From Investment to Innovation

Modelling India's path to high-income status

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From Investment to Innovation: Modelling India's path to high-income status

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Executive summary

Of all 108 middle-income countries from 1990, only 34 have currently developed into high-income countries. As the majority of people living in poverty reside in middle-income countries, these countries hold the key to improving global living standards. India aims to escape the middle-income range and has set out a mission to reach high-income status in 2047 in its *Viksit Bharat* plan.

However, India's growth rate has started to decline, and an increasing number of economists and politicians fear that India is headed for a middle-income trap; a growth slowdown in the middle-income range. This phenomenon has been studied extensively, but not using a System Dynamics (SD) approach. With his thesis, I have aimed to fill this knowledge gap and to deliver valuable insights for India's path to full development. Discovering new knowledge on the middle-income trap contributes to the United Nations' Sustainable Development Goals, which are an important part of my Engineering and Policy Analysis (EPA) program.

Modelling India's way to high-income status was done using the World Bank's 3i strategy, a three-step method that recommends countries to use methods of investment, infusion and innovation to develop from a lower-middle-income country into an upper-middle-income and later a high-income country. This strategy was modelled in SD to answer the research question: *How can India use the 3i strategy to avoid growth stagnation and achieve high-income status in 2047?*

The first step in answering this question was the conduct of a literature review. Although the exact definition of the middle-income range and the duration a country needs to spend in it to be defined as "trapped" differ, the overall definition of the middle-income trap was identified to be a state in which the country is squeezed between two competitors. Low-income countries can dominate labour-intensive industries through their low-wage advantage, while high-income countries dominate in more innovative and technological sectors, as they are further developed and more productive than middle-income countries. Economic growth rates in middle-income countries decline because they fail to make a switch from a strategy of imitation to one of innovation, as they often have few educated workers and little access to advanced infrastructure and foreign financing.

The importance of these factors is confirmed by empirical research, which also points to unfavourable demographic factors and high growth rates in the past as determinants of a growth stagnation. Countries that have 'escaped' the middle-income trap managed to do so by investing adequately in innovation and education, and experienced the greatest returns to R&D investments. European middle-income countries were often supported to develop into high-income countries through the benefits of their European Union memberships.

To gain knowledge on how the middle-income trap could be modelled in SD, different growth models were studied. The Solow model's exogenous growth (Solow, 1956) makes it unfit for purpose, while features from the models from Romer (1990), Jones (1995), Lucas (1988) and Aghion and Howitt (1998) could be used to model endogenous productivity growth.

India's economy was modelled in SD, which describes relationships between factors using stocks and flows. In SD, results from actions produce reactions, which impact new actions. This is called *feedback*. When a parameter's current value (indirectly) determines its future value, there is a *feedback loop*. Feedback loops are a key part of systems thinking; they often feature delays and can either be reinforcing or balancing.

To build confidence in the model outcomes for those not involved in the model construction and justify recommendations, the model was validated using structural and behavioural validation

tests from Forrester and Senge (1980).
The simulation outcomes were analysed using Robust Decision Making methods. By performing an uncertainty analysis, a scenario discovery through the Patient Rule Induction Method (PRIM) and an optimisation, the models' dynamics under deep uncertainty were studied, to give recommendations on India's path to high-income status. This was done using the Exploratory Modelling and Analysis (EMA) Workbench, a Python library.
The SD model, which was built in Vensim (Ventana Systems, 2010), consists of a labour force and a physical capital stock which determine the output in a Cobb-Douglas function. The total factor productivity determines how effectively these inputs are converted into economic output and is determined endogenously. Productivity growth occurs via knowledge spillovers from Foreign Direct Investment (FDI) and knowledge gains from Research and Development (R&D) efforts. Foreign investment is attracted by high human capital values, high infrastructure quality, low wages, high GDP and high GDP growth. India's absorptive capacity and the technological distance between India and the global technological frontier determine the amount of spillovers as a result of the foreign investment.
The amount of knowledge gained from R&D is determined by the size of the R&D labour force, which depends on the available budget and the availability of highly educated workers. Total factor productivity and the Human Capital Index, determined by the average number of schooling years per worker and the quality of education, determine output per worker.
Simulating the model returns a GDP of 22 trillion US$ by 2047, which would not be enough for India to achieve its Viksit Bharat target. As a consequence of the low R&D budget, productivity growth declines after 2040, causing GDP growth to do the same. Throughout the simulation, R&D becomes an even greater driver of productivity growth, as returns to FDI decrease. Because of the closing technological distance, the productivity growth generated per unit of FDI declines, while the increasing total factor productivity and Human Capital Index cause the productivity growth per researcher to grow continuously.
The uncertainty analysis showed a large outcome range for GDP. Because of a reinforcing feedback loop, in which increased productivity growth leads to even more productivity growth as a result of increased R&D output, relatively small differences in parameter values can lead to great differences in final GDP. While in most cases, the amount of spillovers from FDI decreases over time, it increases in some experiments where R&D productivity is relatively low.
Feature scoring, which measures the importance of variable changes in the determination of outcome values, showed the importance of R&D costs for the determination of GDP. This is supported by PRIM results, in which a subrange in the uncertainty space was discovered where a high share of successful experiments are located as a result of low R&D costs. Therefore, a second analysis was performed in which the R&D investment rate was increased from 0.6 to 0.65%. This resulted in a higher share of experiments in which India achieves its 2047 goal, which confirms the importance of adequate investment in innovation.
Performing a budget optimisation led to different results for the short term and long term. To produce the highest GDP in the Viksit Bharat year 2047, India must invest heavily in infrastructure. This directly adds to GDP via the Cobb-Douglas function, but also increases productivity growth via FDI spillovers. However, when optimising for GDP in 2075, the analysis found that investing in education is the most important. Decreasing returns on infrastructure investment make it a less suitable investment for long-term growth, while the results of education investments have a significant impact in the long run. This insight matches existing theory and is the most important finding of this research.
Overall, the outcomes of this study match the expectations set by economic theory and other studies, which also discovered education and innovation as the two most important drivers of

growth towards high-income status. Compared to some studies, the importance of FDI-driven productivity growth in this research's outcomes is relatively low, which could have impacted the optimisation results.

Determining more variable values within the model would have led to more realistic results; they are now kept constant to save time. This is also why Institutional quality was not included in the model. While SD offered valuable insights into the dynamics between different growth drivers, the method also offered limited options for policy recommendations, as I was not able to recommend specific tax rates or subsidies that would lead to an optimal outcome.

Furthermore, the model has a lot of strengths; it was validated in multiple ways, produces outcomes that match economic theory and other studies and is understandable and relatively easily reproduced. Using SD enabled me to gather insight into important feedback loops. The different budget allocations for the short term and long term indicate a dilemma for policymakers and decision makers: while education investments are the best option for the long term, infrastructure investment leads to more immediate results, which is why some policymakers may opt to invest in infrastructure. In the future, the model could be expanded by adding Institutional Quality as a determinant of productivity growth and by using investment rates that change over time. The latter could be optimised to create a policy roadmap for middle-income countries.

Overall, India's target of reaching full development by 2047 is assessed as overly ambitious. The chances of still achieving the target could be increased by investing in infrastructure, but for optimal long-term growth, education investment is recommended. This is the main outcome of this research.

In the conclusion, the research questions are answered. The middle-income trap is defined as a situation in which middle-income countries struggle to generate growth because they cannot compete with the low wages of low-income countries and the more developed high-income countries. In the middle-income range, the roles of growth drivers change: the returns to conventional input accumulation decrease, which is why growth must be generated by increasing productivity growth. This happens through FDI knowledge spillovers and R&D efforts. Because of the closing technological distance, the latter becomes the main driver of growth in the higher middle-income range. For optimal output, investment in education and R&D is recommended; this has the most impact in the long term.

This research adds to the current stock of knowledge on the middle-income trap, as the outcomes confirm the conclusions from existing studies. The use of System Dynamics has allowed me to make estimations on India's future growth patterns, which could be useful to policymakers in combination with existing knowledge. By further expanding the model, more insights about how investment rates should change over time can be given to support India in its path towards full development.

Preface

This thesis marks the completion of my Master's degree in Engineering and Policy Analysis or EPA at the Delft University of Technology. The research presented here examines India's challenges in achieving high-income status and seeks to identify an optimal budget allocation strategy to maximise long-term economic growth. This topic caught my attention immediately. I have always been interested in foreign countries and their development, and this research connects well to my elective courses. I am grateful that I got to apply what I have learned in the past years on this subject, and to have discovered outcomes that match my expectations and existing knowledge on the middle-income trap.

I would like to express my gratitude to my supervisors Cees van Beers, Roman Stöllinger and Willem Auping, for their continuous support and constructive feedback throughout this project. I also extend my thanks to the faculty of Technology and Policy Management for the past two years in which I have been a part of EPA, and to my family and close friends who have supported me during this project.

This research was conducted from February to August 2025 in Delft, the Netherlands.

Jeroen van Til

Delft, August 12th, 2025

Use of AI Tools

Throughout this thesis project, Artificial Intelligence (AI) was used to offer support in creating formulas, finding scientific papers and for writing purposes. For the literature review, ChatGPT was used to summarise scientific papers and scan them for information about specific subjects, and to find relevant papers, if searching on Google Scholar did not lead to satisfactory results. During the construction of the model, ChatGPT was used to find data, to find existing formulas and to help me create new formulas. In cases where formulas were not linear, I would ask ChatGPT for instructions on how I could model certain relationships, such as decreasing returns to investments. The outputs from ChatGPT were never simply copied and pasted into the model; the chatbot was used to give inspiration and offer an overview of the possible ways in which I could model certain relationships.

During the model analysis, I have used ChatGPT to help me solve Python errors or to help me extract specific data from a large dictionary of results. The scripts are not written by ChatGPT, I did this myself with help from the examples from previous courses and the website of the EMA Workbench.

Finally, I have used the Grammarly browser extension and ChatGPT to correct spelling errors and reformulate (parts of) sentences. With the help of AI, Grammarly scans the text and highlights words or sentences that contain errors or that can be improved. ChatGPT was used to rephrase short sections of text to improve clarity. Outputs were never copied; the chatbot was solely used to gather inspiration. The outputs were always reviewed and edited to maintain academic integrity.

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List of Abbreviations

AI Artificial Intelligence. vii

BRICS Brazil, Russia, India, China and South Africa. 6

EMA Exploratory Modelling and Analysis. vii, 23

EPA Engineering and Policy Analysis. 1, 2, 40

FDI Foreign Direct Investment. x, xi, 5, 6, 15–18, 20, 21, 26–29, 31, 34, 36–38, 41, 42, 53, 68, 69, 73, 79, 81

GDP Gross Domestic Product. x, xi, 1, 3, 4, 7, 9, 13–20, 23, 25–39, 41, 51, 68, 71, 79

HCI Human Capital Index. 19, 30

HLO Harmonized Learning Outcome. 19, 30

LFPR Labour Force Participation Rate. 18

PRIM Patient Rule Induction Method. xi, xii, 12, 13, 23, 32, 33, 76–78

R&D Research and Development. x, xi, 5–10, 13–17, 20–22, 26–41, 54, 63, 69, 74, 81

SD System Dynamics. 1, 3, 4, 7, 10, 11, 15, 23, 38–40, 42

STEM Science, Technology, Engineering and Mathematics. 6, 22, 40, 41

TFP Total Factor Productivity. 7

1 Introduction

Since 1990, only 34 countries in the middle-income range have developed into high-income countries. The remaining 108 did not; they have stayed in the middle-income range. As a result, three-fourths of the global population live in a middle-income country. Of all people living in extreme poverty, two-thirds have a middle-income country as their home (World Bank, 2024c). These countries hold the key to improving global living standards; it is therefore crucial to discover what is holding back their economic development.

India, the most populous (middle-income) country on the planet, has great ambitions to leave the middle-income range. In their '*Viksit Bharat*' plan, the national government has set out a mission for India to become a fully developed and high-income country by 2047 (Jacob, 2024). Specifically, this would mean that poverty has vanished, that education standards, women's employment and healthcare quality have significantly improved, and that India produces a Gross Domestic Product (GDP) of 30 trillion US$ (Dhumne, 2025).

However, India's ambitions are met with serious challenges. To achieve the Viksit Bharat target, India's GDP must increase yearly by 7.9% for the coming 22 years (Shrok & Ghosh, 2024). Achieving this would be difficult, especially given that India's growth in the fiscal year 2024-2025 is expected to be around 6.5% (Ministry of Statistics and Programme Implementation, 2025), which would indicate that India's economy is slowing down. Moreover, India experiences significant problems in its development: the transition from low-productivity to high-productivity sectors has been relatively slow, and the average employment rate remains low compared to other middle-income countries (World Bank, 2025). Therefore, more and more economists and politicians fear that India is headed for a so-called *middle-income trap* (Biswas, 2024; Sharma, 2025).

The middle-income trap has become a popular term to describe a country's slowed-down growth in the middle-income range, of which the causes are still disputed. Many fingers point towards diminishing returns on physical capital investments (Agénor, 2016), while others (Daude, 2010; Eichengreen et al., 2013) blame meagre human capital as the limiting factor for economic convergence towards more developed countries. Aiyar et al. (2013) identify institutional quality, demographic factors and infrastructure quality among the determinants of middle-income range growth stagnation. Limited access to finance also plays a role in growth slowdowns (Agénor & Canuto, 2017).

To get a clearer image of India's future perspective, it is crucial to explore how, together, these factors could cause a growth slowdown. Because these factors not only impact economic growth, but also the size of other determinants of economic growth, the interactions between them can help to explain the dynamics of the middle-income trap. System Dynamics (SD) modelling would be the ideal method to study those relationships; its models use feedback and delays to explain the complex system behaviour (Forrester, 1958) and excel in capturing dynamic complexity and simulating scenarios for policy testing (Rahmandad & Sterman, 2012; Sterman, 2000). For a complex system such as a national economy, SD modelling would be a suitable way to explore how, for instance, delayed human capital growth impacts productivity growth, or what demographic factors can impact access to finance, to paint a complete picture of India's situation.

However, very little work on the middle-income trap uses SD as their method of choice, as many researchers use regression or growth accounting techniques. Other than Hryhoriev (2024), who analyses the effects of national economic recessions on the probability of falling into a middle-income trap, there are no publications about SD studies on the middle-income trap, which indicates a gap in the literature.

As part of my master's program Engineering and Policy Analysis (EPA) at the Delft University

of Technology, I have aimed to fill this knowledge gap on the middle-income trap by performing a case study of India. SD modelling is one of the modelling techniques that is taught in this program, which makes it a suitable method for an EPA thesis. The newly discovered knowledge can be of great value to the achievement of the United Nations' seventeen Sustainable Development Goals. Achieving these goals is part of the United Nations' Grand Challenges, which are a key feature of the EPA program. New insights on the mechanics behind the Middle-Income Trap would lead to more *Decent Work and Economic Growth* (goal 8), and can also play a role in achieving many of the other sixteen goals, such as *No Poverty*, *Quality Education* and *Industry, Innovation and Infrastructure* (United Nations, n.d.).
To model India's path to high-income, the 3i strategy of the World Bank (2024c) was used as a framework. This is a three-step plan based on economic theory and academic research is designed to help middle-income countries reach high-income status through the three i's of investment, infusion and innovation. By *investing*, India can build a solid basis to later experience growth through the *infusion* of foreign technologies and *innovation* of new ones.

1.1 Research Question

In an SD approach, this study models the mechanisms that can lead to growth and stagnation in India, to answer the research question:

How can India use the 3i strategy to avoid growth stagnation and achieve high-income status in 2047?

This main question is broken down into three sub-questions to get a comprehensive insight into India's economic growth drivers.

1. *Why is maintaining growth difficult for a country in the middle-income range?*
   To get a good understanding of the middle-income trap, it is important to know what factors lead to slowed-down growth in middle-income countries and to understand the economic theory behind the middle-income trap. This is studied in the first sub-question
2. *How do the roles of economic growth drivers change over time for middle-income countries?*
   The 3i strategy recommends that middle-income countries change their productivity growth strategy throughout their development in the middle-income range, by adding methods of infusion and innovation to the initial strategy of investment. By understanding the changing roles of each growth driver, advice on the use of the 3i strategy can be given.
3. *How should the Indian government allocate its resources across different types of investments to maximise long-term economic growth?*
   By implementing the optimal budget allocation policy, India can make the best use of the 3i strategy. This sub-question is aimed at finding the budget allocation that leads to the highest economic output, to give insight into how the 3i strategy can be translated into economic policy.

1.2 Methodology

The first sub-question was aimed to learn more about the middle-income trap, and was answered through the conduct of a literature review on economic theory and scientific literature.
To get insight into strategies to escape the middle-income trap, the second sub-question was formulated to target the three i's of the 3i strategy. The literature review gives initial insights into this sub-question, which is ultimately answered based on the results of the SD-model. Here, the mechanisms behind the exhaustion of different growth drivers are discovered, and the

evolving roles of productivity drivers are evaluated.
Finally, the model and its outcomes were further analysed to find out how India can increase its chances of entering the high-income range by discovering the budget allocation that leads to the highest GDP. The literature review already gave insights into what such a budget allocation could look like, and the model aims to confirm these insights.
Together, these three sub-questions lead to the final conclusions and recommendations for India's path to high-income status.

1.3 Report Outline

This thesis report starts with a literature review, in which the middle-income trap, relevant growth models, the 3i strategy and the main drivers of economic growth are studied. Next, Chapter 3 will explain the SD modelling approach, as well as the model validation and analysis techniques. Chapter 4 then explains the structure of the built model and the experimental setup, and Chapter 5 showcases the results of both the regular runs and the uncertainty and optimisation runs. Finally, Chapter 6 discusses the quality and implications of the model results and Chapter 7 gives the concluding remarks.

2 Literature Review

To understand why the majority of the middle-income countries fail to reach high-income status and learn how this problem can be modelled in SD, existing literature on the middle-income trap and economic growth models was studied. The outcomes of the literature review answer the first sub-question and offer valuable insights that help to answer sub-questions 2 and 3.

2.1 Defining the Middle-Income Trap

The Middle-Income Trap is mentioned for the first time in *An East Asian Renaissance: Ideas for Economic Growth*, introducing the problem of slowed-down growth in middle-income countries. In the book, Gill and Kharas (2007) propose development strategies to combat the domestic side-effects of the rapid growth that East Asia experienced during the decades before. When introducing the term, the researchers addressed the problem that the middle-income countries were squeezed between low-income countries that could dominate mature industries because of their low-wage advantage, and high-income countries that could dominate in more innovative and technological sectors. Countries entering the middle-income range lose their low-wage advantages that allowed them to dominate in labour-intensive industries, and are not developed enough to compete with high-income countries in innovative sectors. Since the first mention, the middle-income trap has become a popular term among researchers and policymakers, as over 1300 articles in Google Scholar include the exact words in their titles.

Since the introduction of the term, researchers have come up with varying measurements to classify when countries are "stuck in the middle-income range". Felipe et al. (2012), for instance, propose a split into a lower and an upper middle-income range, and introduce periods of 28 and 14 years, respectively, to develop from that range into the next income range. If countries do not manage to do so, they *"fall into"* the lower- or upper-middle-income trap. Woo et al. (2012) do not split the middle-income range in two, and use a period of fifty years as a threshold for being trapped,

The time a country must spend in the middle-income range to be qualified as "stuck" is not the only point on which definitions vary; the size of the middle-income range is also disputed. Many authors, such as Felipe et al. (2012) and Aiyar et al. (2013), refer to the World Bank's middle-income range that is updated yearly. Currently, middle-income countries are defined as countries with a per capita income between $1136 and $13845 USD in the fiscal year of 2024 (World Bank, 2024b). Woo et al. (2012) and Robertson et al. (2013) do not use absolutes to define the middle-income range. Instead, they define it as per capita income relative to the United States, using ranges of 20 to 55% and 8 to 36% of the American GDP per capita, respectively.

The lack of a consistent definition of the middle-income trap does not worry the term's inventors; they are glad the problem has become more well-known. When reflecting on what has happened since introducing the middle-income trap, Gill and Kharas (2015) write that to them *"the middle-income trap was more the absence of a satisfactory growth theory that could inform development policy in middle-income economies than the articulation of a generalised development phenomenon. It was a trap of ignorance about the nature of economic growth in middle-income countries"*. Therefore, it is crucial to study what determines growth stagnation or economic flourishing in middle-income countries.

2.1.1 Growth Stagnation

According to Glawe and Wagner (2016), two main theories occur in economic literature to explain why growth stagnation occurs in the middle-income range. They are focused on the exhaustion of a previous growth driver, which is either the shifting of labour or low-wage imitation. The first theory is related to the Lewis model (Lewis, 1954), which describes how output growth is a result of shifting labour from the traditional agricultural sector to the modern industrial sector, where wages and marginal productivity are higher. Middle-income countries have already shifted their labour force towards more productive sectors, and can no longer experience productivity gains from this method.

The second theory names labour-intensive low-wage imitation as the earlier driver of economic growth. As wages in middle-income countries have become too high to manufacture cheap imitations of products from developed countries, the middle-income countries experience lower economic growth.

The middle-income trap has also been studied empirically to discover factors responsible for economic growth and stagnation. Eichengreen et al. (2012) identify high growth rates in the past and unfavourable demographics among determining factors for a growth slowdown. Jimenez et al. (2012) emphasise the importance of educational quality, which is confirmed by Agénor (2016), who points to a lack of access towards advanced infrastructure and finance as other key causes. Little access to advanced infrastructure hinders knowledge spillovers and limits productivity.

