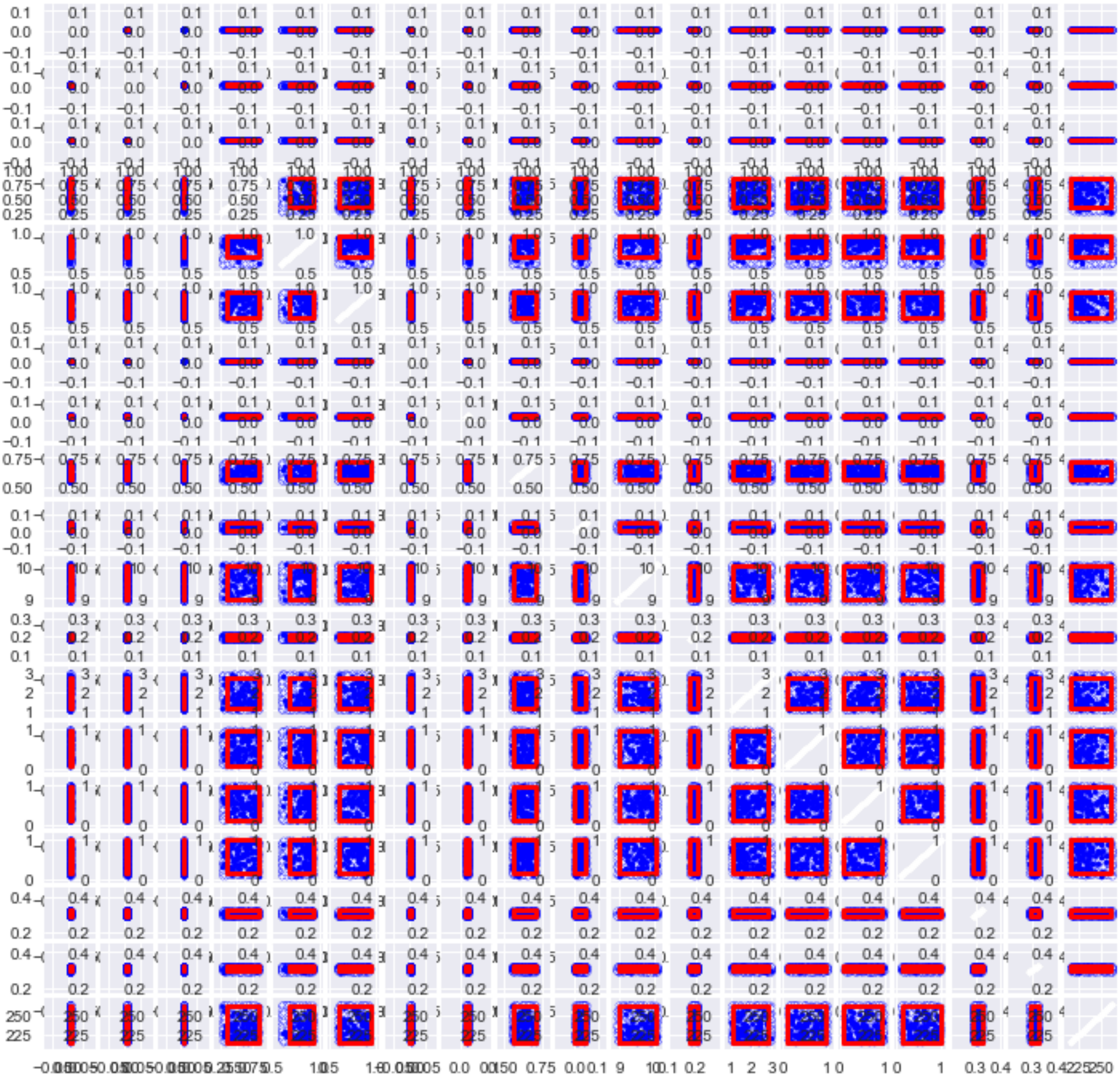


Figure 99 PRIM analysis $\xi_{\mathbb{M}}$ above current levels

Unemployment projection $\varepsilon_{\mathbb{M}}$ above current unemployment rate:

```
def classifyMIQiii(data):
    ooi = 'MI Avg ft Unemployment rate'
    outcome = np.mean(outcomes[ooi], axis=1)
    classes = np.zeros(outcome.shape[0])
    classes[outcome>0.044] = 1
    return classes

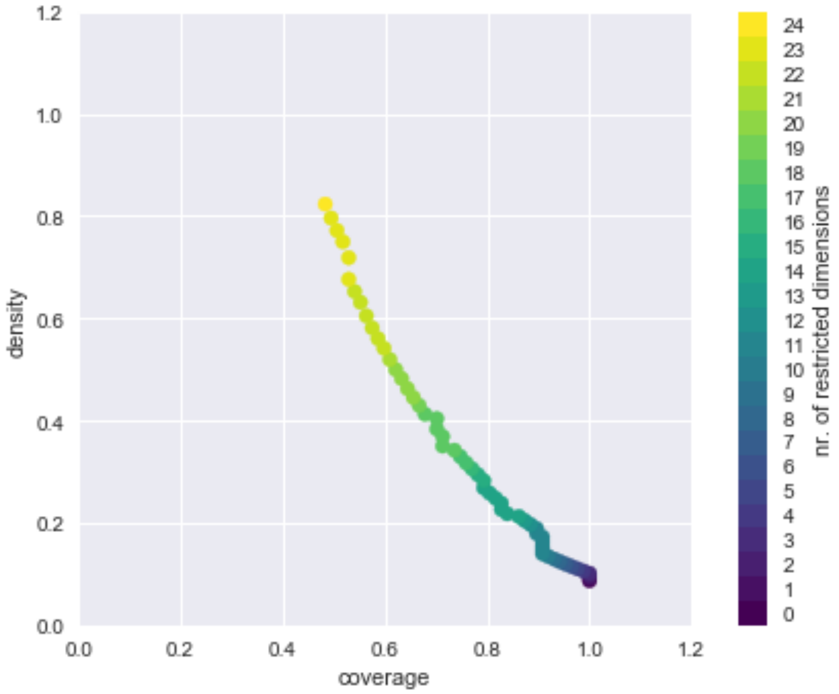
prim_obj = prim.setup_prim(results, classifyMIQiii, threshold=0.8)
box_16 = prim_obj.find_box()
```

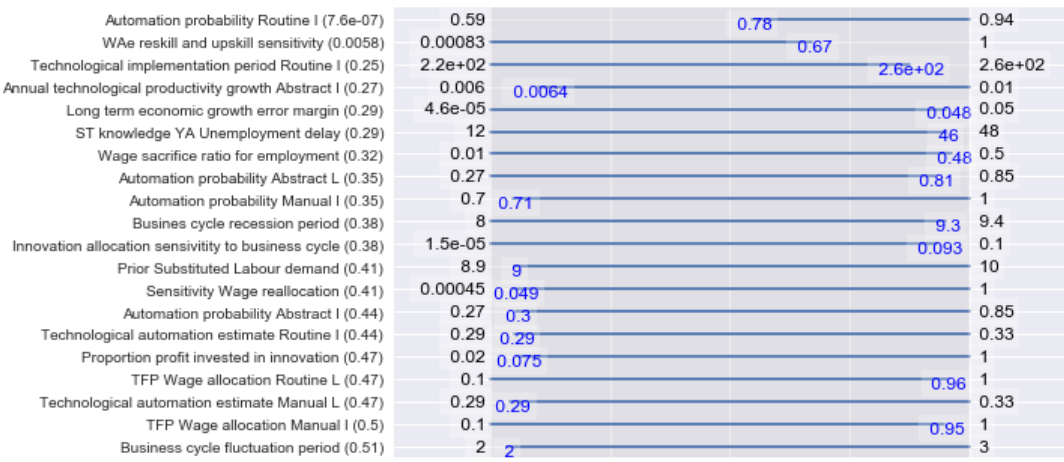
```
[MainProcess/INFO] 1000 points remaining, containing 87 cases of interest
[MainProcess/INFO] mean: 0.8235294117647058, mass: 0.051, coverage: 0.4827586206896552, d
ensity: 0.8235294117647058 restricted_dimensions: 24.0

coverage     0.643678
density      0.462810
mass         0.121000
mean         0.462810
res dim     20.000000
Name: 40, dtype: float64

                                                      box 40              \
                                                         min         max
Automation probability Routine I                    0.781185    0.939861
WAe reskill and upskill sensitivity                 0.000831    0.672794
Technological implementation period Routine I     216.002765  257.958970
Annual technological productivity growth Abstra...  0.006406    0.009997