2.1.2 Escaping the Middle-Income Trap

The countries that managed to escape the middle-income trap are opposites of the stagnating ones. They have attracted more foreign investors (Galvan et al., 2022) and a higher share of secondary and tertiary education graduates (Eichengreen et al., 2013). They have made a timely shift from a strategy of imitation to one of innovation, and promote high-value-added sectors (Glawe & Wagner, 2016). To get the most out of their innovation, they have built strong and transparent institutions, which ensure the rule of law and reduce corruption (Gill & Kharas, 2007; Glawe & Wagner, 2016). Hartmann et al. (2021) points to specific skill development and improved access to international knowledge as determinants for growth in the middle-income range.

The list of escapees of the middle-income trap includes mostly countries from Europe and East Asia, as many case studies can be found about countries such as Ireland, Hungary, Singapore, Taiwan and South Korea.

Feitosa (2020) describes how South Korea became a high-income country by making investments in innovation and learning. Specifically, direct investments in Research and Development (R&D), technical training and advanced infrastructure are mentioned as important growth drivers. Moreover, the author describes how Korea could not rely on conventional factor accumulation of capital and labour and the inflow of Foreign Direct Investment (FDI) to maintain economic growth. The World Bank (2024c) confirms South Korea's success, writing that "*Korea's growth was powered by a potent mix of high investment rates and infusion, aided by an industrial policy that encouraged firms to adopt foreign technologies*".

Oppositely, Cherif and Hasanov (2016) explain how Malaysia struggles to turn into a high-income country, as they are too focused on conventional factor accumulation, FDI-led manufacturing and limited R&D spending.

Furthermore, European countries such as Hungary and Poland benefited strongly from their European Union membership, which led to financial benefits and higher economic growth.

2.2 The 3i Strategy

Based on economic theory and scientific research, the World Bank (2024c) proposed the 3i strategy in its *World Development Report 2024* to explain how countries can develop from the middle to the high-income range. This strategy consists of three phases, *1i*, *2i* and *3i*.

1i phase

Countries that have just reached middle-income status must have a strategy of accelerated investment to support future growth. By investing in infrastructure, education and the strengthening of institutions to ensure economic stability and the enforcement of laws, these countries create a solid basis to attract foreign and domestic investors. The 1i phase alone is not sufficient to achieve high-income status, because returns to investments decrease. Therefore, after some time, developing countries must implement a *2i* strategy that focuses on both investment and the infusion of foreign technologies.

2i phase

In the 2i phase, middle-income countries increase their productivity by adding *"measures to infuse modern technologies and successful business processes from around the world into their national economies"*. By importing foreign technologies and processes and diffusing them domestically, middle-income countries can experience knowledge spillover effects, which boost productivity.

Foreign technologies and processes can be "imported" by attracting FDI. For Brazil, Russia, India, China and South Africa (BRICS), the inflow of foreign investment is determined by market size, infrastructure quality and trade openness (Asongu et al., 2018). Islam and Beloucif (2023) endorse this, and name labour costs, economic prospects and human capital as other important predictors of FDI attraction.

The success of the 2i phase is determined by the domestic ability to consume and apply new knowledge. Cohen and Levinthal (1989) introduced the term *absorptive capacity* for this, arguing that firms can only experience knowledge spillovers when they can absorb and apply that knowledge. When considering an economy rather than a single firm, Nelson and Phelps (1966) argue that education enhances an economy's ability to adopt new technologies. Educated workers, especially those working in management, are quicker to implement new technologies and experience more productivity growth. As the economy grows, the returns to education increase because the demand for educated workers rises.

The size of the spillover effects is determined by the gap between foreign and domestic productivity, which Gerschenkron (1966) describes as *Economic Backwardness.* Countries that industrialise later can achieve faster economic growth by learning from the experiences and innovations of more advanced economies that have already industrialised. Gerschenkron observed that less-developed countries had an advantage of backwardness, as their delayed development allowed them to bypass certain stages of development by learning from other countries.

3i phase

Finally, in the upper middle-income range, developing countries switch to a 3i strategy by adding a strategy of innovation via R&D. By investing in R&D capacity, strengthening intellectual property rights and promoting Science, Technology, Engineering and Mathematics (STEM) fields to new students, middle-income countries can develop original innovations and sustain their growth towards high-income status (World Bank, 2024c).

Implementing R&D in the upper-middle income range is a strategy that matches scientific evidence. The R&D expenses of firms are known to increase productivity (Mansfield, 1968; Minasian, 1962; Terleckyj, 1974). Their returns follow an inverted U-curve: they are the highest for countries in the upper-middle-income range. Less developed countries lack the infrastructure, knowledge and institutions to create greater returns, while higher-developed countries have

become too advanced to be able to benefit from basic R&D, the innovations needed to create similar productivity gains are more complex, high-risk and time-consuming (Cirera & Maloney, 2017).
The need for adequate infrastructure and knowledge makes it difficult for middle-income countries to switch to a strategy of innovation, as building infrastructure and improving education standards takes time. It is therefore important to make timely investments in these sectors. If investments are made too late, a slowdown occurs.

2.3 Economic Growth Models

To discover how middle-income countries and the 3i strategy can be modelled in SD, I have reviewed existing economic growth models that simulate the effects of investments, infusion and innovation.

2.3.1 Solow Growth Model

In 1956, Robert Solow introduced a new framework that explains economic growth based on capital accumulation, labour force growth, and technological progress (Solow, 1956). The model uses the Cobb-Douglas (Cobb & Douglas, 1928) production function:

$$Y(t) = AK(t)^{\alpha}L(t)^{1-\alpha} \tag{2.1}$$

In this formula, Y represents economic output or GDP, A represents Total Factor Productivity (TFP), K represents capital, L represents the labour force size and α represents the output elasticity of capital, which measures how much impact a change in capital has on total output. For example, an elasticity of 0.6 indicates that a 1% change in capital leads to a 0.6% change in GDP (Solow, 1956).
Each year, a share of the output, the savings rate s, is used to purchase new capital. However, capital also depreciates annually at a rate δ. This leads to the equation of capital accumulation:

$$\frac{dK}{dt} = sY(t) - \delta K(t) \tag{2.2}$$

As the capital stock increases, the returns to adding one more unit of capital decline over time, which eventually leads to a state of equilibrium where depreciation is equal to investment, and the capital stock per worker stays constant. The diminishing returns to capital investment imply that long-term growth must come from technological progress (increasing A), which in this model is assumed to be exogenous (Acemoglu, 2009). This makes the Solow model unfit for modelling developing countries, which develop through endogenous productivity growth.

2.3.2 Endogenous Growth from R&D

In Romer's endogenous growth model (Romer, 1990), productivity growth is determined endogenously, through R&D efforts. Total factor productivity growth $\dot{A}$ is determined in the following way.

$$\dot{A}(t) = \delta * A(t) * L_A \tag{2.3}$$

Here, δ represents the efficiency of R&D, L_A is the labour force allocated to R&D, and A is the current total factor productivity. Solving this differential equation gives:

$$A(t) = A(0) * e^{\delta L_A t} \tag{2.4}$$

This formula implies that government policies focused on education and R&D can lead to long-term economic growth, because they increase the R&D labour force size and the productivity of researchers.
Later, Jones (1995) made a small adjustment to this model, as he discovered evidence that there are decreasing returns to expanding the R&D labour force. Doubling the number of researchers did, in most cases, not lead to a doubling of productivity growth rate $\dot{A}/A$, and creating significant productivity gains was found to become more difficult when productivity is already at a high level. By introducing elasticity values, the formula changed to:

$$\dot{A}(t) = \delta * L_A(t)^\lambda * A(t)^\phi \tag{2.5}$$

Here, elasticities λ and ϕ are lower than 1, indicating decreasing returns. This means that to maintain constant productivity growth, the size of L_A must increase at a constant positive rate.

2.3.3 Lucas Model

In the Lucas Model, the total output is determined by capital and effective labour, measured as *human capital*. This is a popular term in modern economics introduced by Schultz (1961), who argued that investments in training, education and health boost an individual's productivity. Similar to investments in physical capital, investments in human capital can lead to economic growth. In their report, the World Bank (2024c) often emphasises its importance.
Lucas determines economic output in a Cobb-Douglas style function:

$$Y(t) = A * K(t)^\alpha (u * h(t) * L(t))^{1-\alpha} \tag{2.6}$$

Here, u is the share of an individual's time allocated to work rather than education by each individual in the labour force, and h is the human capital level per worker, which grows endogenously:

$$\dot{h}(t) = \delta * (1 - u) * h(t) \tag{2.7}$$

Here, δ is the productivity of education, measuring how effectively time spent learning contributes to human capital. $(1 - u)$ is the individual's time allocated to learning new skills. Policies encouraging workers to spend time learning have a positive impact on growth in this model. By optimising δ and setting conditions in which individuals can afford to allocate more time to learning and less to working, economic growth is created.
While A is assumed to be constant, the Lucas model can still be classified as an endogenous growth model, as human capital accumulation leads to more productive conversion of inputs into economic output (Lucas, 1988).

2.3.4 Aghion and Howitt's model

Before fixating on innovation as a driver of economic growth, the World Bank (2024c) advises middle-income countries to focus on the infusion of existing foreign technologies to boost productivity. This happens in the Aghion and Howitt (1998) model, where productivity growth depends on both innovation and imitation. This model is an open economy model in which economic growth is influenced by the productivity of a foreign country.

$$\dot{A}(t) = \delta * R_D + \mu * (\frac{A^*(t)}{A(t)} - 1) \tag{2.8}$$

Here, δ is the efficiency of R&D, R_D is the R&D effort or investment, μ is the imitation intensity, $A^*(t)$ is the total factor productivity at the technological frontier and $A(t)$ is the domestic total factor productivity. This formula implies Gerschenkron's backwardness; less developed countries can experience greater productivity gains and catch up with the global technological leaders, as the second part of the sum is higher for them. The rate of catching up depends on the imitation intensity, which is decided by trade openness and absorptive capacity (Aghion & Howitt, 1998).

To simulate the effect of investment, infusion and innovation, the SD model consists of elements from all of these economic growth models, which together, determine the GDP.

3 Methods

The model used for this research was built using an SD approach, in which stocks, flows, and delays describe relationships between different variables. The analysis of the model outcomes was done using Robust Decision Making methods, such as uncertainty analysis, scenario discovery and optimisation.

3.1 System Dynamics

System Dynamics is a methodological framework designed to understand the behaviour of complex systems over time. SD focuses on the internal feedback structures within systems and how their interactions generate specific behaviour. In this research, the outcomes of the model give insight into the changing roles of economic growth drivers, while the analysis methods aim to find the optimal budget allocation policy for India. This way, sub-questions 2 and 3 are answered.

3.1.1 Stocks and Flows

When modelling in SD, one uses stocks and flows, see Figure 1. The stock is an integration, of which the value changes because of the inflows and outflows that happen over time (Forrester, 1958). They behave in the following way:

$$s(t) = s(t_0) + \int_{t_0}^{t} inflow(t) - outflow(t)dt \tag{3.1}$$

SD applications, such as Vensim (Ventana Systems, 2010), use integration techniques such as Euler (Euler, 1768) and Runge-Kutta 4 (Kutta, 1901; Runge, 1895) to solve integrations.

3.1.2 Feedback Loops

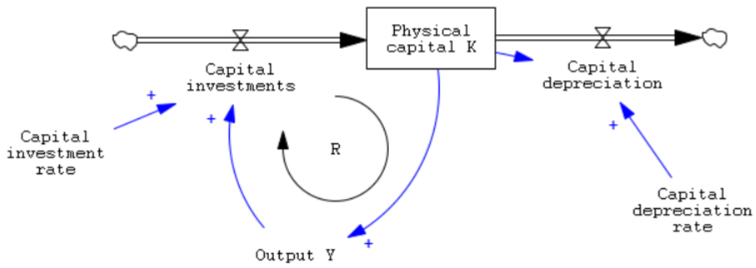
Rather than taking a linear approach, in which an action leads to a result and nothing more, SD modellers view problems from a systems thinking perspective, in which the consequences of actions lead to new actions, leading to new results and possibly unexpected and undesired effects. The results produce *feedback*, which indicates that there is a two-way causality between the action and the results (Forrester, 1958). The action affects the outcome, and the outcome also affects future actions.

Feedback loops can either be *reinforcing* or *balancing* (Roberts, 1978), as shown in Figure 1, in which the type of feedback loop is indicated with an R or B. In a reinforcing feedback loop, a variable increase will eventually lead to an additional increase in that same variable. This happens on the left side, where capital investments lead to a higher capital stock (indicated by the inflowing arrow), leading to a higher output, which enables the government to spend more on capital. The second feedback loop is balancing: Having more R&D workers leads to higher productivity gains, which leads to a higher output, which then leads to higher wages for R&D workers, meaning that the workforce shrinks in case the budget remains constant.

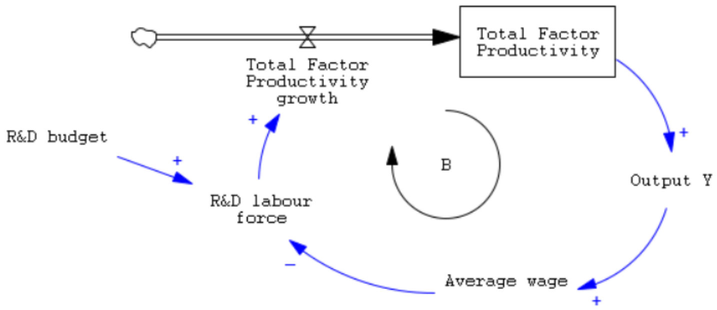
3.1.3 Delays and non-linearity

The addition of an inflow to the total stock value does not always happen immediately; it can also be delayed. In Figure 1, this is indicated by the hourglass figure on the flow arrows.

Delayed flows, for instance, occur in population models. In these models, the population is split up into a population of interfertile children (0-15y), a fertile population (15-45y) and an infertile adult population (45+). The three population groups are all stocks, and the total population



(a) Reinforcing feedback loop



(b) Balancing feedback loop

Figure 1: Examples of different types of feedback loops

increases through the birth of children, which is an inflow to the stock of children. Fifteen years later, these children will become part of the fertile population. The flow from the children stock to the fertile population stock will be the delayed value of the births of fifteen years ago. This leads to a feedback loop that needs at least 15 years to arise: increased birth rates lead to higher birth rates much later, when the previous newborns have become fertile adults.
In systems thinking, systems are not assumed to be linear but rather complex. Contrary to many models in economic literature, SD systems do not always reach an equilibrium state, but can be unstable and oscillating (Forrester, 1961). The non-linearity, as well as the delays and feedback loops, make the systems modelled in SD too complex to be able to predict its outcomes without a computer (Sterman, 1994).

3.1.4 Advantages of using System Dynamics

SD is a suitable method for modelling India's economy, as it can be used to capture the feedback between sub-systems of the economy. Also, it can handle non-linear interactions and delays, key parts of macroeconomic behaviour. According to Forrester (1961), these mechanisms are at the core of economic systems, making no method more suitable for modelling dynamic economies over time.
Furthermore, SD is ideal for mid- to long-term economic planning, enabling modellers to capture structural trends in behaviour rather than short-term shocks (Sterman, 2000).
Finally, the effect of policies and their performance in different scenarios can be simulated in SD. Feedback can be used to make polices adaptive, for instance by letting it depend on budget availability.

3.1.5 Model validation

To justify recommendations and build confidence in the model for persons who were not involved in the construction of the model, the model was validated according to Forrester and Senge (1980). These authors propose a selection of tests to validate model structure and behaviour. Structure validating tests indicate how well the model's structure represents the real-world system, while behaviour validation tests whether the model output matches real-world data and known patterns.

3.2 Model Analysis and Strategy Optimisation

The analysis of the model behaviour and its validation were done using Robust Decision Making methods. By defining objectives, exploring scenarios, detecting vulnerabilities and testing policies, these methods support decision making in deep uncertainty; situations where there are no reliable predictions or agreed-upon probabilities for future outcomes (Lempert, 2019). As there is no general consensus on whether India's target of full development by 2047 will be achieved, these methods suit the problem.

3.2.1 Uncertainty analysis

To discover the outcome range of the model simulation, the uncertainty ranges of all constants were determined. Using sampling techniques, scenarios with different parameter values were created to discover the minimum and maximum outcome values. Analysing the outcome range gives insight into the effects of a policy and helps to understand the model dynamics by analysing outcome sensitivity to variable changes.
The latter was done using the *Feature scoring* method, which ranks the relative importance of a variable for a specified outcome. The score between 0 and 1 indicates by which degree a variable's value determines the outcome value (Kwakkel, 2017). These importance scores show the outcome's sensitivity to parameter changes and indicate which variable values can be influenced by a policy to get the desired outcome.

3.2.2 Scenario Discovery

The optimal scenarios for the achievement of the Viksit Bharat target were identified using the Patient Rule Induction Method (PRIM), which finds subspaces in the uncertainty space with a high share of *outcomes of interest*.
The PRIM algorithm uses a logical and intuitive approach to identify the subspace where a relatively high number of desired outcomes are located. After running a set number of experiments with varying parameters, the desired outcomes are marked as outcomes of interest. The PRIM algorithm then *peels off* (removes) a small part of the results to find a subspace with a higher share of outcomes of interest. Peeling leads to a smaller subspace (lower *coverage* of the uncertainty space) with a higher percentage of outcomes of interest. The programmer decides at what rate experiments are removed (the *peeling rate*) and sets a minimum threshold for the density of the final subspace.
In this case, a part of the experiments led to the achievement of high-income status for India, say 10%. This is the *density*. As I was interested in knowing which parameter values led to an increased success rate, I let the algorithm find a smaller subspace in the uncertainty range in which more than 10% of the results are outcomes of interest, implying that this is a result of the shortened value ranges of the parameters.
The peeling is repeated to find a subspace with a density as high as possible, until re-running the algorithm no longer leads to a higher density. After finishing, the algorithm returns a *PRIM box*.

This contains the ranges in the uncertainty space that result in the high density of outcomes of interest, combined with probability statistics on the likelihood that the high share of desirable results is a result of the parameter values (Friedman & Fisher, 1999; Kwakkel, 2017, 2023). In the algorithm, the probability value is called *qp*.
Figure 2 shows an example of a PRIM plot, which plots each subspace as a dot. The algorithm starts in the bottom right, where all outcomes are included (coverage of 1.0), of which a small share is labelled as *cases of interest* (low density). By repeated peeling and restricting dimensions (setting ranges for each parameter), fewer outcomes remain and the density increases. Each time a box with a higher density is found, a new dot is plotted on the map, causing the curve to move from the bottom-right to the top-left of the plot. This continues until the algorithm is no longer able to identify a subspace with an increased density. This is when it returns the final box, which is the furthest top-left dot on the plot.
The application of PRIM should be determined based on the results; if a majority of the experiments lead to desirable results, it is more valuable to find a subspace with a majority of undesirable results, and vice versa. Similarly, the ideal rate at which the algorithm peels off experiments and the threshold that is set at the start of the algorithm should be determined based on the composition of the outcome range; they should not be defined before knowing the outcomes.

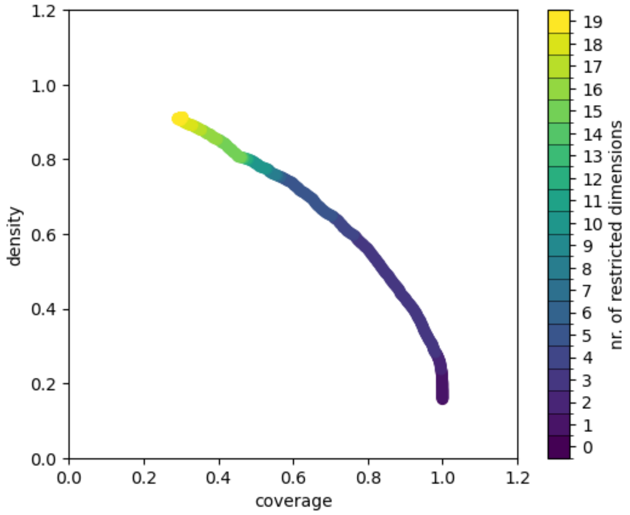


Figure 2: Example of a PRIM plot

The results of a PRIM analysis can indicate the limiting and determining factors for India's economic growth, and offer ideas for a policy. This is done in Hamarat et al. (2012), where the authors find that a high density of undesirable results occurs in the higher range within the uncertainty range of their *Technology lifetime* parameter, and design a policy aimed at shortening this lifetime. When applying this method to a middle-income trap model, one could imagine that a high share of successful experiments (experiments in which the high-income range is entered) occurs when certain costs of R&D are in the lower range, or when returns to education or infrastructure investments are relatively high.
In this research, the PRIM algorithm was used to study how the Indian government can increase its chances of preventing a growth slowdown and reach high-income status before 2047. An experiment was labelled as successful when the high-income range was entered before or during 2047. This happens when India has a GDP of more than 30 trillion US$ (Dhumne, 2025).