Long term economic growth error margin              0.000046    0.047560
ST knowledge YA Unemployment delay                 12.005793   46.193910
Wage sacrifice ratio for employment                 0.010194    0.481831
Automation probability Abstract L                   0.270490    0.807617
Automation probability Manual I                     0.714833    0.999792
Busines cycle recession period                      8.000810    9.330986
Innovation allocation sensitivity to business c...  0.000015    0.093256
Prior Substituted Labour demand                     8.959936   10.099452
Sensitivity Wage reallocation                       0.048791    0.998587
Automation probability Abstract I                   0.302036    0.849482
Technological automation estimate Routine I         0.290889    0.325986
Proportion profit invested in innovation            0.075002    0.999886
TFP Wage allocation Routine L                       0.100300    0.957658
Technological automation estimate Manual L          0.290584    0.325997
TFP Wage allocation Manual I                        0.100637    0.953010
Business cycle fluctuation period                   2.034892    2.999754


                                                               qp values
Automation probability Routine I                    [7.6262870573139893e-07]
WAe reskill and upskill sensitivity                  [0.0057913569016311865]
Technological implementation period Routine I          [0.25099088840741879]
Annual technological productivity growth Abstra...      [0.2746151929361923]
Long term economic growth error margin                 [0.29189634508307105]
ST knowledge YA Unemployment delay                     [0.29189634508307105]
Wage sacrifice ratio for employment                    [0.31834764966236129]
Automation probability Abstract L                      [0.34616366712705604]
Automation probability Manual I                        [0.34616366712705604]
Busines cycle recession period                         [0.38259460853200095]
Innovation allocation sensitivity to business c...     [0.38259460853200095]
Prior Substituted Labour demand                        [0.40553868501845747]
Sensitivity Wage reallocation                          [0.40553868501845747]
Automation probability Abstract I                       [0.4435722266885947]
Technological automation estimate Routine I             [0.4435722266885947]
Proportion profit invested in innovation               [0.46906811942807586]
TFP Wage allocation Routine L                          [0.46906811942807586]
Technological automation estimate Manual L             [0.46906811942807586]
TFP Wage allocation Manual I                           [0.50198276681699128]