3.2.3 Optimisation

Finally, I have run a constrained optimisation script to identify how India's budget should be allocated between infrastructure, education and R&D to produce the highest GDP. The total share of GDP that India can spend on these growth drivers was kept constant, meaning that a higher investment in one driver must come with a lower investment in another. The optimal budget allocation helps to explain model behaviour and was used to give policy recommendations. Furthermore, the optimisation outcome is used to answer sub-question 3 and ultimately, the research question.

4 Model Structure

The model built to study India's pathway to high-income status consists of multiple sub-models that determine the final output of India's economy. This chapter gives an overview of the full model, describes the model validation process and shows the experimental setup.

4.1 Model Overview

Figure 3 gives a schematic overview of the structure of the model. Boxed factors represent stocks; the other variables are auxiliaries. Arrows indicate relationships between different variables, which, if necessary, are explained in *italic*.

Similar to the growth models studied earlier, productivity growth in the model is driven by knowledge gains from R&D and knowledge spillovers from FDI. Knowledge gains from R&D are generated by researchers; a bigger R&D labour force leads to more productivity growth. Investing in the R&D sector enables expansion of the labour force.

FDI is attracted based on the Human Capital Index value, the relative quality of infrastructure, India's wage relative to OECD countries, previous GDP growth and the current GDP. The last three relationships are all captured in the arrow between FDI and GDP. The amount of knowledge spillovers that is experienced as a result of attracting FDI depends on the technological distance between India and the global technological leader and India's absorptive capacity, determined by infrastructure quality and the Human Capital Index.

In Appendix A1.2, screenshots of the Vensim model can be found, to offer insight into how the formulas are translated into an SD model.

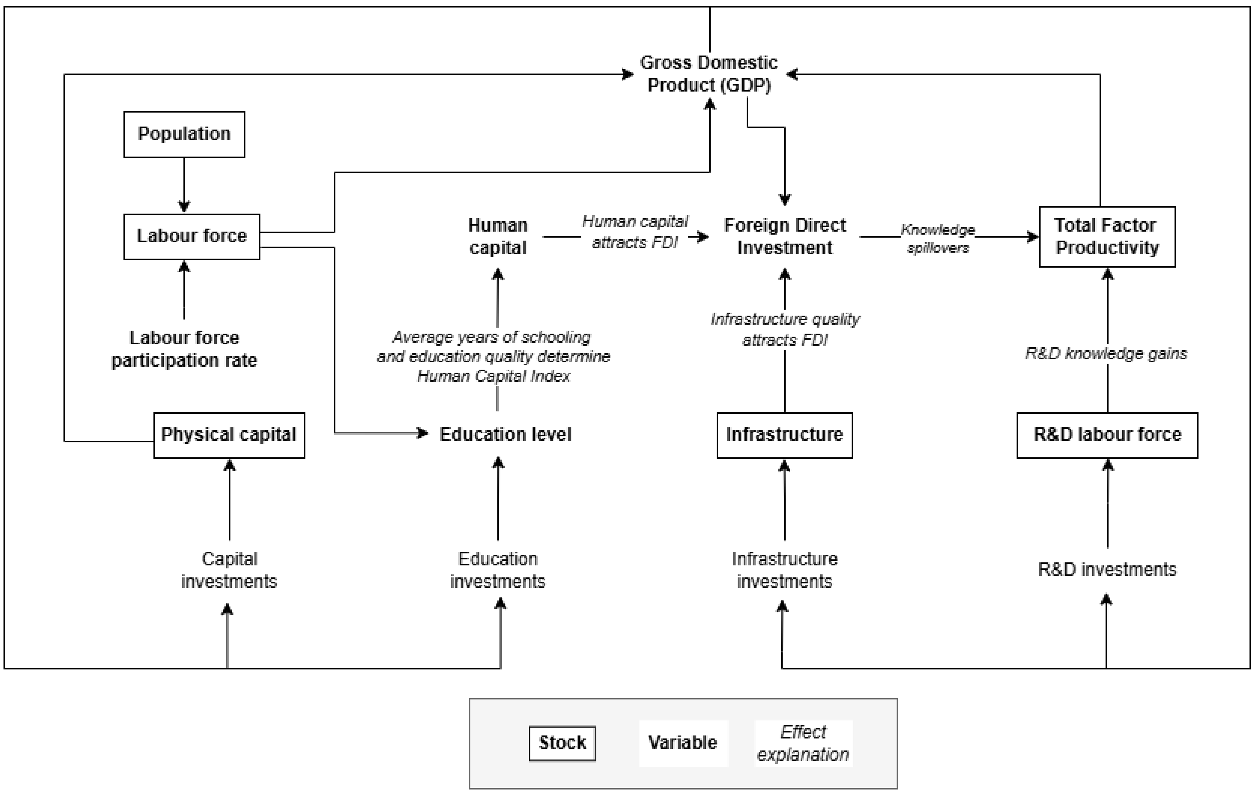


Figure 3: Overview of the System Dynamics model

Productivity growth is calculated as the sum of knowledge gains from R&D and knowledge spillovers from FDI and is added to the current productivity, leading to a new Total Factor Productivity. This determines how efficiently capital and labour inputs are converted into economic output.
Capital is formed through capital investments, and the labour force size depends on the labour force participation rates of all population groups. Similar to the real world, highly educated people participate in the labour force more often.
Investing in education leads to a greater labour force and more human capital. As labour force participation increases with the education level, investing in education enrolment leads to a larger workforce. Furthermore, it boosts the Human Capital Index value. This is calculated as a function of educational quality and the average number of schooling years per new worker; investing in educational quality and enrolments leads to more schooling years with better quality of education.
The next sections will go more deeply into the model structure and explain the most important formulas.

4.2 Gross Domestic Product

The GDP is determined in a classic Cobb-Douglas function, using total factor productivity, capital, labour force and output elasticities.

$$Y(t) = A(t)K(t)^{\alpha}L(t)^{1-\alpha} \tag{4.1}$$

I assume India to be a constant returns-to-scale economy. This is recommended by Acemoglu (2009), because using decreasing or increasing return-to-scale could lead to extreme and unrealistic values when modelling for an extended period. Therefore, the two elasticities α and $(1-\alpha)$ add up to 1, meaning that doubling the inputs leads to a GDP that is twice as high.

4.3 Total Factor Productivity

Total factor productivity determines how efficiently labour and capital inputs are used for creating economic output. India's total factor productivity grows through R&D results and knowledge spillovers from FDI. This way, insights from Romer (1990), Jones (1995) and Aghion and Howitt (1998) on productivity growth are combined. Total factor productivity growth from R&D is determined in the following way:

$$\dot{A}(t) = \dot{A}_{R\&D}(t) + \dot{A}_{FDI}(t) \tag{4.2}$$

$$\dot{A}_{R\&D}(t) = \mu * A(t)^{\epsilon_A} * HCI(t) * L_A(t)^{\epsilon_L} \tag{4.3}$$

Here μ is the R&D efficiency in creating productivity gains, *A(t)* is the total factor productivity, ϵ_A is the elasticity of total factor productivity growth to current total factor productivity, HCI is the Human Capital Index (which is further explained in Chapter 4.7), L_A is the labour force working in R&D and ϵ_L is the elasticity of total factor productivity growth to the labour force size. Both ϵ's are smaller than 1, indicating diminishing returns, matching Jones (1995).

Spillovers from FDI are determined in the following way:

$$\dot{A}_{FDI} = \lambda * AC(t) * FDI(t)^{\epsilon_{FDI}} * TD(t) \tag{4.4}$$

Here, λ is the FDI efficiency, scaling how FDI leads to a certain increase in productivity. *FDI(t)* is the absolute amount of foreign direct investment flowing in, and AC(t) is the absorptive capacity, which is the product of relative infrastructure quality and the Human Capital Index.

TD(t) is the technological distance, the difference between India's total factor productivity and the total factor productivity of the global technological frontier. The ϵ is an elasticity value, indicating diminishing returns to FDI attraction.

As India's productivity grows, the technological distance will shrink, leading to fewer knowledge spillovers. To continuously experience spillover effects from FDI, India must invest in its human capital and infrastructure. This not only attracts FDI (see Equation 4.5), but also increases spillovers per unit of inflowing investment.
This formula features Gerschenkron's backwardness; if India is further behind the technological frontier, it experiences more knowledge spillovers and can develop quicker (Gerschenkron, 1966).

4.4 Foreign Direct Investment

The amount of attracted FDI in India is estimated by the following equation, based on the most important factors that determine FDI inflow found in Chapter 2.2. A29.

$$\mathit{ln(fdi(t))} = ln(fdi_0) + Y(t)^{\epsilon_Y} * i(t)^{\epsilon_i} * HCI(t)^{\epsilon_{HCI}} * \dot{Y}_5(t)^{\epsilon_{Y5}} / w(t)^{\epsilon_w} \tag{4.5}$$

Following the existing literature, Equation 4.5 determines the natural logarithm of the FDI inflow relative to GDP. Using logarithms helps to linearise relationships and stabilise values (Feenstra & Taylor, 2017).
In the formula, fdi_0 is a base level of FDI relative to GDP, and the other factors determine how much more investment is attracted. Here, Y is the current GDP, i is the relative infrastructure quality, defined as the infrastructure stock per capita in India divided by the per capita stock from an average OECD country. HCI represents the Human Capital Index, $\dot{Y}_5$ is the average GDP growth rate of the past five years and w is India's average wage relative to an OECD country. The ϵ 's represent elasticities.
This equation implies that in order to keep attracting foreign investment while wages rise, India should focus on improving its human capital and infrastructure quality.

4.5 Research and Development

When India approaches the technological frontier, returns to attraction of FDI decrease, and it must switch from an *infusion* (2i) to an *innovation* (3i) strategy, in which growth is achieved through R&D.

The R&D budget is calculated as a fixed share of GDP. Dependent on the available budget and the available number of higher education graduates, the R&D labour force size evolves. Each year, a certain share of that year's tertiary education graduates becomes available to be hired for R&D. The wage per R&D worker is defined as a multiple of the average Indian wage. By setting a number to what share of R&D expenses goes towards wages, the total cost per researcher is determined, which determines the degree by which the labour force is expanded.
Both the number of available graduates and the R&D budget are limiting factors. For example, if there is a budget to hire 50,000 more researchers, but there are only 20,000 newly graduated workers available, the labour force grows by 20,000. Similarly, if there are enough available graduates but not enough budget, the number of graduates that will be hired must fit in the budget. The value of the labour force stock is then used in Equation 4.3 to help determine productivity growth from R&D efforts.

4.6 Physical Capital and Infrastructure

The physical capital and infrastructure stocks behave in the same way. Through public investments and FDI, they increase. The stock values annually decrease through a fixed depreciation rate. The capital stock is used to determine the total economic output Y. The behaviour of the capital stock can be seen in Equation 4.6:

$$\dot{K}(t) = \theta_K * Y(t) + f_K * FDI(t) - d_K * K(t) \tag{4.6}$$

Here, $K(t)$ represents capital, θ_K represents the share of GDP $Y(t)$ that is invested in capital, f_K represents the share of inflowing $FDI(t)$ that is invested in capital and d_K is the rate of capital depreciation.

$$\theta_K = \theta_I + \theta_{PK} \tag{4.7}$$

The capital stock holds all tangible assets that are used to produce goods and services, such as machinery, buildings, vehicles and infrastructure. Because infrastructure quality attracts foreign investors and determines the amount of knowledge spillovers, its stock is modelled separately. However, it is also included in total capital stock, as it is part of the total stock and is needed to determine total output. Therefore, the total capital saving rate is the sum of the infrastructure saving rate θ_I and the remaining physical capital saving rate θ_{PK}. Similarly, the share of FDI going into capital is split up into a share going into infrastructure and a share going into remaining physical capital. The infrastructure capital and the other physical capital both depreciate at the same rate d_K

This leads to a mix of indirect and direct benefits from investing in infrastructure: improved saving rates lead to a higher GDP through the Cobb-Douglas function, but also boost productivity because of their role in creating knowledge spillovers. Investment in other physical capital assets, such as machines and buildings, does not directly influence knowledge spillover generation; it is only used to produce goods and services.

4.7 Education, Labour Force and Human Capital

In a separate sub-model, the education levels of the population are determined. The education sub-model consists of three stocks: *People in primary education, People in secondary education* and *People in tertiary education*. Of all children born, a certain share, the *Primary school enrolment rate*, later enters the primary school stock. The number of births is determined in a standard population sub-model, which is explained in Appendix A1.1

After 8 years, the *Primary school duration*, these primary school students leave the stock, either to the stock of *People in secondary education* or to the labour force sub-model. Similarly, secondary school students continue to pursue tertiary education or move to the labour force model.

A fixed share of students, the value of which depends on the level of education, do not finish their education and leave the stock of students. Depending on this *dropout rate*, they leave the education sub-model and go to the labour force sub-model, joining the working age population of their highest completed education level. A student who drops out of a tertiary education institute, for example, joins the secondary degree working-age population.

$$\frac{d(\textit{Students})}{dt} = \textit{New graduates coming in - Students graduating - Dropouts} \tag{4.8}$$

What share of graduates or dropouts actually joins the labour force is decided by the Labour Force Participation Rate (LFPR), which, based on available data, is different for each combination of level of education and gender. Persons who have finished their education are assumed to join the labour force immediately, meaning that primary and secondary school graduates add to the labour force aged 15-19 years, and tertiary education graduates join the 20-24-year labour force. The model assumes full employment, meaning all graduates who enter the labour force

add to the economic output. Over time, the labour force ages, meaning that the 20-24 year old labour force at one point becomes the 25-29 year old, and 5 years later the 30-34 year old labour force.
Each year, a certain number of workers leave the labour force because they retire or pass away. This number is based on the retirement and mortality rates per age group. Although India's retirement age is currently 58 years (World Bank, 2023c), not all workers in the model leave the labour force at this age. The retirement rate is derived from the declines in the current labour force participation rate per age group. According to the Ministry of Statistics and Programme Implementation (2024), this decline starts at the age group 40-44 years. In the model, the younger workers' retirement rate is assumed to be zero.

Investments in education increase the enrolment rates of each level of education, as they allow the government to pay for (part of) an individual's tuition fee. An investment leads to more enrolments based on an annual cost per student, which is different per level of education and increases with GDP per capita. In the model, the current national policy to increase Gross Enrolment Rates, which aims for full primary and secondary education enrolment in 2030 and 50% tertiary education in 2035 (Ministry of Statistics and Programme Implementation, 2024) is already implemented. In case enough budget is allocated towards education, these targets are met. If not, the same enrolment targets are used, but it takes more years to accomplish. To clarify, an enrolment rate of 50% means that half of the eligible population decides to enter tertiary education, but they do not all graduate.
Any budget that is left after raising the enrolment rates is spent on improving education quality, which is measured by the Harmonized Learning Outcome (HLO). This is a method in which regional and international measures of education test results are standardised between 300-625 (Patrinos et al., 2018). The model determines HLO growth via investments in *Teacher quality*. Investments in improving the quality of teaching help to grow the HLO.

$$\frac{d(HLO)}{dt} = \beta * Q(t) * (625 - HLO(t)) - d_{HLO} * HLO(t) \tag{4.9}$$

Specifically, the HLO evolves according to Equation 4.9, in which β is the rate by which teacher quality contributes to educational quality, $Q(t)$ is the teacher quality and d_{HLO} is the depreciation rate of the educational quality, which describes how the quality of education declines when teaching methods and teaching material become outdated.
This formula is part of a reinforcing feedback loop: a higher HLO leads to higher returns on the training of new teachers, which increases teacher quality growth, which then increases HLO growth. However, as the HLO approaches the maximal value of 625, growth also decreases.

Education investments also lead to a higher human capital value. This is modelled in a function based on Kraay (2018), who expresses human capital as a number between 0 and 1, called the *Human Capital Index (HCI)*. The model determines the HCI in the following way:

$$HCI(t) = e^{\phi * (s_{NG}(t) * HLO(t)/625 - s^*)} \tag{4.10}$$

Here, ϕ represents a fixed return on education of 0.08, s_{NG} is the number of *Schooling years per new worker*, HLO is the Harmonised Learning Outcome that measures educational quality, and s^* is a benchmark value of 14 years of education. By comparing India's HLO to the maximum value of 625 and the average number of schooling years to the benchmark of 14, this formula expresses human capital as the average level of education, relative to the optimal duration and quality of education.

4.8 Use of Subscripts

Throughout the model, the population, labour force, and scholars are split up into 5-year age groups, separated by gender. This is accomplished using subscripts. Rather than creating new stocks and variables for each sub-group, subscripting allows the user to assign multiple values to each variable, one for each sub-group (Ventana Systems, n.d.). Men and women, for instance, have different labour force participation rates, and mortality rates are not constant during an individual's lifetime. Using subscripts allowed me to gain a better insight into the differences in education levels and labour force involvement of each age group and gender.

4.9 Implementing the 3i Strategy

The drivers of the 3i strategy (investment, infusion and innovation) are all included in the model. By investing in infrastructure and education, India can form a solid basis to attract FDI for knowledge spillovers and to optimise returns to R&D. In the model, there is no built-in policy to simulate the effects of investing in certain drivers of growth, which is recommended to do in each phase. These effects will be measured in Chapter 5.2, where the optimal budget allocation is found to maximise Indian GDP.

4.10 Data Sources

A significant amount of data was needed to model the initial state of India and to determine the effects of certain drivers on economic growth. These numbers were derived from public databases such as the World Bank database, Data for India and the United Nations database. Data on education was mostly copied from government reports, while modelling variables such as elasticities were copied from or estimated based on scientific papers. Additionally, I had to make some assumptions for scaling purposes or for simplicity. In Table A1, an overview is given of all constants, with their units, value and a reference or a short explanation on how their values were determined. Here, Table 1 gives a brief overview of all types of data sources that were used to build the model.

Table 1: Data sources used to build the model

Data type	**Description**	**Data sources**
Demographic data	Initial population, fertility rate, life expectancy, etc.	Our World in Data, United Nations database
Education and labour	Labour force participation rates, initial education enrolment rates	Government reports, Data for India, World Bank data
Elasticities	GDP elasticities to labour and capital, impact of determinants of FDI attraction, R&D and FDI spillovers	Academic sources, own assumptions based on academic sources
Investment rates	Shares of GDP invested in specific drivers of growth	World Bank data, Government reports, Bank reports

4.11 Model Validation

Throughout the modelling process, the model was validated in multiple ways, as it passed validation tests from Forrester and Senge (1980).

Structure Validation

Firstly, the model passes the structure-verification test. To achieve this, *"the model must not contradict knowledge about the structure of the real system"*. As all equations are either taken from proven economic models or based on relationships found in scientific literature, these estimations certainly do not contradict existing knowledge and the test is passed.
The extreme-conditions test, in which the model's performance in extreme scenarios is simulated, is passed by almost all sub-models. Simulating extreme scenarios helps to identify modelling errors; many formulas may seem logical until their outcomes in extreme scenarios are evaluated. In the case of this model, this means that productivity growth from R&D must be zero if the R&D labour force is empty and that no FDI knowledge spillovers occur when there is no FDI inflow or when the technological distance is zero. This was all tested, which led to logical and correct results.
The education sub-model is the only part of the model that does not pass the extreme-conditions test: a small number of students still graduate and pursue further education when using a 100% dropout rate. This is caused by the fact that dropouts are determined as a certain share of the stock of students, while the number of graduates is determined as a delay of the inflow of newly enrolled students. In the case of the primary school, which takes 8 years to complete, the number of graduates is determined as an 8-year delay of the inflow of new enrolments, minus the dropouts. The outflow of dropouts is determined based on the stock of students; each year, a certain share of students drop out. This is not modelled as a delay, because the students who drop out do not all drop out after the same number of years after their enrolment. The small differences in yearly enrolment cause that using a full dropout rate may not lead to zero graduations, as the number of enrolments from 8 years ago slightly differs from one-eighth of the current number of students, which leads to a small negative or positive number of graduates. As fertility rates and, therefore, the absolute enrolment decrease in India, this leads to a low positive number of graduates.
This is a minor limitation, but it does not harm the outcomes. The estimations on the behaviour of the student stocks are accurate, as long as the dropout rate is not 100%, which it never comes close to in any of the uncertainty runs.
The model is further validated by the fact that it matches the research purposes. It describes the relationships between all important growth drivers and showcases how investments in these drivers impact economic output. The model does not show how India compares to other competing middle-income countries, or what specific taxes it could impose to impact behaviour. This is outside of the scope; the purpose of the model is to give a more general overview of the changing roles of growth drivers and the trade-offs between investing in different growth drivers.

Behaviour Validation

The model's behaviour was validated throughout the modelling process using symptom generation tests, several behaviour-prediction tests and behaviour-sensitivity tests.
Symptom-generation tests check if the model can reproduce behaviour that motivated the research, which it does. In this case, it was tested if the model could produce decreasing growth rates, as a consequence of decreasing returns to growth driver investments. This test was passed. Because of diminishing returns to accumulation of labour and capital, closing technological

distance and decreasing returns to productivity gains, India's productivity growth gradually decreases when the labour force no longer expands, which matches Jones (1995), and imitates the middle-income trap (Gill & Kharas, 2007).
The behaviour was further validated by comparing its overall behavioural responses to parameter changes and testing its behaviour under extreme policies (unrealistic investment rates). The model's behaviour is logical and matches the evidence in the literature review. Extreme capital and infrastructure investment rates lead to higher GDP, which matches (Solow, 1956). Extreme educational investments lead to enrolment rates that match the targets set by the Ministry of Education (2020) and a high Harmonised Learning Outcome. Furthermore, using an extreme R&D investment rate leads to higher productivity gains but not to extreme productivity growth, as the labour force expansion is limited by the amount of available graduates. This is logical, and matches World Bank (2024c), who recommends governments to incentivise students to graduate in STEM fields to grow a larger R&D labour force.

4.12 Experimental Setup

The model simulates a period of 50 years, running from 2025 to 2075. Approximately halfway, in 2047, India aims to achieve high-income status according to the Viksit Bharat plan (Jacob, 2024). However, it is uncertain whether India will achieve this, so the model must simulate for a longer period.
The choice to end the simulation in 2075 was also made to be able to see the full effects of education enrolment increases. I wanted to use a time period that was longer than the standard time an Indian spends in the labour force, which is 45 years (Chawla & Singh, 2024). Modelling for a longer time than these 45 years allowed me to completely replace the current labour force, so that the effects of education policies on the composition of the labour force are more visible.
The model uses years as the unit of time and a time-step of 0.125 years, which was determined according to Auping et al. (2024). Here, the authors recommend choosing a time-step between half and one-tenth of the smallest time constant used in the model as a starting point, and then halving the time step until the new time step does not lead to new visible changes in the plots. Using this strategy, the halving of the initially chosen time step of 0.25 years leads to the final time step of 0.125 years.
The model runs are executed in Vensim (Ventana Systems, 2010), with integrations being performed using the Euler method of integration (Euler, 1768). Because the model uses functions determining minimums and maximums, and features if-then-else structures, it contains discontinuous derivatives, making the Euler method a more suitable technique than any of the Runge-Kutta methods (Kutta, 1901; Runge, 1895), which cannot handle large discontinuities in the derivatives (Auping et al., 2024).

The analysis of the model is done using the Exploratory Modelling and Analysis (EMA) Workbench by Kwakkel (2017). This Python library has a built-in Vensim connection that enables users to run experiments on SD models in a Python environment. The workbench offers more analysis tools than Vensim and is easier to use.

The uncertainty analysis to define the outcome range was run using 30,000 scenarios with changing parameter values, according to Table 2. The scenarios were created using the Latin Hypercube sampling method (McKay et al., 1979), to ensure full coverage of the input space. The sources from which the uncertainty ranges are derived are included in the Appendix, in Table A2.
For the PRIM analysis that was run on the outcome range, a peeling rate of 0.01 was used, and the threshold for the final PRIM box was set at 0.50. This means that at each iteration of the algorithm, 1% of the initial 30,000 outcomes is removed, to ultimately discover a PRIM box in which at least half of the outcomes are labelled as outcomes of interest.
The optimisation was performed on the base run of the model and aimed at finding the highest GDP in 2047 and 2075. In total, 10,000 different combinations of investment rates were tested and compared, which are within the ranges of Table 3. These combinations were created using the Latin-Hypercube sampling method. The sum of the three investment rates could not exceed 0.104, which is the sum of the current investment rates. This way, the trade-off between different investments was studied.

Table 2: Uncertainty Parameters with Ranges

Parameter Name	Unit	Range
Capital depreciation rate	Dmnl	[0.035, 0.065]
Developed country infrastructure stock increase rate	1/Year	[0.01, 0.03]
FDI spillover elasticity of FDI flow	Dmnl	[0.05, 0.15]
FDI spillover elasticity of TD	Dmnl	[0.9, 1.1]
FDI spillovers scaling factor	1/Year	[0.0002, 0.0003]
HLO depreciation rate	1/Year	[0.005, 0.015]
OECD wage growth rate	1/Year	[0.01, 0.03]
Output elasticity of capital	Dmnl	[0.3, 0.5]
Primary degree LFPR [Female]	Dmnl	[0.25, 0.35]
Primary degree LFPR [Male]	Dmnl	[0.7, 0.8]
Primary school dropout rate	Dmnl	[0.01, 0.02]
RD relative wage	Dmnl	[3.5, 6.5]
RD spillovers scaling factor	1/Year	[0.0038, 0.0046]
Return on teacher investments	1/(Year*USD*Persons)	[0.5e-5, 1.5e-5]
Secondary degree LFPR [Female]	Dmnl	[0.35, 0.45]
Secondary degree LFPR [Male]	Dmnl	[0.8, 0.9]
Secondary school dropout rate	Dmnl	[0.04, 0.20]
Share of FDI into infrastructure	Dmnl	[0.25, 0.35]
Share of graduates able to join RD labour force	Dmnl	[0.0075, 0.0125]
Share of labour in RD cost	Dmnl	[0.4, 0.5]
Teacher quality contribution to HLO	1/Year	[0.2, 0.4]
Technological frontier TFP growth rate	1/Year	[0.01, 0.025]
Tertiary degree LFPR [Female]	Dmnl	[0.5, 0.6]
Tertiary degree LFPR [Male]	Dmnl	[0.85, 0.95]
Tertiary education dropout rate	Dmnl	[0.2, 0.3]
Uneducated LFPR [Female]	Dmnl	[0.2, 0.25]
Uneducated LFPR [Male]	Dmnl	[0.65, 0.7]

Table 3: Overview of the budget optimisation

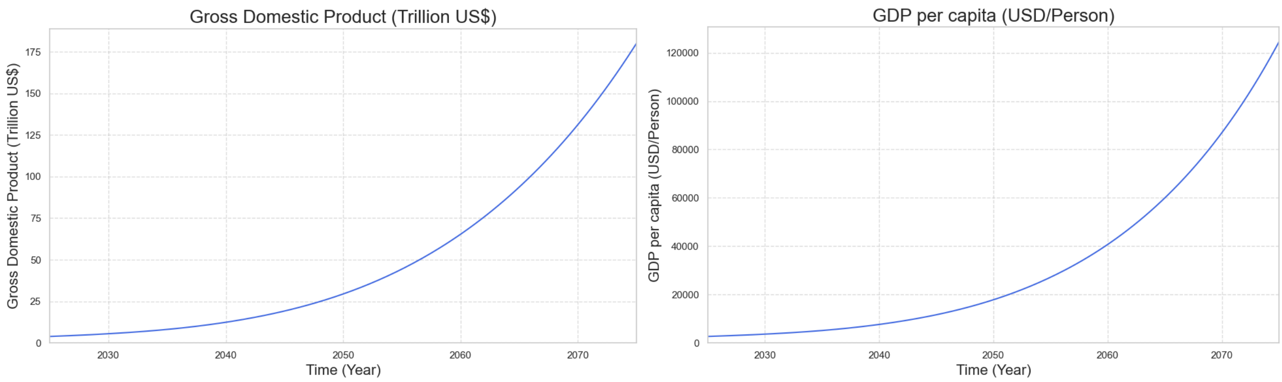
Investment rate	Minimum	Maximum	Current rate
Education	0.03	0.10	0.046
R&D	0.00	0.04	0.006
Infrastructure	0.02	0.10	0.053
Total investment			**0.105**

5 Model Performance

When running the model, India does not meet its target of reaching a GDP of 30 trillion US$ by 2047, the year specified in the Viksit Bharat plan. Instead, it reaches a GDP of 22.3 trillion US$ in the first quarter of 2047, which is a GDP per capita of 13,529 US$ per person. This implies that India would still be a middle-income country, as Shrok and Ghosh (2024) predict the upper boundary of the middle-income range to be around $20,000 at that time.

Although India's economic growth continues to increase for a while, the model simulation shows that a slowdown occurs around 2040, as shown in Figure 5a. This matches the annual growth patterns of productivity, see Figure 5b. The GDP growth rate reaches its peak value later than the productivity growth rate, which is at its highest in 2038.

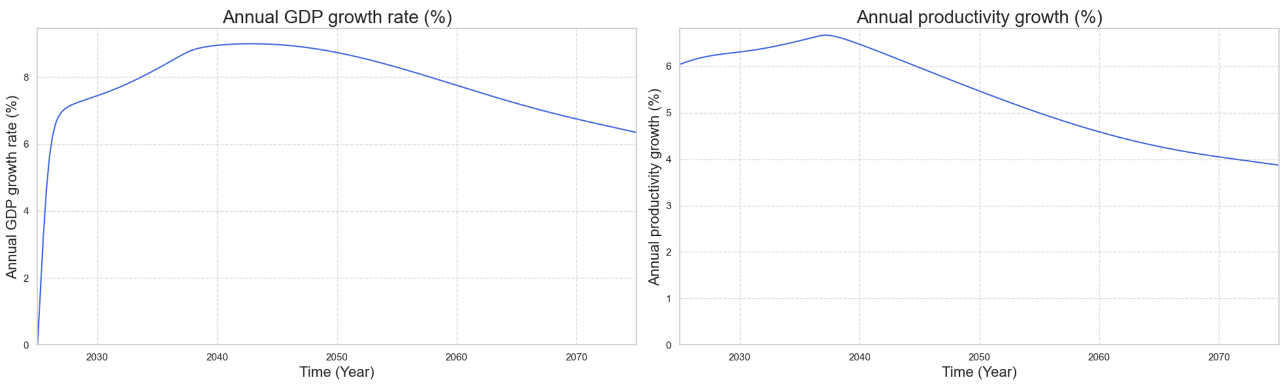
Because the GDP growth can only be calculated from 2026 (as it needs a year to be able to compare its current value to that of the year before), the growth rate starts off at 6% in 2026 and then increases up to almost 10%, before gradually decreasing back to 6% at the end of the simulation.



(a) GDP over time

(b) GDP per capita over time

Figure 4: GDP and GDP per capita over time



(a) Annual GDP growth over time

(b) Annual productivity growth over time

Figure 5: Annual GDP and total factor productivity growth rates

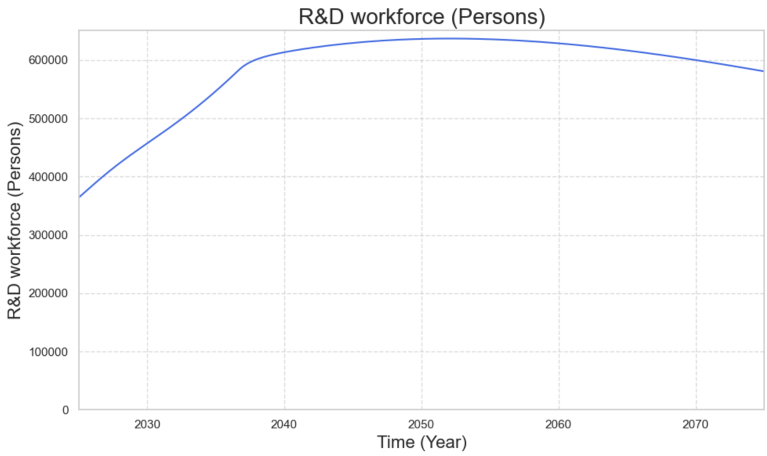


Figure 6: R&D workforce size over time

The GDP and productivity growth rates evolve similarly to the number of R&D workers, see Figure 6. Expansion of this workforce is limited by budget and by the number of available graduates, as explained in Chapter 4. Around 2038, the curve bends and the workforce virtually stops growing; this is the point where the R&D budget becomes the constraining factor, while before, it was the limited number of higher education graduates. After this point, productivity growth starts to decline, see Figure 5b. This indicates the great dependence of productivity growth on R&D efforts.

While the share of GDP spent on R&D stays constant, the size of the R&D workforce declines from around 2050 to 2075. This indicates the high costs of R&D and that the total costs per worker must grow at a greater rate than India's GDP.

Similar to what is prescribed in the 3i strategy, the relative role of FDI in creating productivity growth declines over time. This can be seen in Figure 7. Although the absolute amount of FDI inflow keeps increasing over time (see Figure A16), its relative contribution to productivity growth declines, as productivity growth from R&D increases at a greater rate.

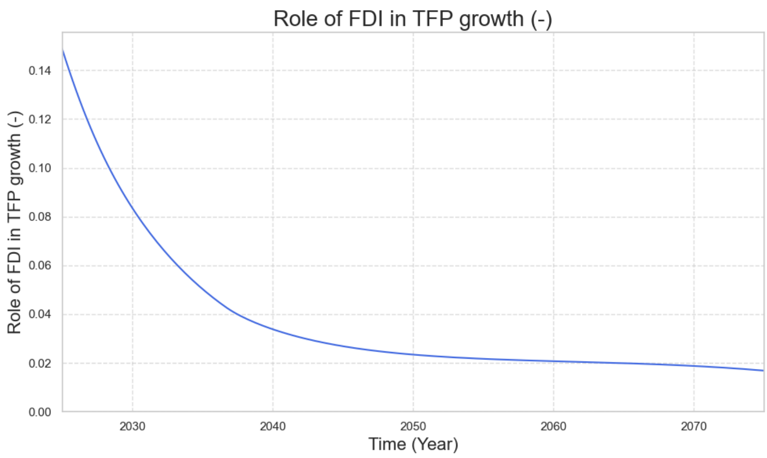
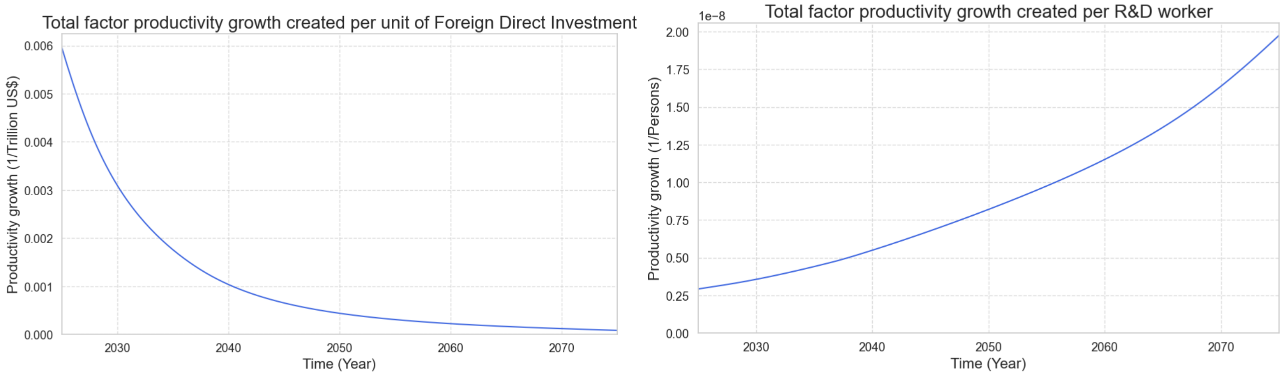


Figure 7: The role of FDI in creating productivity growth over time

The declining role of FDI can be explained by looking at the decreasing returns to FDI attraction and the increasing returns to R&D efforts over time, see Figure 8. Because of the shrinking technological distance between India and the technological frontier, the productivity growth per inflowing unit of FDI declines, while for R&D, the opposite happens: The increasing productivity of R&D and human capital index boost the output per researcher over time.

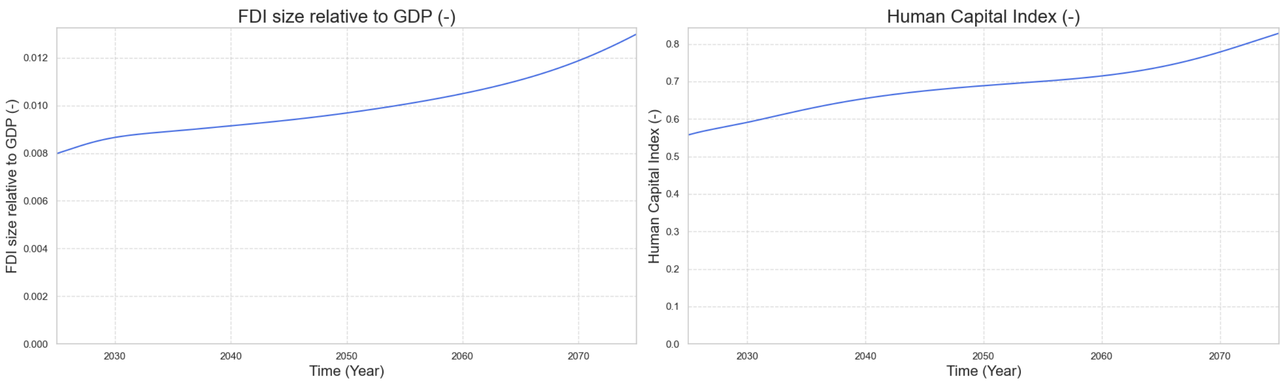


(a) Productivity growth per trillion US$ FDI inflow

(b) Productivity growth per R&D worker

Figure 8: Productivity growth per R&D worker

The amount of human capital, measured as the Human Capital Index, increases from 0.55 to 0.82 throughout the simulation. It experiences the most growth in the final 15 years of the simulation, which is when the enrolment has increased according to the planning of the Ministry of Statistics and Programme Implementation (2024).
As a result of the increased human capital value, India becomes a more attractive country to invest in; although the average wage increases, its improving infrastructure quality, human capital and market size lead to increased attraction of FDI. In 50 years, the relative FDI inflow increases from 8% to 12.5% of India's GDP. Figure 9 shows the similarity between the curves of relative FDI inflow and the Human Capital Index; both increase gradually and grow the fastest at the end of the simulation, indicating the positive effect of human capital growth on the attraction of FDI.



(a) FDI inflow relative to GDP over time

(b) Human Capital Index over time

Figure 9: Productivity growth per R&D worker

The plots of other relevant outcomes can be found in Appendix A2.

5.1 Uncertainty Analysis

Running 30,000 runs with the uncertainty ranges from Table 2 led to 3611 experiments in which India reaches its Viksit Bharat target of having a 30 trillion dollar GDP before 2047. This is 12% of the experiments. In the following plots, the most important outcome ranges are shown.

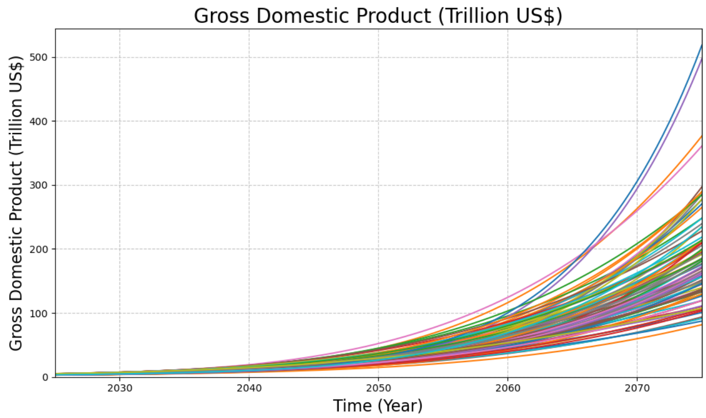
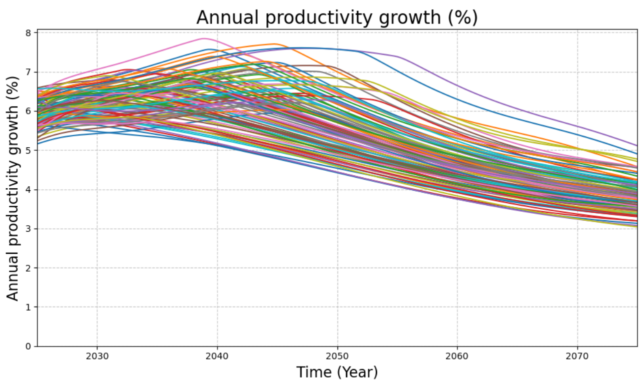


Figure 10: Outcome range of the GDP

The plot of the outcome range of the GDP (Figure 10) shows a great difference between its minimum and maximum value, which is caused by the cumulative effect that determines GDP. Favourable parameter values lead to higher productivity growth, which boosts GDP, which boosts the capital and infrastructure stocks and educational quality. This then leads to greater returns to FDI attraction and R&D efforts, which boosts GDP even more. This shows how small differences in initial parameter values can cause large differences in the long term. For 2047, GDP ranges between 10.6 and 45.6 trillion US$.



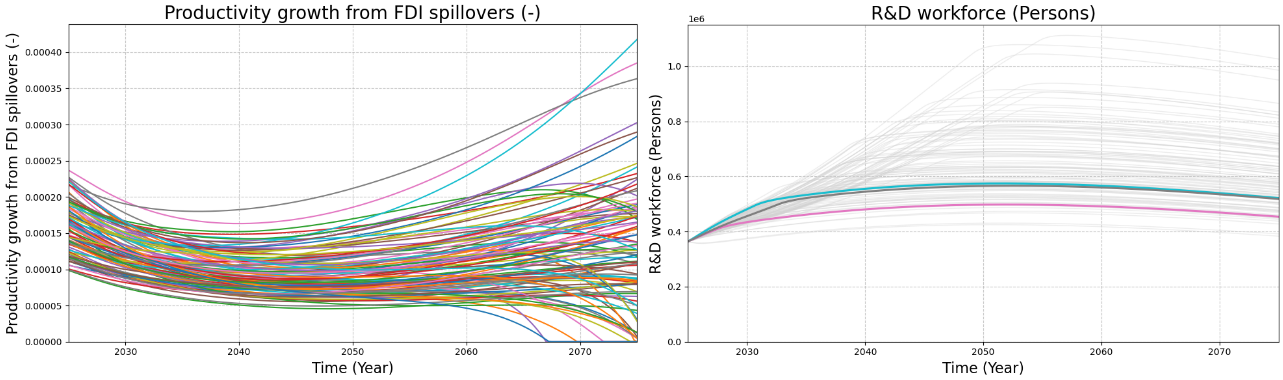
(a) Outcome range of the annual productivity growth rate

(b) Outcome range of the R&D workforce size

Figure 11: Outcome ranges of the productivity growth rate and the R&D workforce size

The varying final values of India's GDP can be linked to the behaviour of the R&D workforce size. This is shown in Figure 11, which shows the outcome ranges of the annual productivity growth and the R&D workforce size. The longer the R&D force keeps expanding, the longer the productivity growth rate (and also the GDP growth rate) keeps increasing.
The blue and purple curves at the top of Figure 11b are examples of this effect. In these experiments, the workforce expands for the longest time, which leads to the longest maintained productivity growth in Figure 11a.