Business cycle fluctuation period                      [0.50781509150725501]
```





coverage	0.644
density	0.463

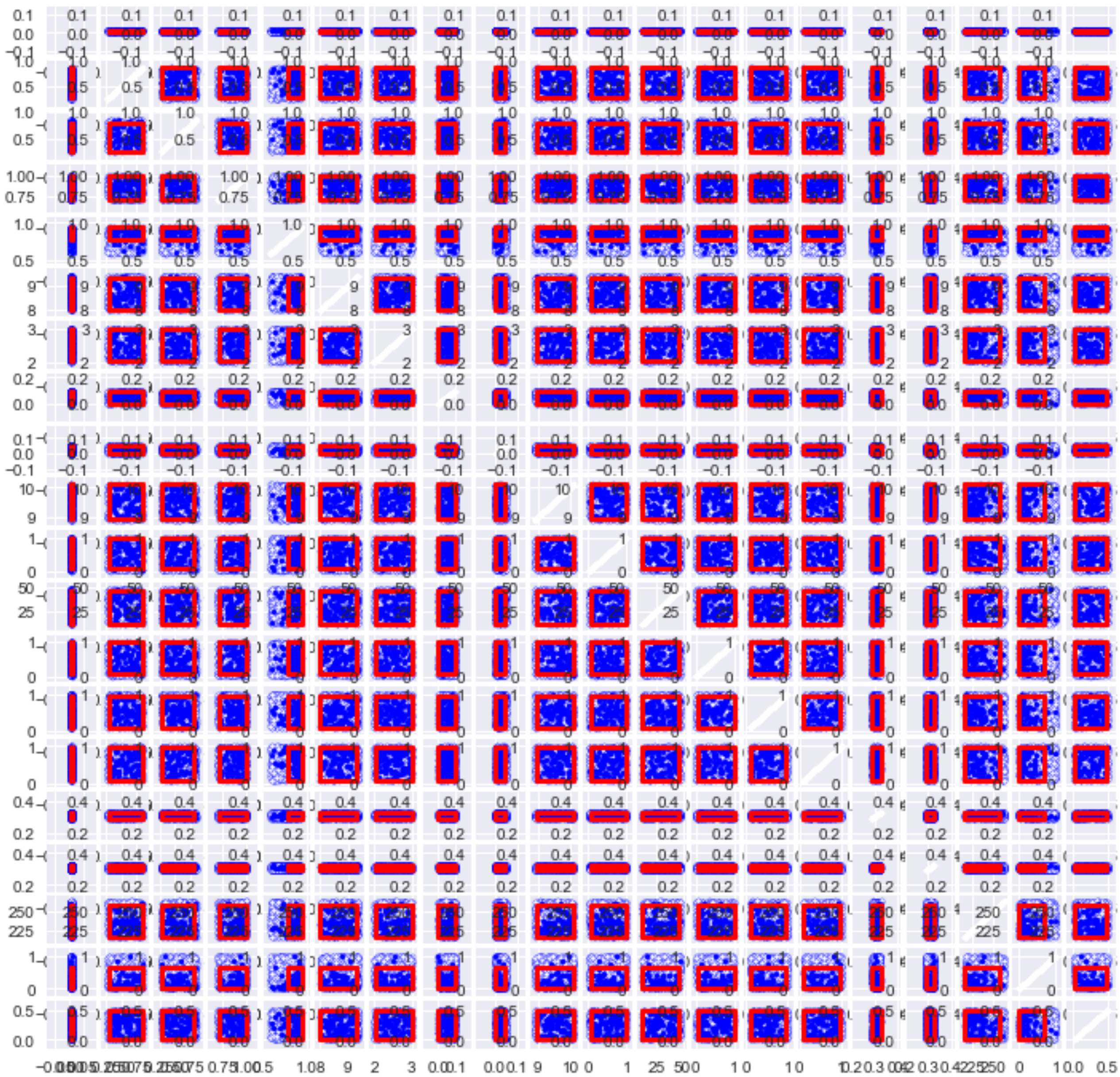


Figure 100 PRIM analysis $\varepsilon_{\mathbb{M}}$ above current levels

Unemployment projection $\xi_{\mathbb{L}}$ above current unemployment rate:

```
def classifyLLQiii(data):
    ooi = 'LL Avg ft Unemployment rate'
    outcome = np.mean(outcomes[ooi], axis=1)
    classes = np.zeros(outcome.shape[0])
    classes[outcome>0.057] = 1
    return classes

prim_obj = prim.setup_prim(results, classifyLLQiii, threshold=0.8)
box_17 = prim_obj.find_box()
```

```
[MainProcess/INFO] 1000 points remaining, containing 8 cases of interest
[MainProcess/INFO] box does not meet threshold criteria, value is 0.1568627450980392,
returning dump box
```

Unemployment projection $\varepsilon_{\mathbb{L}}$ above current unemployment rate:

```
def classifyLIQiii(data):
    ooi = 'LI Avg ft Unemployment rate'
    outcome = np.mean(outcomes[ooi], axis=1)
    classes = np.zeros(outcome.shape[0])
    classes[outcome>0.062] = 1
    return classes

prim_obj = prim.setup_prim(results, classifyLIQiii, threshold=0.8)
box_18 = prim_obj.find_box()
```

```
[MainProcess/INFO] 1000 points remaining, containing 22 cases of interest
[MainProcess/INFO] box does not meet threshold criteria, value is 0.43137254901960786,
returning dump box
```

Unemployment projection $\xi_{\mathbb{L}}$ above 4.4%:

```
def classifyMLQiii(data):
    ooi = 'ML Avg ft Unemployment rate'
    outcome = np.mean(outcomes[ooi], axis=1)
    classes = np.zeros(outcome.shape[0])
    classes[outcome>0.04] = 1
    return classes

prim_obj = prim.setup_prim(results, classifyMLQiii, threshold=0.8)
box_15 = prim_obj.find_box()
```

```
[MainProcess/INFO] 1000 points remaining, containing 71 cases of interest
[MainProcess/INFO] box does not meet threshold criteria, value is 0.7647058823529411,
returning dump box
```

Unemployment projection $\varepsilon_{\mathbb{L}}$ above 4.4%:

```
def classifyLIQiii(data):
    ooi = 'LI Avg ft Unemployment rate'
    outcome = np.mean(outcomes[ooi], axis=1)
    classes = np.zeros(outcome.shape[0])
    classes[outcome>0.044] = 1
    return classes

prim_obj = prim.setup_prim(results, classifyLIQiii, threshold=0.8)
box_18 = prim_obj.find_box()
```

```
[MainProcess/INFO] 1000 points remaining, containing 126 cases of interest
[MainProcess/INFO] mean: 0.8888888888888888, mass: 0.054, coverage: 0.38095238095238093,
density: 0.8888888888888888 restricted_dimensions: 20.0
```

```
coverage     0.531746
density      0.553719
mass         0.121000
mean         0.553719
res dim     19.000000
Name: 40, dtype: float64

                                                       box 40              \