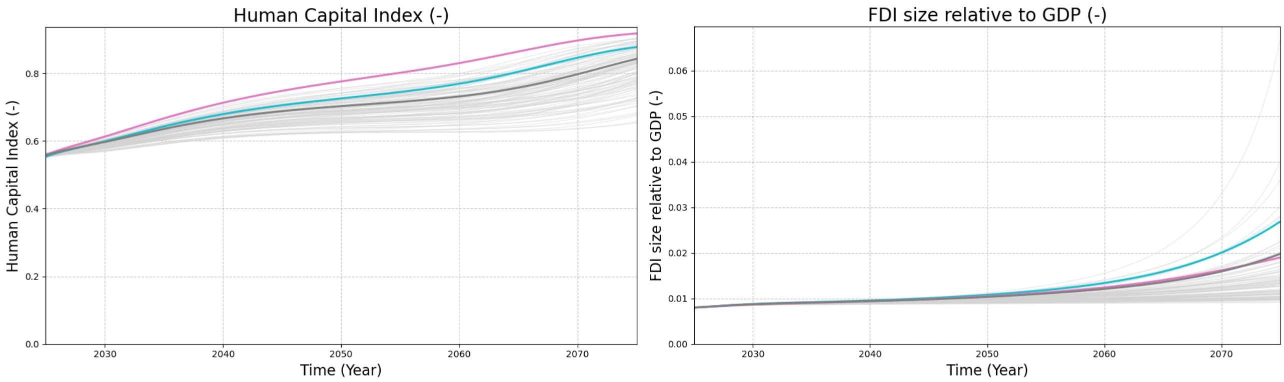
While in most experiments, the total amount of productivity growth from FDI spillovers decreases over time, it increased in a few experiments where the contribution of R&D is limited. This can be seen in Figures 12 and 13, which focus on the three curves in which productivity growth from FDI is the highest in Figure 12a. In these experiments, the expansion of the R&D workforce stops early, which leads to relatively low productivity growth and a larger technological distance. This, in combination with a relatively high Human Capital Index and inflow of FDI relative to GDP, results in an increased amount of FDI spillovers.



(a) Outcome range of productivity growth from FDI

(b) Outcome range of the R&D workforce size

Figure 12: Outcome ranges of FDI productivity growth and R&D workforce size



(a) Outcome range of the Human Capital Index

(b) Outcome range of the relative FDI inflow

Figure 13: Outcome ranges of the Human Capital Index and the FDI inflow relative to GDP

This helps to showcase how productivity growth from R&D has reinforcing and balancing effects. R&D is part of a reinforcing feedback loop: increased R&D efforts lead to higher productivity, and higher productivity leads to higher returns per researcher, leading to even more productivity growth. Oppositely, increased growth from R&D leads to fewer spillovers from FDI, as the technological distance has shrunk. To experience the most spillovers from FDI, one must experience the least knowledge gains from the other growth driver, R&D, to maintain a large technological distance.

5.1.1 Parameter sensitivity

After exploring the outcome range, the model's sensitivity to parameter changes was studied using a Feature Scoring approach. The outcomes are shown in Figure 14, in which the outcomes' sensitivity to the most important variables is shown in a heat map.
The names of the most important variables are on the y-axis, and the outcomes are on the x-axis. Values on the grid indicate relative importance, meaning that a variable with a score of 0.5 can be attributed 50% of the predictive power for the specified outcome. This heat map does not show all variables from Table A3, only those which have a score higher than 0.1 for any of the outcomes.

Figure 14: Feature scoring results

For the final GDP, the relative wage in the R&D sector is the most important determinant, as it can be held accountable for over 50% of GDP determination. Furthermore, the scaling factor that determines the amount of R&D knowledge gains per worker plays an important role. The importance of human capital becomes visible here too, as the degree to which teacher quality contributes to educational quality, which is the most important determinant for the Human Capital Index, also has a significant impact on the final GDP. As the Human Capital Index determines the output per R&D worker, this relationship matches the expectations.
The final value of the HCI depends not only on the degree to which teacher quality contributes to educational quality HLO, but also on the depreciation rate of the HLO and the return on teacher investments. This is logical, as all three are direct determinants of either educational quality or human capital.
The average number of R&D workers depends on the relative researcher wage, as well as on the output elasticity of capital. This shows the impact of available budget on R&D: with a favourable output elasticity, GDP is higher, which means that the absolute budget for R&D will be higher.

Finally, there is a clear difference in the determinants for productivity growth from R&D and FDI. While productivity growth from R&D depends on the costs of R&D and the output per worker (via the scaling factor and the Human Capital Index), productivity growth from FDI depends on other factors. As FDI is attracted by good infrastructure quality compared to other countries, the infrastructure development of other (competing) countries plays an important role. The spillover elasticity and spillover scaling factor both determine the amount of spillovers per unit of FDI, making the outcome's sensitivity to these two very logical. Lastly, productivity growth from FDI spillovers depends on the output elasticity of capital. This is because the amount of spillovers depends on infrastructure quality and human capital. With a favourable output elasticity, the calculated GDP is higher, meaning that investments in these two values are increased, which leads to more knowledge spillovers.

5.1.2 Scenario Discovery

Running PRIM analysis on the 3166 out of 30000 experiments in which India achieves high-income status in 2047 also shows the clear importance of the cost of R&D workers. The results are shown in Table 4 and Figure 15. In the Table, **bold** values indicate a minimum or maximum value, and only the statistically significant values ($qp < 0.05$) are shown. The full PRIM experiment can be found in Table A3.

The final PRIM box shows the importance of R&D to output generation. In the box with the highest density of positive outcomes, R&D wages are between 3.5 and 4.9 times the average, there is a relatively high share of available workers who are highly educated, and the number of spillovers per worker is increased as a result of the high scaling factor.

Furthermore, a low output elasticity of capital, which means a high output elasticity of labour, leads to higher output. This means that the labour force must grow faster than the capital stock; to get the most GDP growth, the elasticity of labour input should be as high as possible.

The analysis led to a final box that has a coverage of 0.371 and a density of 0.877, meaning that this box contains 37% of the experiments, of which almost 88% lead to the achievement of the national development goal.

Table 4: PRIM results on the base case

Variable name	Lower bound	Upper bound
R&D relative wage	**3.5**	4.9
Share of graduates able to join R&D labour force	0.0084	**0.0125**
Output elasticity of capital	**0.3**	0.36
Share of labour in R&D cost	0.41	**0.5**
R&D spillovers scaling factor	0.0041	**0.0046**
Coverage		**0.371**
Density		**0.877**

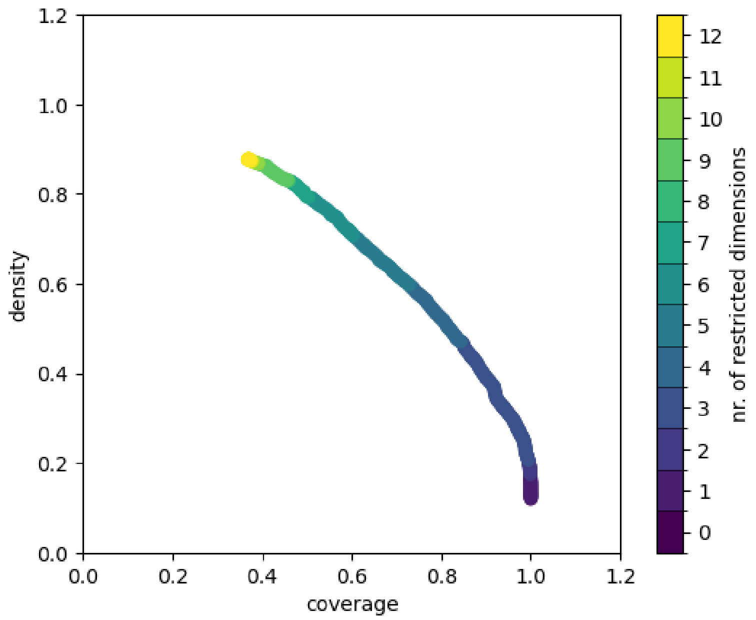


Figure 15: PRIM plot of the base case

Identifying Policies based on PRIM Results

The results of the first PRIM run suggest that the Indian government should impose a policy that leads to a larger R&D workforce. This could be achieved by spending more budget on R&D efforts, to make sure that more graduates can be hired and the workforce grows. To test the effects of such a measure, a second PRIM analysis was run, in which the R&D investment rate was updated from 0.006 to 0.0065.

The imposed policy boosts the share of successful experiments, as in the new run, 4723 of the 30,000 experiments lead to the achievement of the Viksit Bharat target. Compared to the 3166 successful experiments from the first uncertainty run, the success rate has increased by almost 50%.

Performing a new PRIM analysis leads to a box with similar dimensions and parameters, as can be seen in Table 5. Because of the increased budget, the costs of R&D have become a smaller obstacle, which is why the maximum relative wage has increased from 4.9 in Table 4 to 5.1 in the new analysis.

The ranges of the *Share of graduates able to join the R&D labour force* and the *Output elasticity of capital* have become smaller. This is most likely a result of the PRIM algorithm, because logically, the increased R&D budget should not lead to smaller ranges. As the density of this box is over 3% higher than the initial one, the algorithm has found a more specific subrange in this run, which it could not manage in the first one.

Also, the importance of the capital depreciation rate was newly discovered in this box, which replaced the *Share of labour in R&D cost*. A lower capital depreciation rate leads to a higher total capital stock, which leads to a higher GDP. The *Share of labour in R&D cost* from the previous box is not an important determinant in this box; the range that was found for this variable was not statistically significant and therefore not included in the PRIM results.

Table 5: Results of performing PRIM analysis on the basic policy

Variable name	**Lower bound**	**Upper bound**
R&D relative wage	**3.5**	5.1
Share of graduates able to join R&D labour force	0.0085	**0.0125**
Output elasticity of capital	**0.3**	0.35
R&D spillovers scaling factor	0.0041	**0.0046**
Capital depreciation rate	**0.035**	0.062
Coverage		**0.304**
Density		**0.912**

5.2 Budget Optimisation

Running the optimisation leads to two completely different outcomes; high infrastructure investment leads to the highest GDP in 2047, while high education investments lead to the highest GDP in 2075. The optimal budget allocation for 2047's GDP has a lower education investment rate than the current 0.046, a slightly higher R&D investment rate, and a higher infrastructure investment rate. The optimal long-term (2075) budget allocation is very different; it has a much higher education investment rate, a higher R&D investment rate, and a very low infrastructure investment rate; 0.020 was the minimum value set in Table 3.

Table 6: Results of the optimisation experiments

Investment rate	**2047 outcome**	**2075 outcome**
Education	0.040	0.071
R&D	0.008	0.013
Infrastructure	0.057	0.020
Other physical capital (fixed)	0.277	0.277
Total investment	**0.382**	**0.382**
Gross Domestic Product (Trillion US$)	**27.2**	**460.2**

These outcomes showcase the long-term benefits of education investments and the decreasing returns to infrastructure spending. This matches economic theory, which prescribes decreasing returns to capital investments, and often mentions the importance of human capital. The fact that investment in human capital does not have an immediate impact is logical: it takes years to see the effects of education enrolment increases, while infrastructure investment directly adds to GDP via the Cobb-Douglas function. As the Human Capital Index is used in almost all important formulas apart from the output function, it makes sense that this factor is important. It determines the attraction of FDI, the amount of spillovers from FDI and the R&D efficiency.

The fact that the optimal R&D investment rate is greater when optimising for the long term can be explained by the way the R&D workforce is determined. Before 2047, there are no benefits to having a higher R&D investment rate than 0.8%, as the limited number of available graduates hinders expansion of the workforce. Later, when the wages of the researchers have increased, an investment rate increase does work, as the available budget becomes the constraining factor. The results from the optimisation for 2075 suggest that an investment rate of 1.3% is the new boundary: a higher investment would not lead to a larger workforce, as there are no graduates left to be hired.

Performing an uncertainty analysis with the two optimal budget allocations leads to 7727 successful experiments for the 2047 budget allocation and 7290 successful experiments for the 2075 outcome, which are success rates of 25.8 and 24.3%, respectively. Using the 2075 budget allocation policy increases India's chances of meeting the Viksit Bharat target compared to the regular allocation policy, but not as effectively as the 2047 solution.

5.3 Comparing Outcomes from all Budget Allocation Policies

When comparing the outcomes of the three budget allocation policies (the current, the 2047 optimum and the 2075 optimum), the long-term effects of education spending on the Human Capital Index become visible. Until 2040, all three curves in Figure 16 still overlap, as values are similar. It takes around 15 years to begin to see the improved Human Capital Index as a result of the increased education spending. Around 2050, the consequences of the lowered education investment rate of the 2047 budget allocation policy become visible, as this policy leads to a lower Human Capital Index.

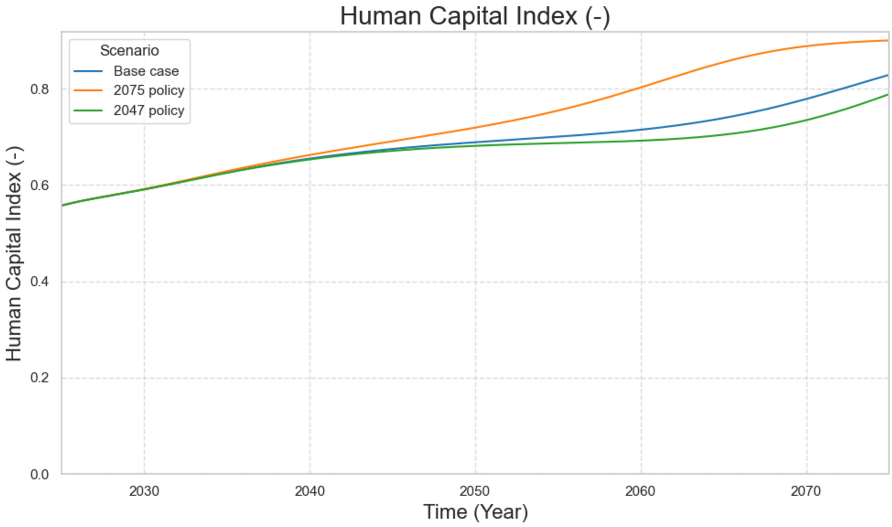
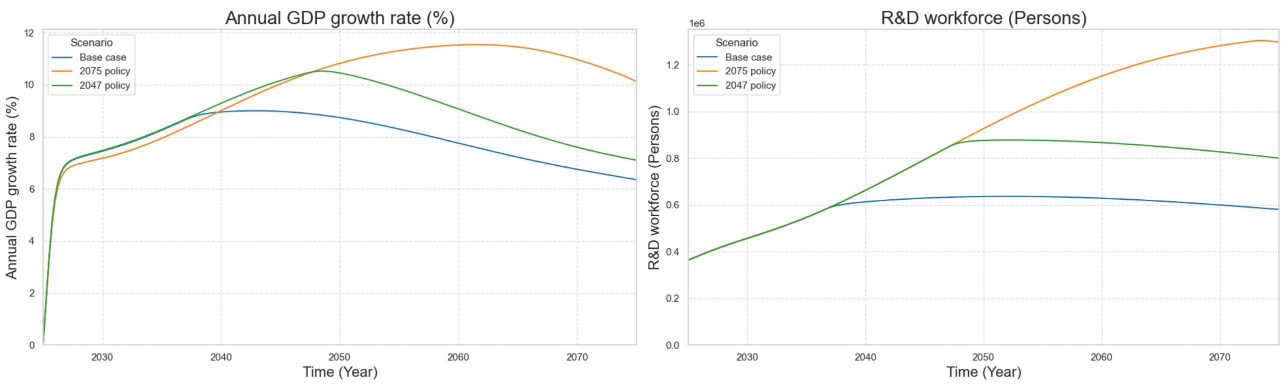


Figure 16: Human Capital Index for each budget allocation policy

Figure 17 shows how an increased R&D investment rates lead to a longer period of increasing GDP growth and stable R&D workforce growth. We see a pattern that is similar to Figure 11b: a higher R&D investment rate leads to a greater R&D budget, which means the workforce can expand for a longer period of time. At the moment when the R&D budget is no longer sufficient to hire the maximum amount of available workers, the curve bends and starts to slowly decline. By picking a higher investment rate, this moment is delayed, and the bending point shifts to the right. As GDP growth strongly depends on the R&D productivity gains, this plot looks very similar.



(a)

(b)

Figure 17: Annual GDP growth rates and R&D workforce size for each budget allocation policy

Figure 17b also explains the R&D investment rates that were found to lead to the highest GDP in 2047. The investment rate of 0.8% that was found is high enough to support expansion of the R&D workforce until 2048, just after the measuring point of 2047. This way, the investment rate is just high enough to lead to the optimal R&D workforce size in 2047, and not too high: a higher investment rate would not have led to a greater R&D workforce.

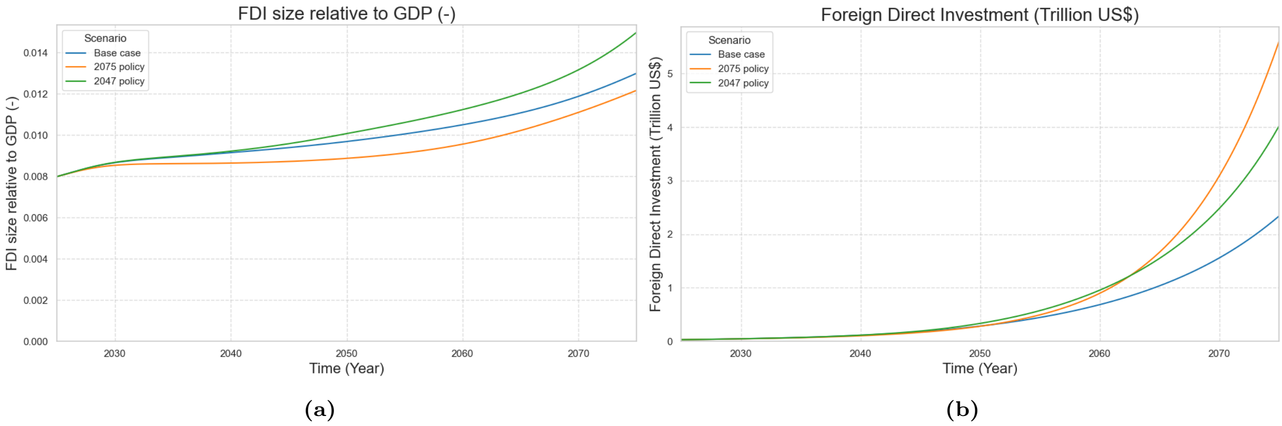


Figure 18: Relative and absolute FDI attraction for each budget allocation policy

Increased infrastructure spending leads to a higher amount of attracted FDI relative to GDP, but not to a higher total amount of FDI. This can be seen in Figure 18: The 2047 budget allocation leads to a final FDI inflow of over 14% of India's GDP, which is more than 2 percentage points higher than the inflow in the other two budget allocation policies. As infrastructure quality determines relative FDI attraction, this is no surprise. However, the absolute amount of FDI turns out to be higher when using the 2075 budget allocation policy. As this policy leads to higher GDP growth and a higher Human Capital Index, it also leads to significant FDI attraction.

6 Discussion

The model outcomes show that to maximise long-term economic growth, India must invest heavily in education. Infrastructure investments would increase the chances of achieving the Viksit Bharat target in time, but in the long term, the returns to these investments are limited. As the education investments have a greater long-term impact, these are the better option. Furthermore, it is important that India keeps steadily increasing its R&D budget, to enable expansion of the R&D workforce.

6.1 Interpretation of the Results

The conclusion that infrastructure investments lead to short-term growth, but not long-term growth, matches the expectations set by economic theory. In accordance to Cohen and Levinthal (1989), the model's infrastructure stock boosts GDP by attracting FDI and by being part of India's *absorptive capacity*, which increases the amount of knowledge spillovers from FDI. Furthermore, infrastructure is part of the capital input in the Cobb-Douglas function, so increases in the infrastructure stock lead to direct increases in economic output (Cobb & Douglas, 1928). This structure explains the decreasing importance of infrastructure for the creation of productivity growth: as the technological distance between India and the technological frontier shrinks, the amount of knowledge spillovers decreases, based on Aghion and Howitt (1998). This means that over time, infrastructure investments have less impact on productivity growth; the effects of the investments become increasingly more similar to those of regular capital investments, of which the returns are not sufficient to create long-term growth (Acemoglu, 2009).