                                                          min         max
Automation probability Routine I                     0.709061    0.939861
Sensitivity Unemployment reallocation                0.149963    0.999333
Annual technological productivity growth Routine I   0.007060    0.009996
Annual technological productivity growth Manual I    0.006754    0.009998
Long term economic growth error margin               0.000046    0.044690
Severe recession amplitude                           0.048909    0.061682
Technological implementation period Routine I      216.002765  259.532197
Annual technological productivity growth Routine L   0.006462    0.009996
Busines cycle recession period                       8.000810    9.320788
Automation probability Routine L                     0.624285    0.939907
Prior Substituted Labour demand                      8.950159   10.099452
Technological automation estimate Abstract I         0.001009    0.009679
Time to first recession                              2.000247    4.813135
Automation probability Abstract I                    0.307839    0.849482
Automation probability Manual I                      0.716043    0.999792
Business cycle fluctuation amplitude                 0.001136    0.003298
Proportion profit invested in innovation             0.071908    0.999886
Severe recession timing                              1.000202    2.847944
Technological implementation period Routine L      216.012360  261.080522


                                                                 qp values
Automation probability Routine I                   [0.00030945735256699265]
Sensitivity Unemployment reallocation                [0.058973902827156054]
Annual technological productivity growth Routine I   [0.062038942017225505]
Annual technological productivity growth Manual I    [0.083047499063817601]
Long term economic growth error margin                [0.12071046217367233]
Severe recession amplitude                             [0.1376266672011956]
Technological implementation period Routine I          [0.1376266672011956]
Annual technological productivity growth Routine L    [0.17769608074628518]
Busines cycle recession period                        [0.22597566811403683]
Automation probability Routine L                      [0.25122120744552068]
Prior Substituted Labour demand                       [0.25330315876209308]
Technological automation estimate Abstract I           [0.2800676982070277]
Time to first recession                               [0.34370697565259112]
Automation probability Abstract I                     [0.37827396196537283]
Automation probability Manual I                       [0.37827396196537283]
Business cycle fluctuation amplitude                   [0.3830439837037683]
Proportion profit invested in innovation              [0.41444326758262595]
Severe recession timing                               [0.41444326758262595]
Technological implementation period Routine L         [0.45825700509347367]
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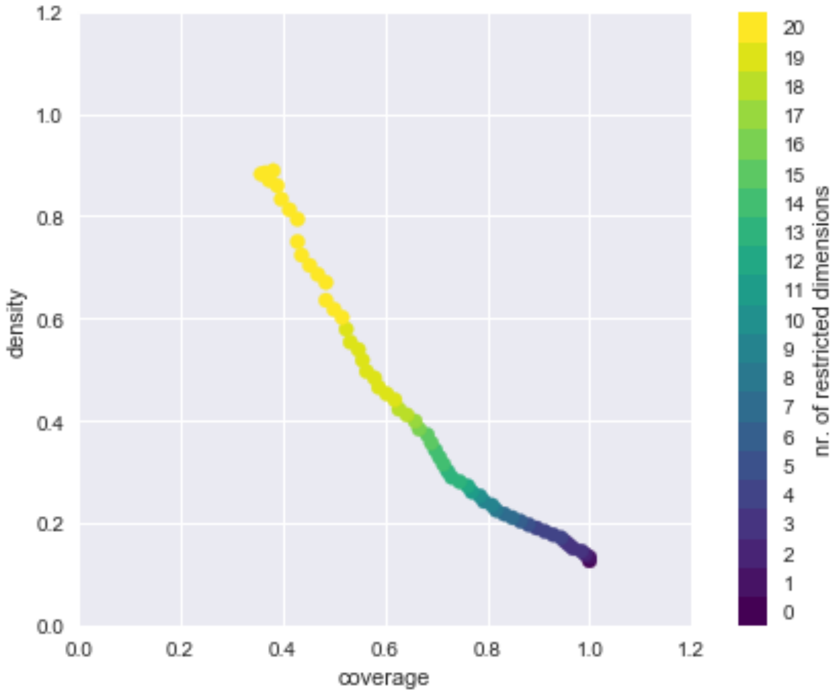

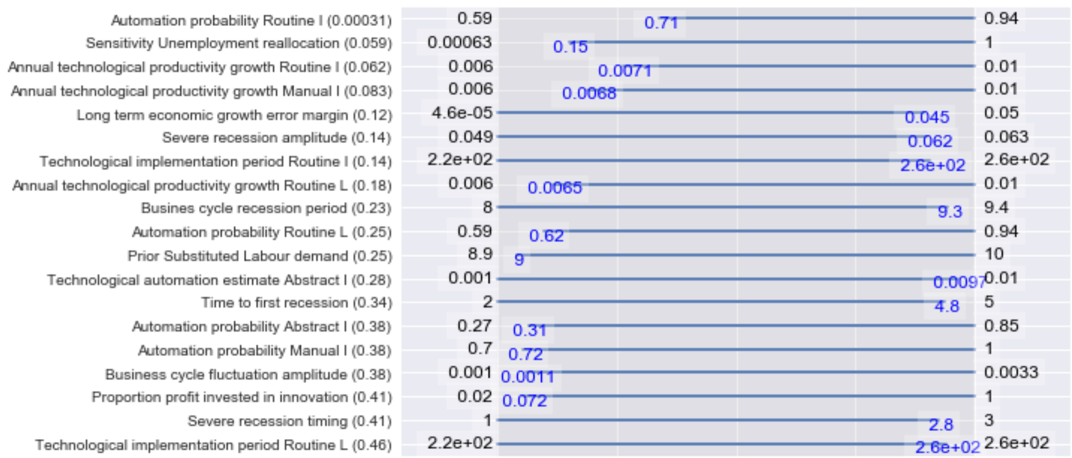

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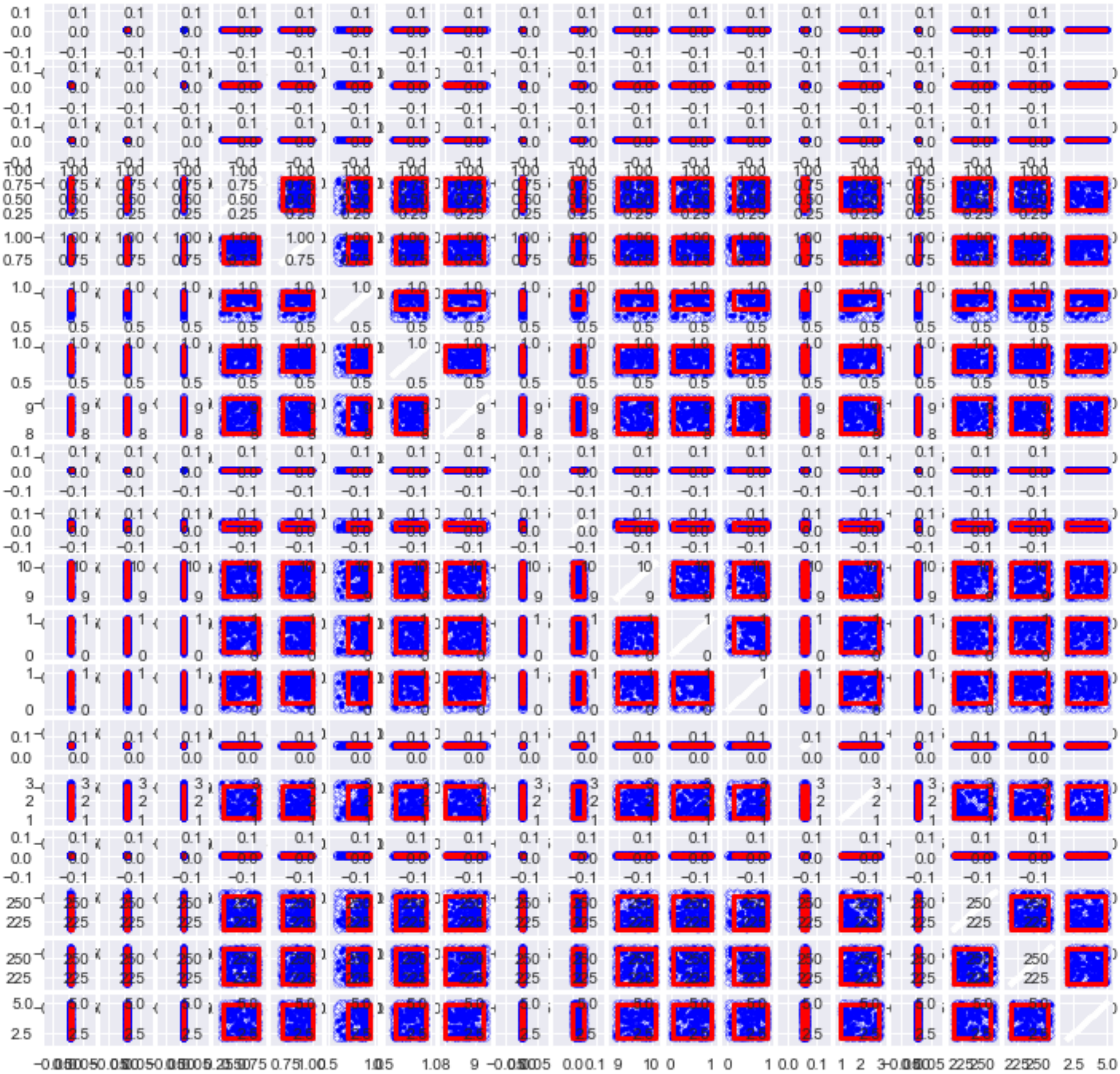

Figure 101 PRIM analysis $\varepsilon_{\mathbb{M}}$ unemployment upper quartile

XX Required Re- and up-skilling

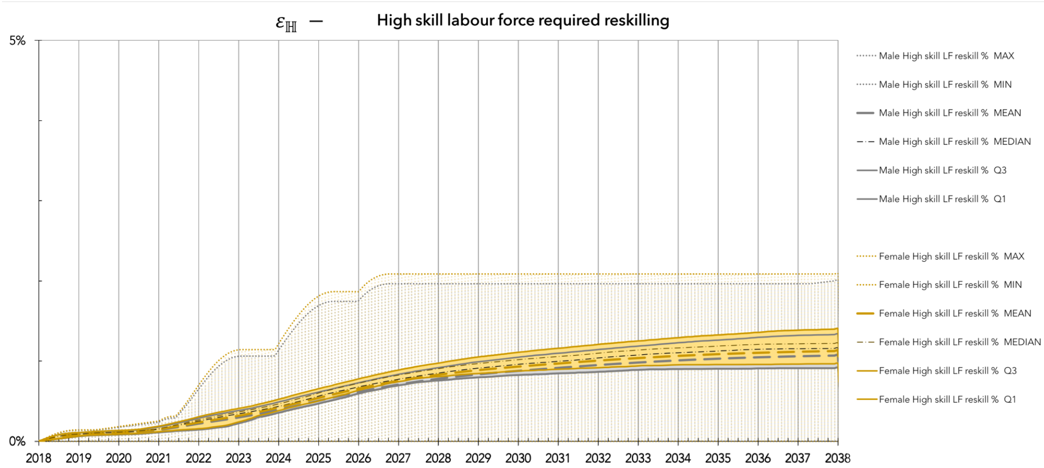

Figure 102 Re-skill projections $\varepsilon_{\mathbb{H}}$ labour force

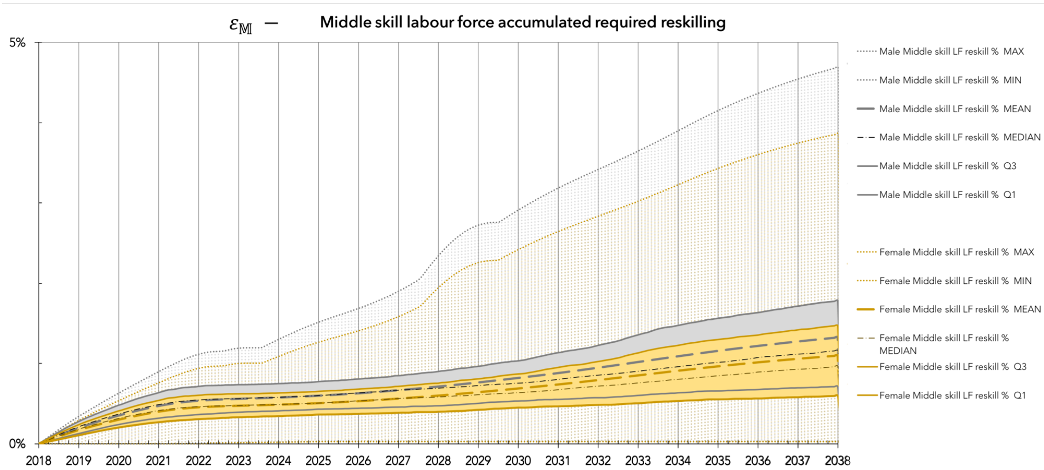

Figure 103 Re-skill projections $\varepsilon_{\mathbb{M}}$ labour force

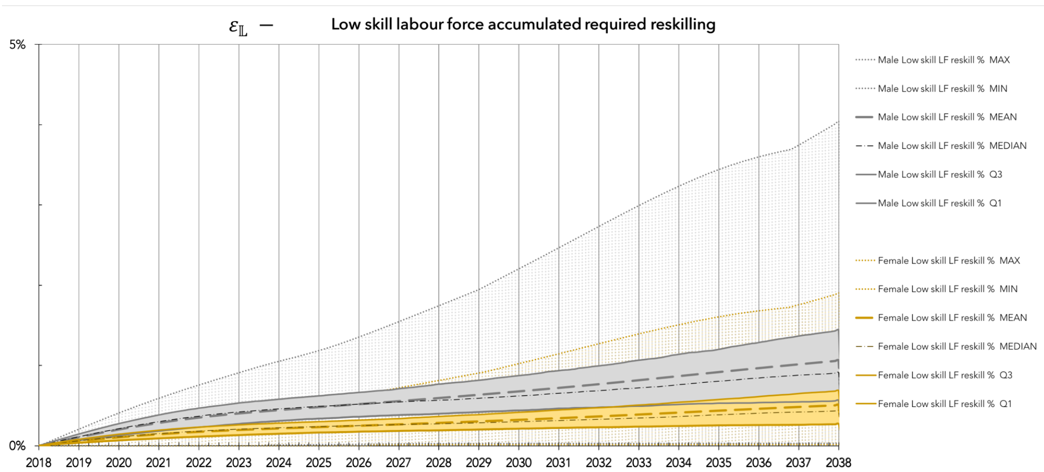

Figure 104 Re-skill projections $\varepsilon_{\mathbb{L}}$ labour force

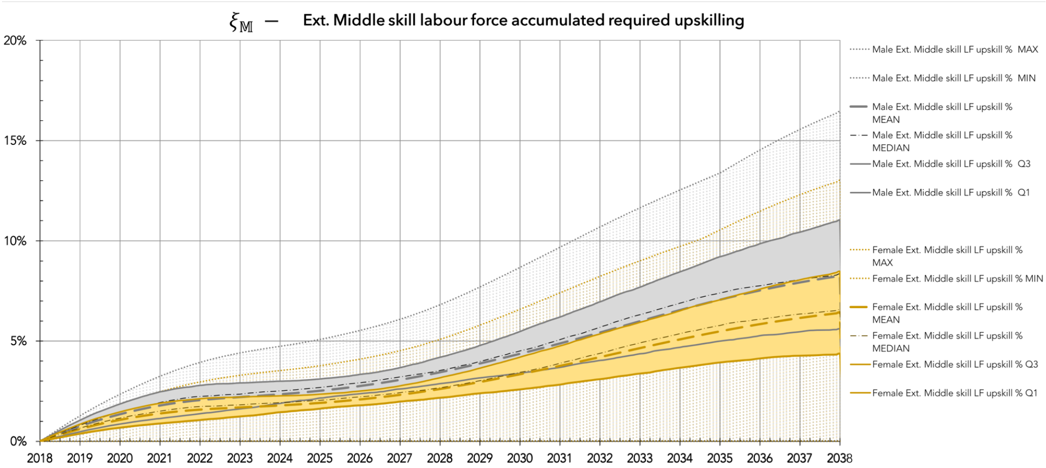

Figure 105 Up-skill projections $\xi_{\mathbb{M}}$ labour force

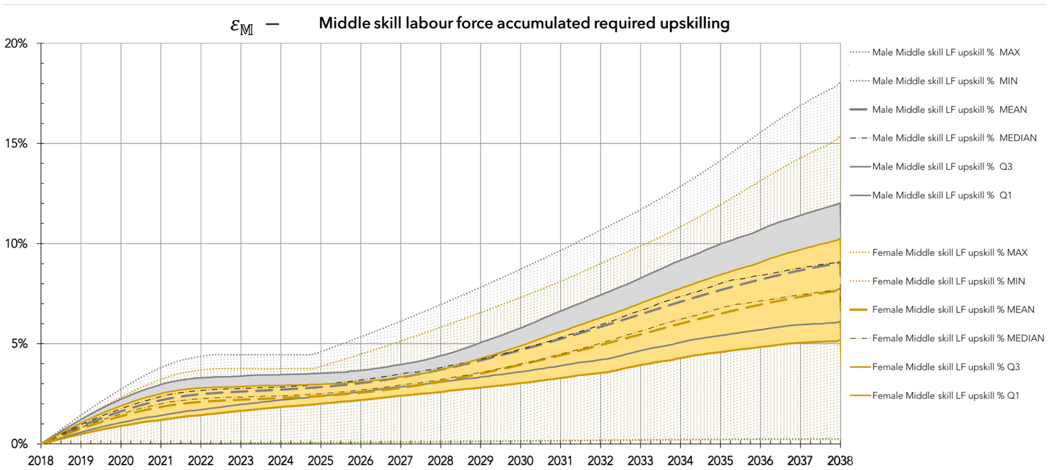

Figure 106 Up-skill projections $\varepsilon_{\mathbb{M}}$ labour force

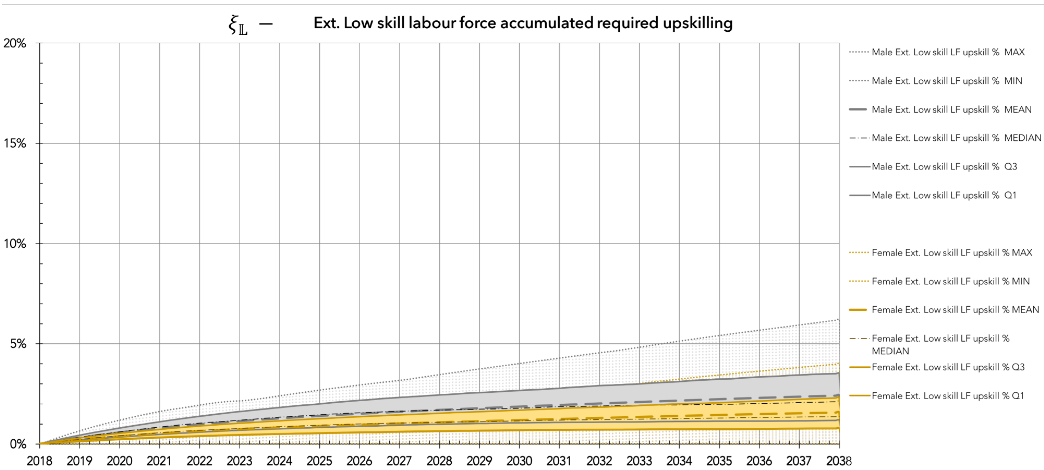

Figure 107 Up-skill projections $\xi_{\mathbb{L}}$ labour force

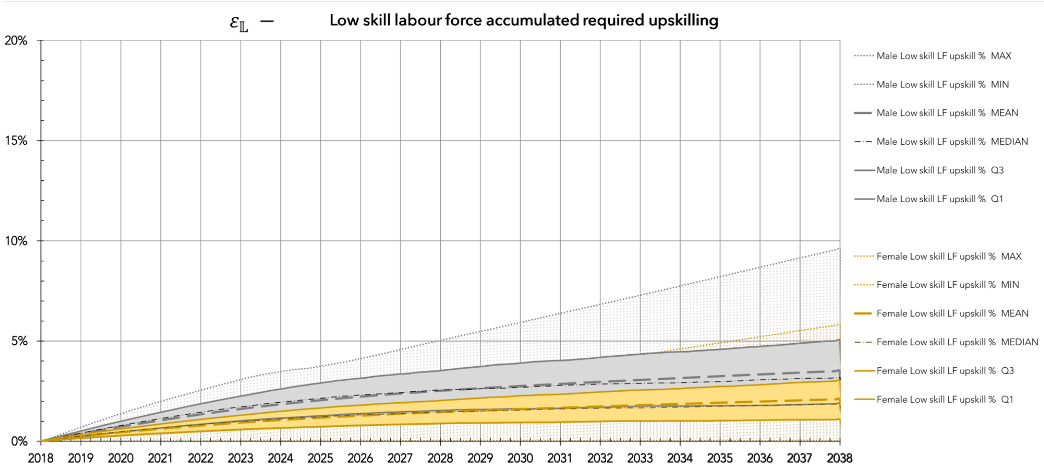

Figure 108 Up-skill projections $\varepsilon_{\mathbb{L}}$ labour force