The outcome that education investments have positive long-term effects also fit the expectations set in the Literature Review. They lead to more human capital, which matches Schultz (1961), are part of the national absorptive capacity (Nelson & Phelps, 1966) and increase R&D efficiency (Romer, 1990). This means education investments lead to greater returns from both productivity growth drivers, which explains why it is important to adequately invest in education enrolment and quality. The delayed benefits of education investments make sense when analysing the model structure. The advantages of increased enrolment only become visible after the additionally enrolled students have graduated, because the Human Capital Index is determined based on the average number of schooling years per new worker. This could take up to 16 years, in case someone completes all three levels of education (Nuffic, n.d.-a, n.d.-b).

Thirdly, the recommendation to continuously increase the R&D budget matches Jones (1995), who states that to maintain the same productivity growth rate, the size of the R&D workforce must grow at a constant positive rate. Due to the high researcher wages, which increase even further when GDP rises, this can only happen when the GDP share allocated to R&D also increases consistently.

6.2 Existing studies

Most of the research outcomes also match existing scientific evidence on the middle-income trap. The decreasing importance of infrastructure matches evidence from Cherif and Hasanov (2016), who state that Malaysia's growth slowdown is a result of excessive focus on conventional factor accumulation and FDI-led manufacturing. High infrastructure investments would make these the two main growth drivers, as they are a form of conventional capital accumulation and attract FDI.

However, Feitosa (2020) names Korea's high stock of advanced infrastructure as one of the reasons behind its development into the high-income range. Similarly, Agénor (2016) points to a lack of access to advanced infrastructure as a determinant of stagnating growth, which contradicts the research outcomes on long-term budget allocation. Compared to these studies, the outcome that the lowest possible infrastructure investment leads to the most economic growth may be slightly exaggerated.

The long-term benefits of education investments match Agénor (2016) and Jimenez et al. (2012), who both state that poor educational quality increases the chances of experiencing a growth stagnation, and Eichengreen et al. (2013), who write that escapees of the middle-income trap often have more secondary and tertiary education graduates. Other studies also identified education as a determining factor for productivity growth from FDI spillovers (Islam & Beloucif, 2023) and R&D knowledge gains (Cirera & Maloney, 2017). The World Bank (2024c) recommends that middle-income countries invest heavily in education.

The importance of increasing the relative R&D spending rate matches Terleckyj (1974) , who identified a pattern between total spending on R&D and productivity growth. Furthermore, the outcome matches (Feitosa, 2020), who identified R&D investments as the factor that led to development into the high-income range in a case study on South Korea.

Compared to Hartmann et al. (2021) and the World Bank (2024c), the impact of knowledge spillovers from FDI in the model is limited. The World Bank presents this as a key driver of economic growth when R&D capacity is still limited, while in the research outcomes, it never accounts for more than 20% of the total productivity growth. This indicates that the model may underestimate the impacts of FDI attraction.

6.3 Limitations

Although the model manages to capture many important mechanisms and delays, there are still some additions that can be made to draw more conclusions on the middle-income trap.

By determining more important variables within the model, rather than keeping them constant, more feedback loops could have been discovered, and the model could have been more realistic. Currently, a few parameters, such as the labour force participation rates, school dropout rates and retirement rates, stay constant throughout the whole simulation, while one could argue that this is unrealistic, and that they could be based on other parameter values. Similar variables, such as the mortality rate and fertility rate, depend on GDP per capita. The choices to determine some values endogenously and keep others fixed were often made because of time constraints. Furthermore, the relationships of mortality and fertility rates with per-capita income were very convincing, while (female) labour force participation rates and dropout rates are also dependent on social and cultural factors (Costagliola, 2021; Garg et al., 2023) that are not included in the model. As a result of these choices, the model is a less realistic representation of reality, in which these rates change over time.

Other factors were not included in the model at all, such as the institutional quality, which was often mentioned as a growth-determining factor in the literature about the middle-income trap. As I found that human capital, total infrastructure, FDI and R&D were mentioned more often and marked as more important in the literature, I decided not to include institutional quality in the model, as there was not enough time to model all relationships. With more time, I would have been able to make more analyses to find the optimal investment rates and study the trade-offs between investing in institutional quality or one of the other factors.

These limitations do not impact the final result. Although the use of constant rates and the missing institutional quality make the model a less realistic representation of the real world, they do not change the existing feedback structures between the drivers of growth, the patterns that can lead to continuous growth or a growth stagnation, and the conclusions that are drawn as a result of these.

While SD is a suitable method for modelling the middle-income trap, there are also a few limitations to its use, which make it difficult to recommend specific policies. The biggest limitation is the inability to model agent interactions and discrete events. SD works well for

capturing behavioural long-term patterns, but is less useful when trying to find targeted policy measures. It is also not possible to recommend specific taxes or subsidies based on the model, because there is no government objective function that can be optimised, which is common in economic research. However, the long-term patterns and delays that were identified are still valuable insights for national policymakers.
Finally, the model outcomes do not continue the trend of India's past behaviour. As mentioned in Chapter 1, India is currently getting increasingly more signs that it is facing a growth slowdown, and the past year's economic growth is predicted to be lower than the year before. However, the annual GDP growth rate in the model increases for over a decade until a growth slowdown occurs. This does not seem realistic and can be seen as a limitation. On the other hand, this does let the model show the differences between periods of increased and decreased growth and helps to identify the causes of a growth slowdown. Therefore, this limitation makes the model outcomes less realistic, but possibly more useful. The outcomes of this research should therefore not be seen as a precise prediction on India's future GDP, it is more important to focus on the identified feedback systems that explain the effect of each investment.
Finally, the fact that increased GDP growth rates are unrealistic confirms that India's Viksit Bharat target may be too ambitious; even when GDP growth rates keep increasing in the coming years, the target is not met.

6.4 Strengths of the Research and Model

The different optimisation outcomes when simulating GDP by 2047 and 2075 are a significant outcome. The results match economic theory and much of the existing evidence on the middle-income trap. Also, they confirm the advice by the World Bank (2024c) for middle-income countries to invest in human capital and innovation to grow GDP, as the returns to conventional factor accumulation diminish over time.
The choice for SD modelling has played a big role in identifying these recommendations. Most other modelling techniques would not have been able to show the delayed effects of education investments and simulate the feedback loops between all drivers of growth. The model captures the accumulating effects and can be used to explain why India must invest in R&D capacity and education.
The results are generated by a model that works as expected and was validated in multiple ways. It passes the common validity tests, is responsive to changes and produces logical behaviour, while not easily reaching extreme values. This is mostly due to elasticity values, which cause decreasing returns, and to the fact that the maximum expansion of the R&D labour force is based on the availability of tertiary education graduates. As a consequence of this maximum, simply increasing the R&D budget does not lead to a direct and proportional increase in R&D labour force size, which limits productivity growth. This helps to showcase the importance of human capital investments.
Finally, the model is understandable and can be produced for other case studies relatively easily. The equations and their behaviour should be understandable for most readers, and most of the data needed to build the model is openly accessible in well-known online databases.

6.5 Implications

The optimisation results show the political relevance of this topic: policymakers must make a decision between investing in short-term or long-term results. Although the outcomes show that educational investments have more advantages in the long term, politicians may also have their own interests; they will want to deliver short-term results, as their potential voters cannot experience the benefits from long-term policies and demand immediate results. The outcomes of this research can be used as an argument for long-term human capital investments, as they show that this is the best option in the long run.

Furthermore, these outcomes confirm the recommendation made by the World Bank (2024c) in the *World Development Report*, to focus on the promotion of STEM fields to new university students. This would increase the share of higher education graduates that could join the R&D labour force, leading to higher productivity growth. In addition to this policy, India should focus on improving its (female) labour force participation rates and dropout rates to get the most out of their education system. Currently, approximately half of the women with any degree join the labour force, and 25% of all the tertiary education students do not finish their degree. This way, a lot of India's potential is wasted. With improved labour force participation rates and lower dropout rates, India could significantly increase the size of its R&D labour force and its total labour force, both of which boost total output.

The outcomes of this research add to the existing stock of knowledge on the middle-income trap, by confirming the importance of investment in education and R&D. The use of SD gave clear insights into the dilemma between short-term and long-term investing and the relevant delays that cause the returns to education investments to occur later.

Apart from confirming existing evidence, the use of SD modelling has enabled me to give estimations on India's future, based on existing relationships between growth drivers and India's current state. The use and analysis of a model help to show why India faces a growth slowdown, and how budget allocation changes would lead to a different outcome.

Finally, this research contributes to the Sustainable Development Goals set by the United Nations (2023), by delivering insights that can help policymakers to create long-term economic growth and arguments to invest in education. By studying the middle-income trap in a systems thinking approach, this thesis was done using a typical EPA perspective.

6.6 Future Research

The outcomes of this study show the trade-off between investing for short-term and long-term results and help to explain why many fear that India is headed for a middle-income trap. However, there are still many ways in which this model can be expanded or used to deliver new policy insights.

To support India in its path to high-income status, it would be valuable to study how investment rates should change over time to create the highest economic output. In the current optimisation, the investment rates stay fixed throughout the whole simulation, while it may be better to change the budget allocation over time. As seen in the model results, the budget share spent on R&D must increase over time to maintain the expansion of the R&D labour force, and infrastructure leads to short-term results, which could support future growth. It would therefore be interesting to create a timeline with changing investment rates over time and a policy roadmap.

Furthermore, the model could be expanded to deliver more insights into investment in institutional quality or specific advanced infrastructure, for example. As the Indian economy is such a large and complex system, it was impossible to fully model it within the set time, meaning there are still ways in which the model could be made more realistic.

7 Conclusion

When determining policies to achieve the Viksit Bharat target, the Indian government has to choose between short-term and long-term success. It can either focus on infrastructure capital to maximise the odds of still achieving the Viksit Bharat target, or it can take a more patient stance and invest in its education to maximise long-term growth.

Investment in infrastructure would lead to immediate output and attract foreign direct investment, but its returns decline over time. At the initial state of the model, FDI is still a relatively important growth driver, as the high technological distance causes India to experience more benefits from FDI. However, as India approaches the technological frontier, infrastructure investments will lead to fewer knowledge spillovers and act as general capital investments, for which the returns have decreased over time.

Investments in education are a better choice, as they create long-term growth. Improved enrolment rates and higher educational quality will lead to a larger R&D workforce and more efficient R&D, as well as more FDI attraction and knowledge spillovers. A higher human capital stock is beneficial to all drivers of growth; investing in education is therefore the best option.

Furthermore, India must continuously increase its GDP share dedicated to R&D investment, to keep up with the growing labour force and the increasing wages.

Answers to the Research Questions

In the literature review, the middle-income trap was defined as a state in which a middle-income country experiences slowed-down growth because it is unable to compete with both low- and high-income countries. The wages in middle-income countries have grown too high to compete with low-income countries in labour-intensive industries, while they are not developed enough to compete with high-income countries in innovative sectors. This causes economic growth to stagnate, leaving countries "stuck in middle-income". Countries that struggle to escape this trap often experience a lack of access to finance and infrastructure, have low education enrolment, low educational quality and weak institutions.

Throughout the middle-income range, the roles of growth drivers change. Literature shows that countries in the lower middle-income range strongly rely on conventional input accumulation; growth is generated through increases in labour force size and capital investment. As a result of the output elasticities towards these inputs, the returns to these inputs decrease over time; long-term growth must therefore be generated through productivity gains.

As productivity grows from knowledge spillovers via the attraction of foreign investment and knowledge gains from R&D efforts, these are the two main growth drivers in the middle-income range. Investing in infrastructure and investing in education are two ways to attract more FDI and experience more knowledge spillovers. This explains why infrastructure investment only leads to short-term success: when India approaches the technological frontier, returns to infrastructure investments decrease.

Close to the technological frontier, R&D will become the sole driver of productivity growth. As India's productivity has become similar to that of the global technological leader, it experiences very little productivity growth from foreign investments, and it must innovate to become more productive. To optimise its R&D returns, middle-income countries must create a large R&D workforce. This is the reason why education investments lead to long-term success; by increasing enrolment rates and promoting STEM fields, the number of researchers can grow. Furthermore, investments in education increase the efficiency of R&D, causing a higher output per worker, which leads to higher productivity and more economic growth.

To create long-term growth, India must therefore allocate a high share of its GDP to education, while increasing the R&D investment rate to be able to keep expanding the R&D labour force.

Investments in infrastructure have little long-term effect and should therefore not be prioritised. They attract FDI and lead to short-term growth, but these investments do not lead to the same long-term growth rates as education investments.

This recommendation is in line with what the existing evidence on the middle-income trap suggests. Therefore, the research outcomes add to the existing knowledge on this topic. By using an SD approach, feedback patterns between growth drivers were identified in a new way, and an insight into India's future development was given. Future research could give more detailed insight into how India's budget allocation should change with the changing roles of the drivers of growth and the impact of other factors, to support India in its path towards full development.

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Appendix

A1 Model structure

A1.1 Explanation of the population sub-model

In a population sub-model, India's number of inhabitants is determined, divided into age groups of 5 years. Newborns are added to the group of 0 to 4-year-olds, and are determined in the following way:

$$\textit{Birth} = \textit{Fertile population} * \textit{Share of women} * \textit{Fertility per woman} / \textit{Fertile period} \quad \text{(A1.1)}$$

The fertility rate per woman is derived from Bhattacharjee et al. (2024), who predict that India's fertility rate will decline from 1.91 in 2021, to 1.29 in 2050, to 1.04 in 2100. I have assumed that between these years, fertility rates drop linearly.

The stock of each age group decreases through deaths and ageing. Deceased persons leave the model, while persons who age move up an age group, until they reach the final age group of persons aged 80 or more.

Mortality is modelled in the following way: the mortality rate of the age group 0 to 4-year-olds, the *Child mortality*, is dependent on GDP per capita, and is derived from Our World in Data (2022). The mortality rate of the final age group *80plus* is 1, meaning that each time step, the current population is replaced by an inflow of ageing 79-year-olds. For the ages in between, the mortality rate is determined by a Gompertz-Makeham function, which consists of an age-dependent term that increases per age (Gompertz, 1825), and an age-independent mortality (Makeham, 1860). The sizes of these terms depend on life expectancy, which evolves with GDP per capita, based on Our World in Data (2024).

A1.2 Vensim Screenshots of the Model

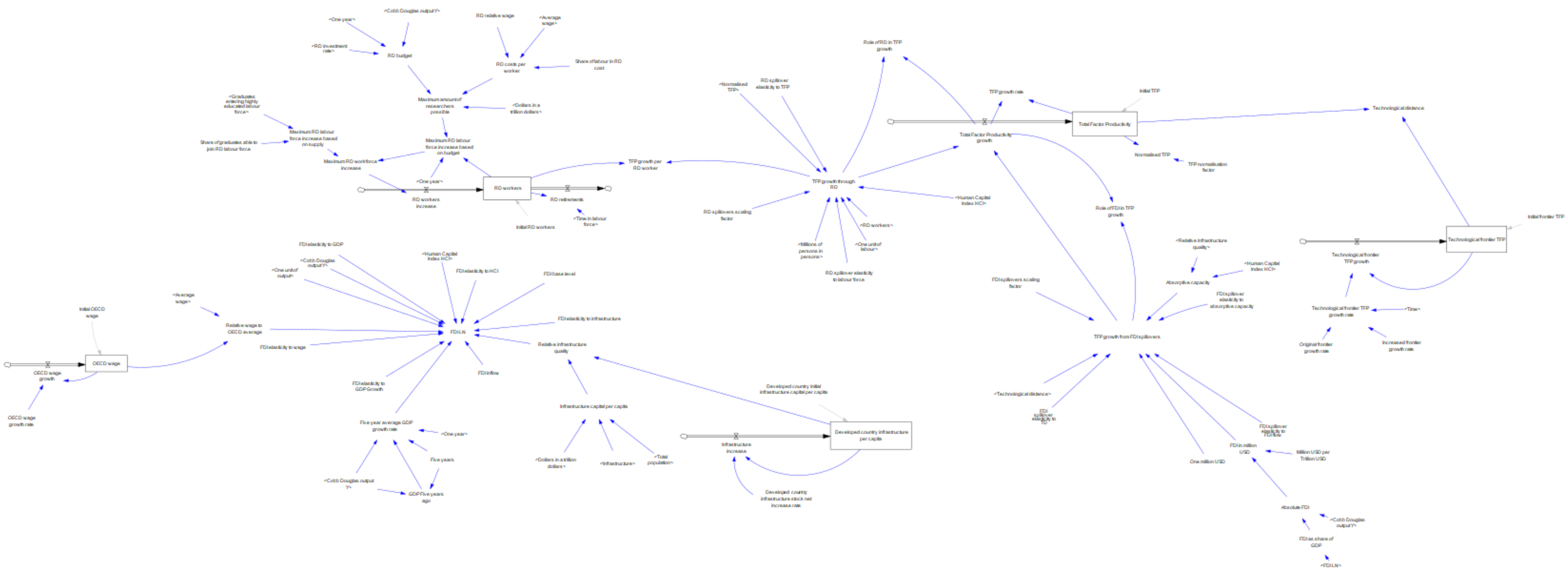

Figure A1: Determination of endogenous productivity growth

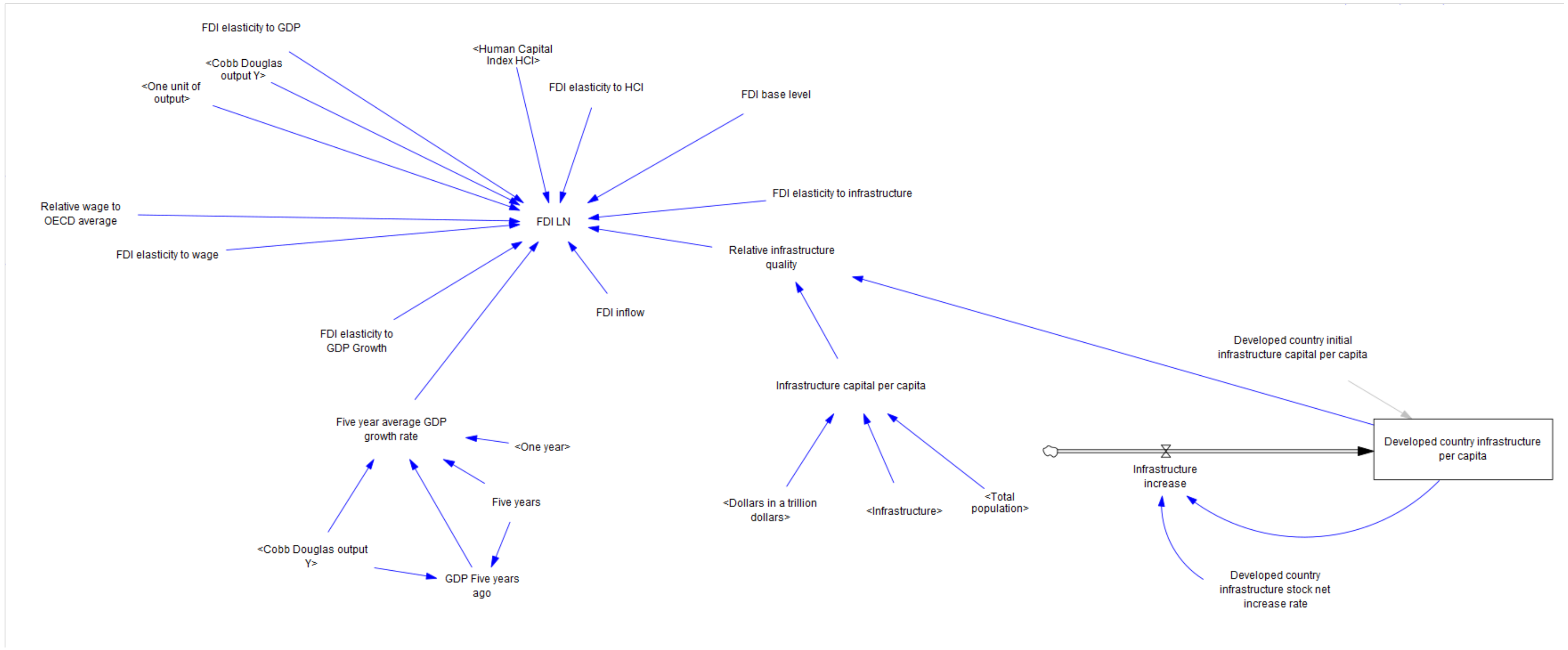

Figure A2: Determination of FDI attraction

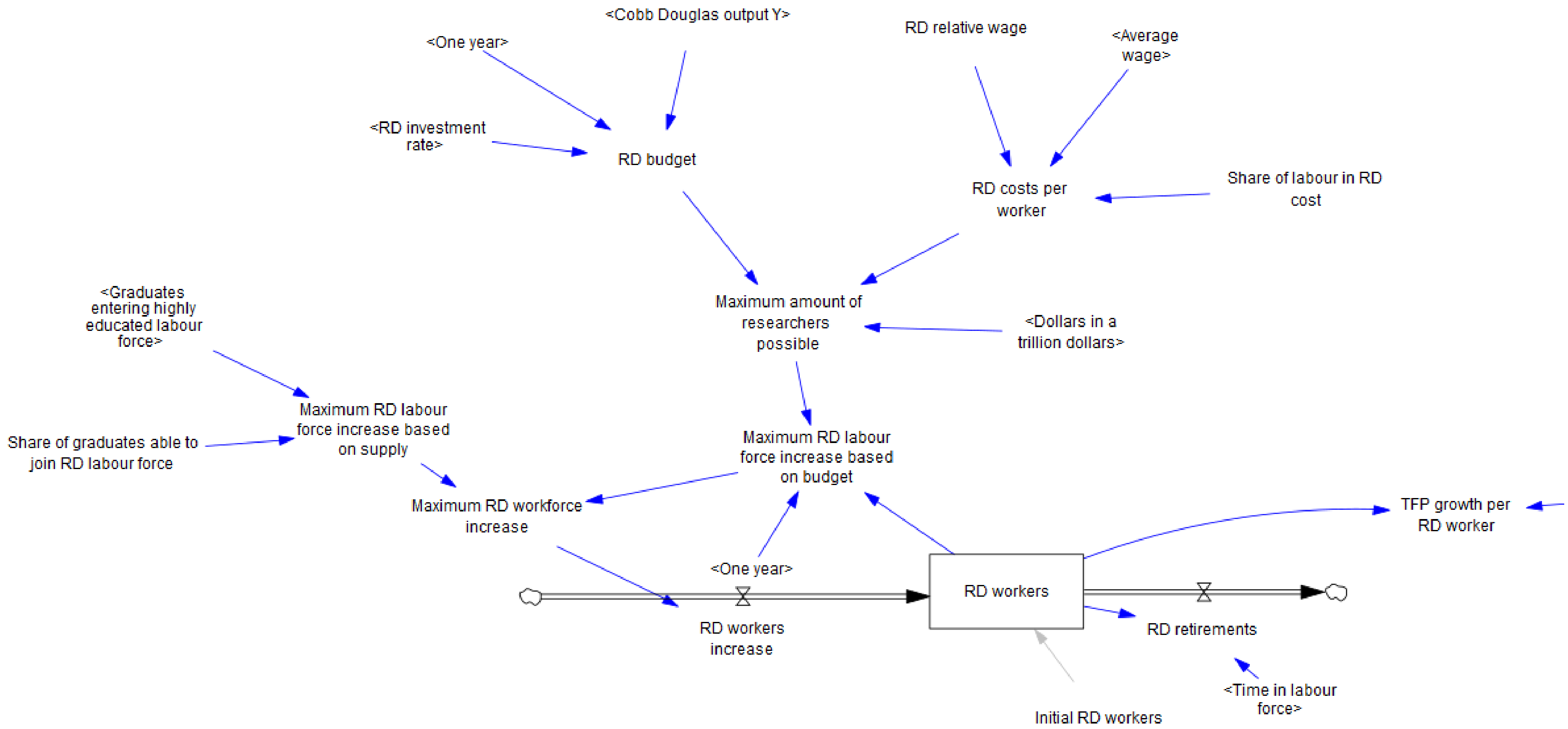

Figure A3: Determination of the R&D workforce size

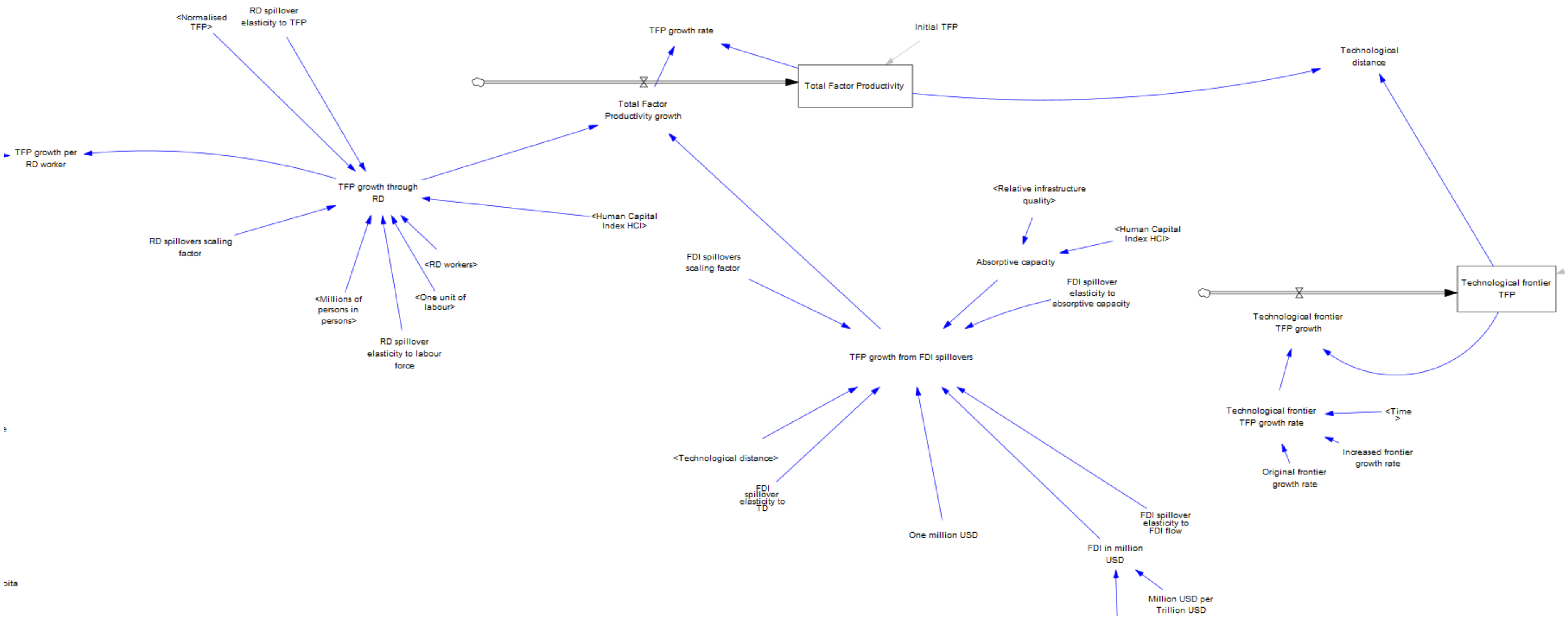

Figure A4: Determination of total factor productivity growth

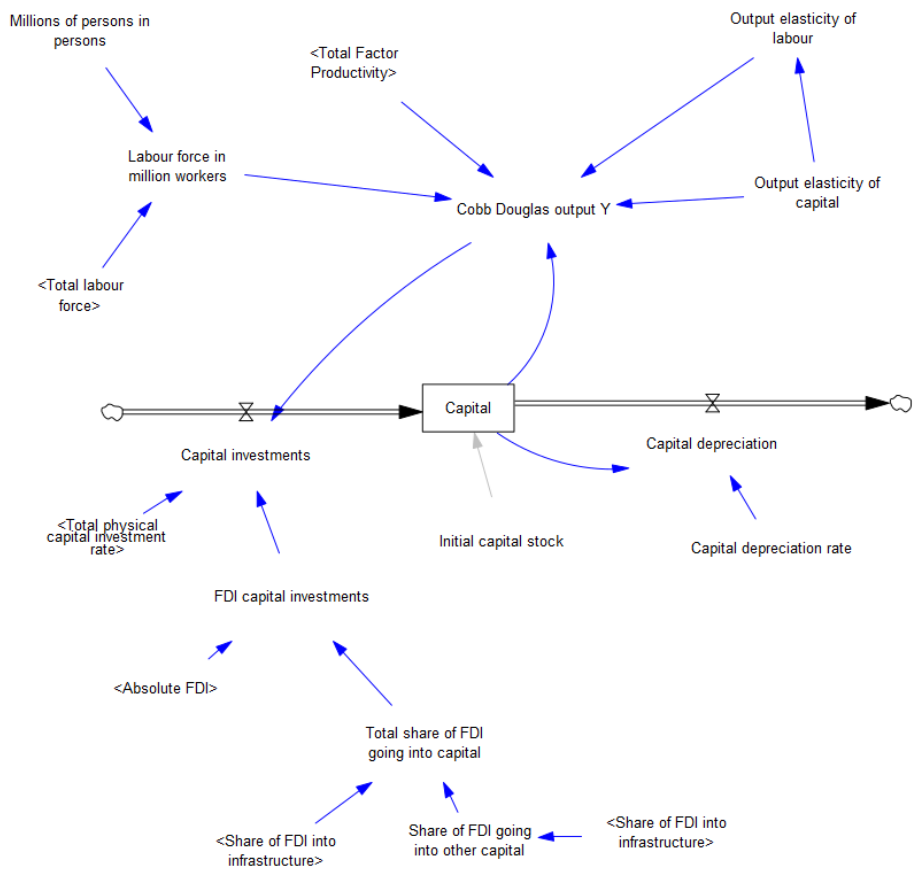

Figure A5: Determination of Cobb-Douglas output

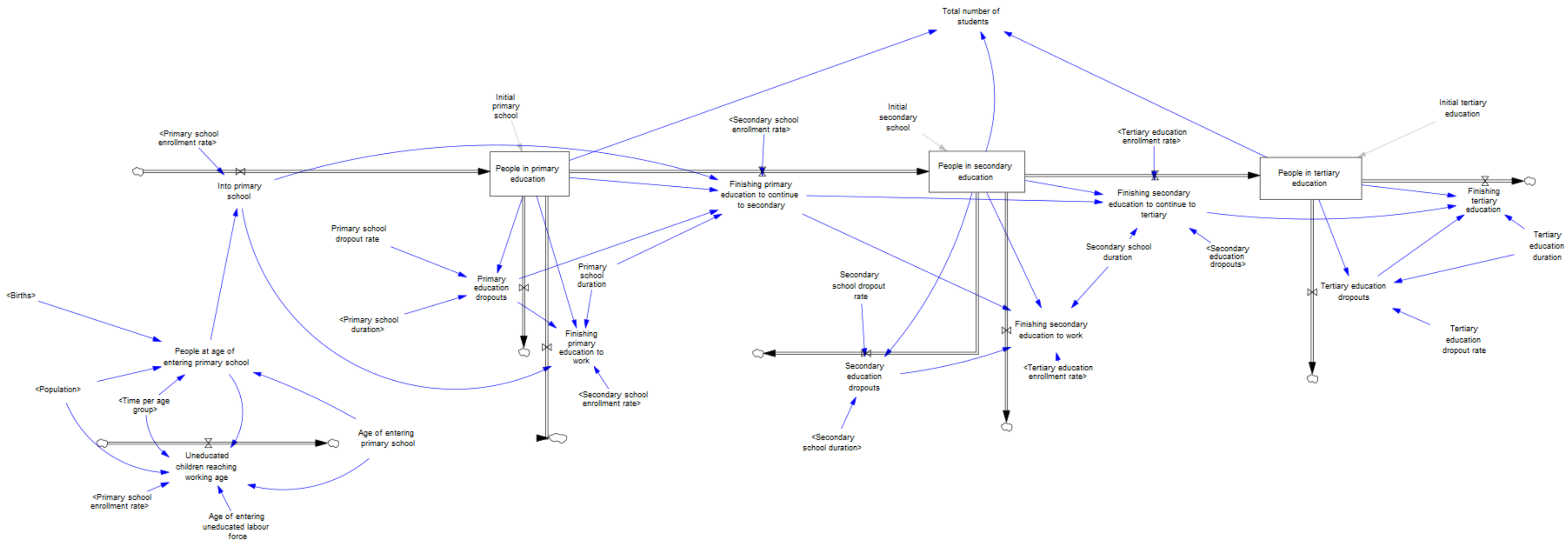

Figure A6: Determination of the education level

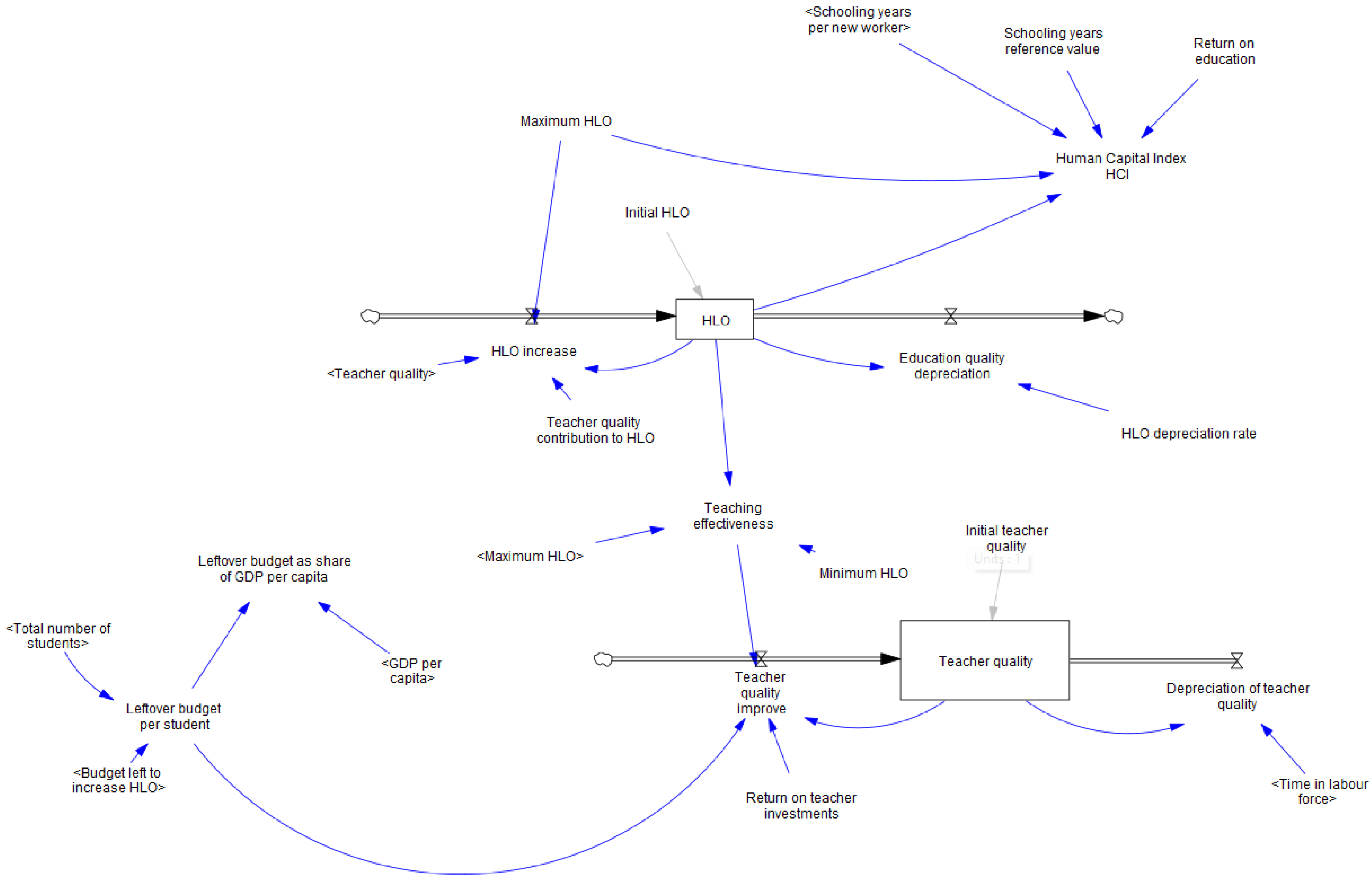

Figure A7: Determination of the Human Capital Index

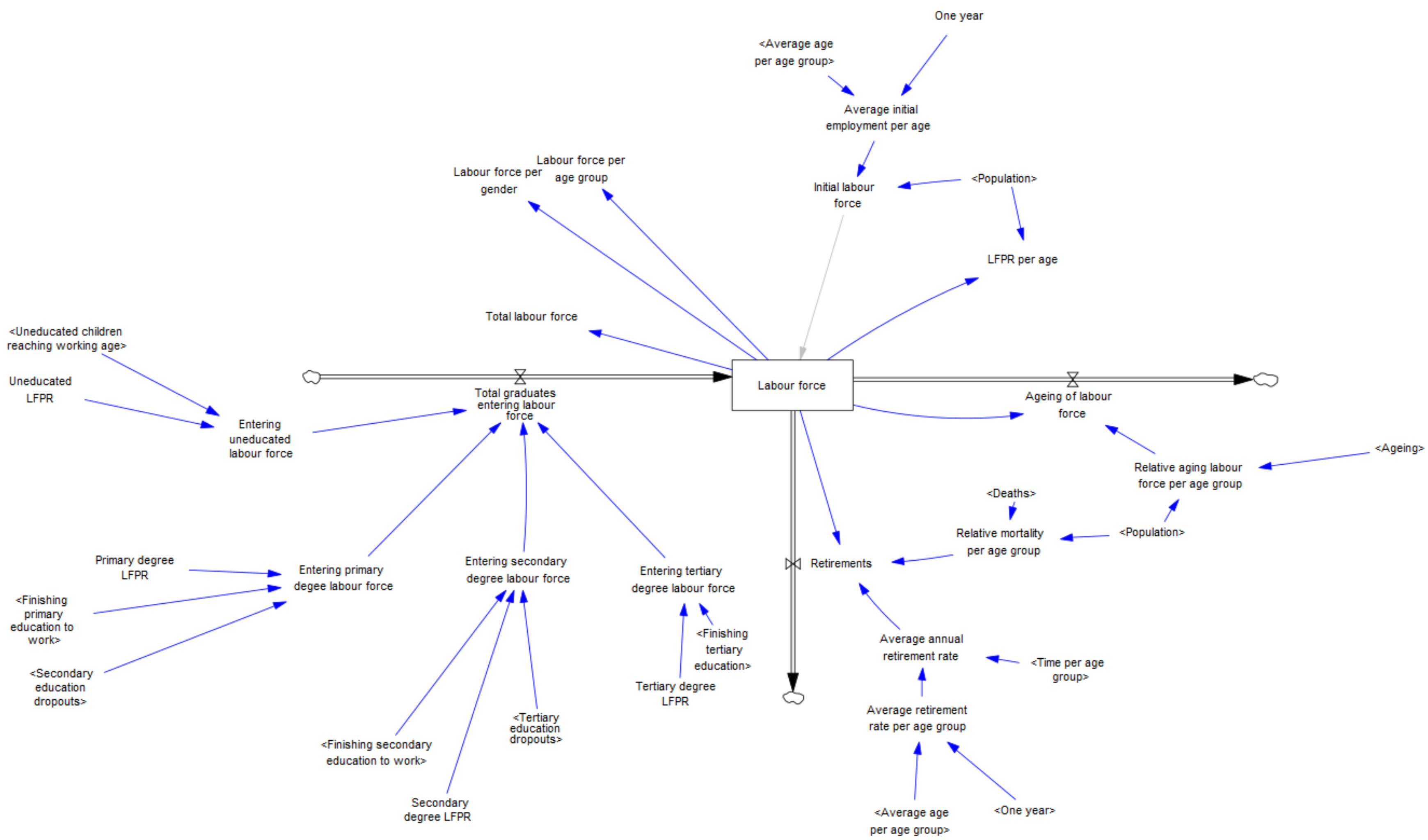

Figure A8: Determination of the labour force size

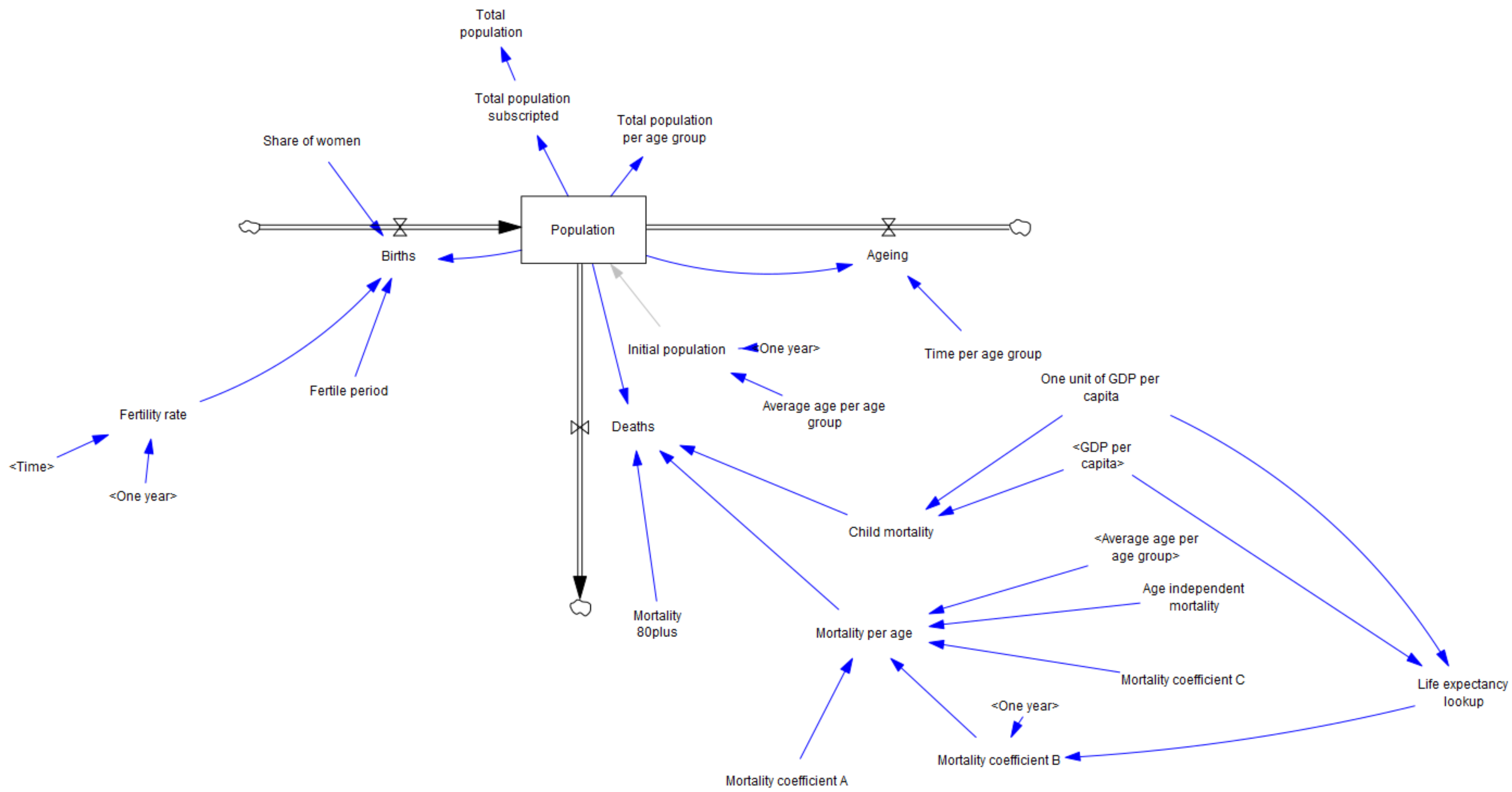

Figure A9: Determination of the total population

Table A1: Overview of all variables and their origins

Variable name	**Unit**	**Value**	**Source**
Age independent mortality	1/Year	0.0015	Based on Gompertz (1825) and Makeham (1860)
Age of entering primary school	Year	6	Nuffic (n.d.-b)
Age of entering uneducated labour force	Year	15	Ministry of Statistics and Programme Implementation (2024)
Average initial employment per age	1	Subscripted	Chawla and Singh (2024) and United Nations (2024)
Average retirement rate per age group	1	Subscripted	Calculated based on Chawla and Singh (2024)
Capital depreciation rate	1/Year	0.05	Mankiw et al. (1992)
Developed infrastructure increase rate	1/Year	0.02	Global Infrastructure Hub (2023)
Developed country initial infrastructure	USD/Persons	30000	Nova Scotia Department of Finance (2024)
Education investment rate	1/Year	0.046	Statista (2025a)
FDI base level	1	-4.83	Calculated based on World Bank (2023a)
FDI elasticity to GDP	1	0.50	Dutta and Roy (2010) and Islam and Beloucif (2023)
FDI elasticity to GDP Growth	1	1	Mishra and Sarbesh (2024)
FDI elasticity to HCI	1	1	Islam and Beloucif (2023)
FDI elasticity to infrastructure	1	1	Islam and Beloucif (2023)
FDI elasticity to wage	1	-1	Islam and Beloucif (2023) and Wei et al. (2022)
FDI spillover elasticity to AC	1	1	Ali et al. (2017) and Xu (2000)
FDI spillover elasticity to FDI flow	1	0.1	Getaneh (2020)
FDI spillover elasticity to TD	1	1	Islam and Beloucif (2023)
FDI spillovers scaling factor	1/Year	0.003	Assumed to fit case
Fertility rate	1	LOOKUP	Bhattacharjee et al. (2024)
HLO depreciation rate	1/Year	0.01	Assumption
Infrastructure depreciation rate	1/Year	0.05	Mankiw et al. (1992)
Infrastructure investment rate	1/Year	0.053	India Brand Equita Foundation (2025)
Initial capital stock	Trillion USD	34.20149994	University of Groningen and UC Davis (2023)
Initial frontier TFP	1	0.2	Hsieh and Klenow (2009) and Saliola and Seker (2012)
Initial HLO	1	350	World Bank (2024d)
Initial infrastructure stock	Trillion USD	4	Estimated based on Edelweiss Alternatives (2024)
Initial highly educated population	Persons	123.292e6	Based on Waghmare (2025b)
Initial OECD wage	USD/Persons	58000	OECD (2023)

Initial population	Persons	Subscripted	United Nations (2024)
Initial primary school[Male, Female]	Persons	98.8e6, 89.8e6	Ministry of Education (2024)
Initial primary school enrolment rate	1	0.97	Calculated based on Waghmare (2025a)
Initial RD workers	Persons	364000	World Bank (2020)
Initial schooling years per worker	Year	6.7	UNDP (2022)
Initial secondary enrolment rate	1	0.74	Calculated based on Waghmare (2025a)
Initial secondary school[Male, Female]	Persons	32e6, 35.1e6	Ministry of Education (2024)
Initial teacher quality	1	0.15	Estimated based on World Bank (2024d)
Initial tertiary education[Male, Female]	Persons	11.0e6, 10e6	Ministry of Education (2022)
Initial tertiary enrolment rate	1	0.284	Calculated based on Waghmare (2025a)
Initial TFP	1	0.020684	Determined based on World Bank (2024a)
Life expectancy lookup	Year	Varies	Our World in Data (2024)
Minimum HLO	1	300	World Bank (2024d)
Mortality 80plus	1/Year	0.5	Based on Gompertz (1825) and Makeham (1860)
Mortality coefficient A	1/Year	1	Based on Gompertz (1825) and Makeham (1860)
Mortality coefficient C	1/Year	0.03	Based on Gompertz (1825) and Makeham (1860)
OECD wage growth rate	1/Year	0.02	OECD (2023)
Other capital investment rate	1/Year	0.277	CEIC (2025)
Output elasticity of capital	1	0.4	Unel (2003)
Primary degree LFPR[Male, Female]	1	0.75, 0.3	Ministry of Statistics and Programme Implementation (2024)
Primary education cost per student	1	0.12	World Bank (n.d.-b)
Primary school dropout rate	1	0.01	Ministry of Education (2022)
Primary school duration	Year	8	Nuffic (n.d.-b)
RD investment rate	1/Year	0.006	Gupta et al. (2023)
RD relative wage	1	5	Assumption, based on Indeed (2025)
RD spillover elasticity to labour	1	0.80	Jones (1995)
RD spillover elasticity to TFP	1	0.60	Jones (1995)
RD spillovers scaling factor	1/Year	0.0045	Assumed to fit case
Return on education	1/Year	0.08	Kraay (2018)
Return on teacher investments	Persons/(Year*USD)	1E-05	Assumed to fit case
Schooling years REFERENCE	Year	14	Kraay (2018)

Secondary degree LFPR[Male, Female]	1	0.85, 0.4	Ministry of Statistics and Programme Implementation (2024)
Secondary education cost per student	1	0.20	World Bank (n.d.-c)
Secondary school dropout rate	1	0.12	Ministry of Education (2022)
Secondary school duration	Year	4	Nuffic (n.d.-b)
Share of FDI into infrastructure	1/Year	0.30	UNCTAD (2023)
Share of FDI going into other capital	1/Year	0.70	Estimated based on UNCTAD (2023)
Share of graduates joining RD labour force	1	0.01	Based on OECD (2024b) and World Bank (2020)
Share of labour in R&D cost	1	0.45	Based on Aubert et al. (2010) and NCSES (2022)
Share of women	1	0.5	Assumed for simplicity
Target for tertiary education enrolment	1	0.5	Ministry of Education (2020)
Target year full primary school enrolment	Year	2030	Ministry of Education (2020)
Target year full secondary school enrolment	Year	2035	Ministry of Education (2020)
Target year tertiary education enrolment	Year	2035	Ministry of Education (2020)
Teacher quality contribution to HLO	1/Year	0.3	Estimated based on Marin et al. (2025)
Technological frontier TFP growth rate	1/Year	0.015	OECD (2024c)
Tertiary degree LFPR[Male, Female]	1	0.9, 0.55	Ministry of Statistics and Programme Implementation (2024)
Tertiary education dropout rate	1	0.25	NUEPA (2023)
Tertiary education duration	Year	4	Estimated based on Nuffic (n.d.-a)
Tertiary education cost per student	1	0.9	World Bank (n.d.-a)
TFP normalisation factor	1	50	Assumed to fit case
Time in labour force	Year	45	Ministry of Statistics and Programme Implementation (2024)
Uneducated LFPR[Male, Female]	1	0.675, 0.225	Ministry of Statistics and Programme Implementation (2024)

Table A2: Overview of the uncertainty analysis, including references

Parameter Name	Unit	Range	Source
Capital depreciation rate	Dmnl	[0.035, 0.065]	Arslanalp et al. (2010) and Mankiw et al. (1992)
Developed country infrastructure stock net increase rate	1/Year	[0.01, 0.03]	Xiao and Le (2019)
FDI spillover elasticity to FDI flow	Dmnl	[0.05, 0.15]	Javorcik (2004)
FDI spillover elasticity to TD	Dmnl	[0.9, 1.1]	Assumption
FDI spillovers scaling factor	1/Year	[0.0002, 0.0003]	Assumption
HLO depreciation rate	1/Year	[0.005, 0.015]	Assumption
OECD wage growth rate	1/Year	[0.01, 0.03]	OECD (2024a)
Output elasticity of capital	Dmnl	[0.3, 0.5]	Bank (2021) and Brown and Wilcox (2009)
Primary degree LFPR [Female]	Dmnl	[0.25, 0.35]	Estimated based on Ministry of Education (2024)
Primary degree LFPR [Male]	Dmnl	[0.7, 0.8]	Estimated based on Ministry of Education (2024)
Primary school dropout rate	Dmnl	[0.01, 0.02]	Min education 2022
RD relative wage	Dmnl	[3.5, 6.5]	Indeed (2025) and SalaryBand (n.d.)
RD spillovers scaling factor	1/Year	[0.0038, 0.0046]	Assumption
Return on teacher investments	1/(Year* USD*Persons)	[0.5e-5, 1.5e-5]	Assumption
Secondary degree LFPR [Female]	Dmnl	[0.35, 0.45]	Estimated based on Ministry of Education (2024)
Secondary degree LFPR [Male]	Dmnl	[0.8, 0.9]	Estimated based on Ministry of Education (2024)
Secondary school dropout rate	Dmnl	[0.04, 0.20]	min edu 2022, pab
Share of FDI into infrastructure	Dmnl	[0.25, 0.35]	UNCTAD (2023)
Share of graduates able to join RD labour force	Dmnl	[0.0075, 0.0125]	Estimated based on Buchholz (2023)
Share of labour in RD cost	Dmnl	[0.4, 0.5]	Estimated based on Aubert et al. (2010) and NCSES (2022)
Teacher quality contribution to HLO	1/Year	[0.2, 0.4]	Estimated based on Marin et al. (2025)
Technological frontier TFP growthrate	1/Year	[0.01, 0.025]	Ranges from OECD (2024c)
Tertiary degree LFPR [Female]	Dmnl	[0.5, 0.6]	Estimated based on Ministry of Education (2024)
Tertiary degree LFPR [Male]	Dmnl	[0.85, 0.95]	Estimated based on Ministry of Education (2024)
Tertiary education dropout rate	Dmnl	[0.2, 0.3]	Estimated based on NUEPA (2023)
Uneducated LFPR [Female]	Dmnl	[0.2, 0.25]	Estimated based on Ministry of Education (2024)
Uneducated LFPR [Male]	Dmnl	[0.65, 0.70]	Estimated based on Ministry of Education (2024)

A2 Model outcomes

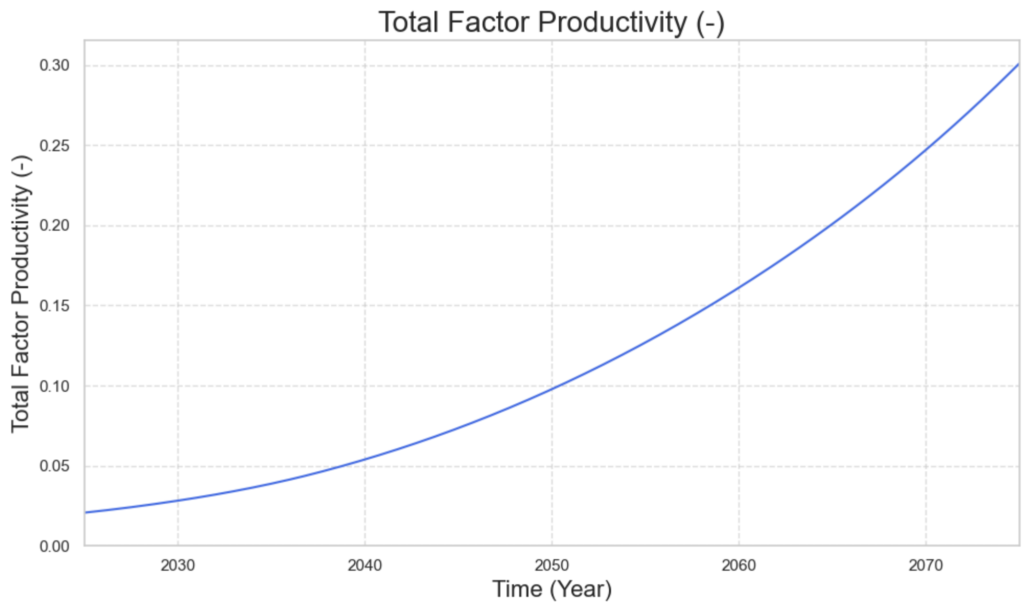

Figure A10: Total factor productivity over time

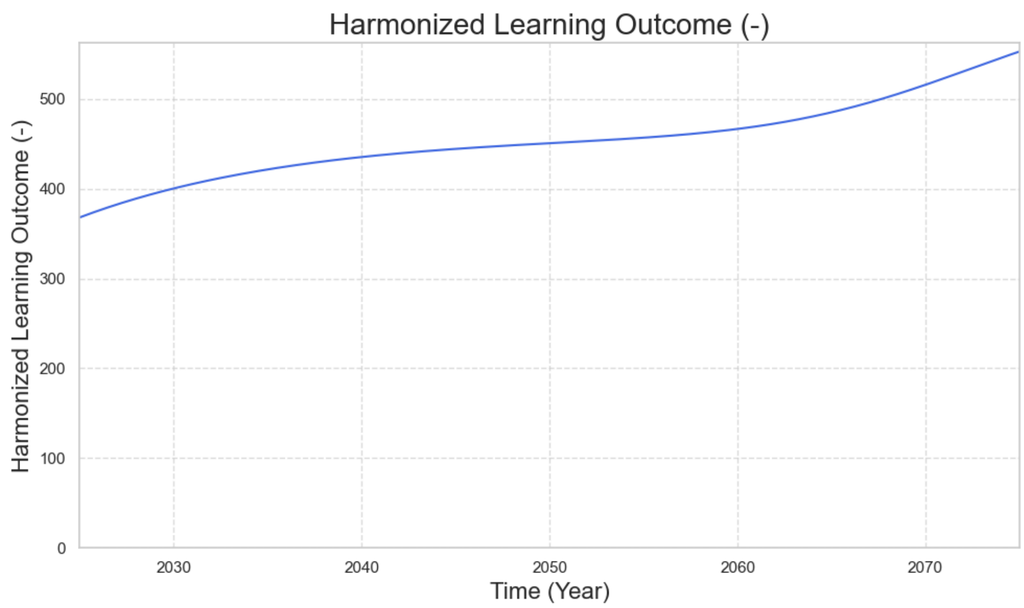

Figure A11: Harmonized Learning Outcome over time

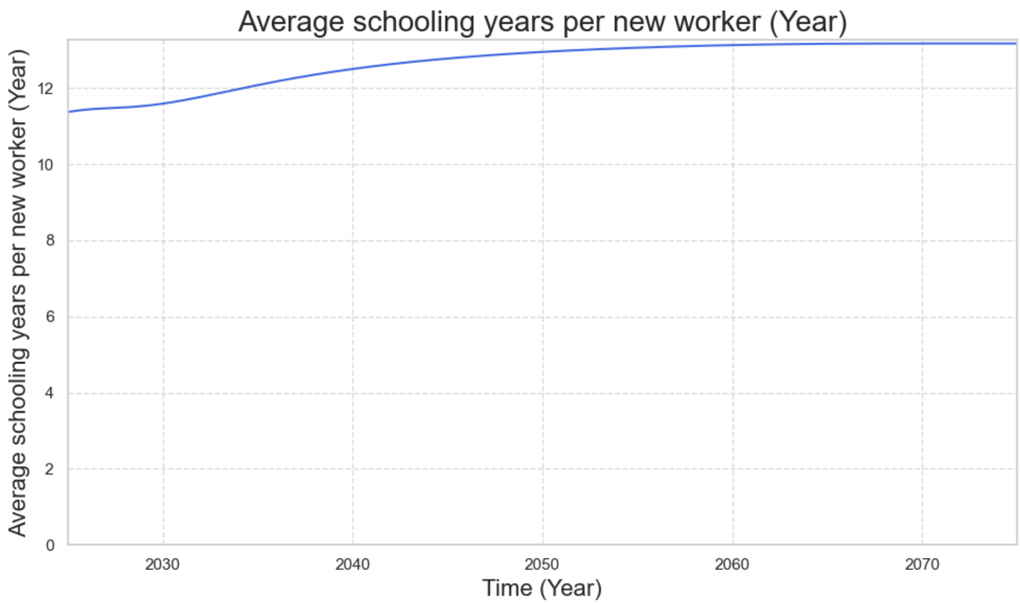

Figure A12: Average number of schooling years per new worker over time

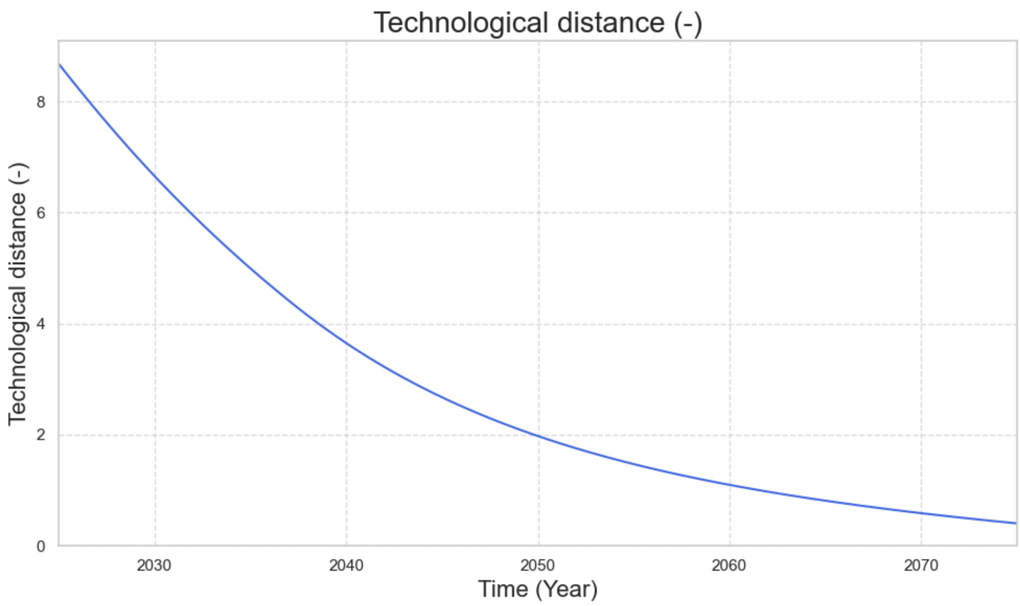

Figure A13: Technological distance over time

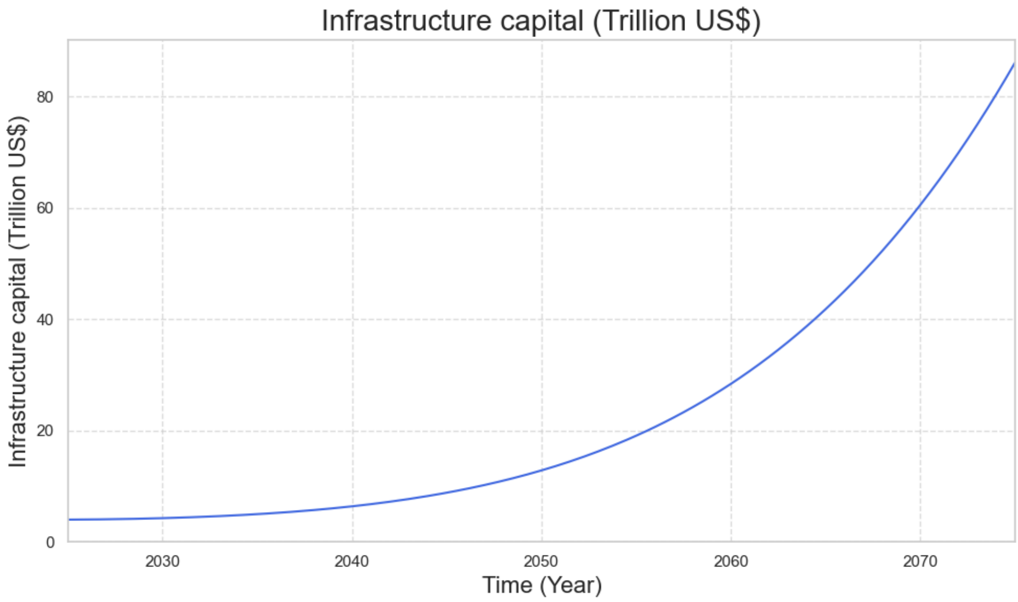

Figure A14: Total infrastructure value over time

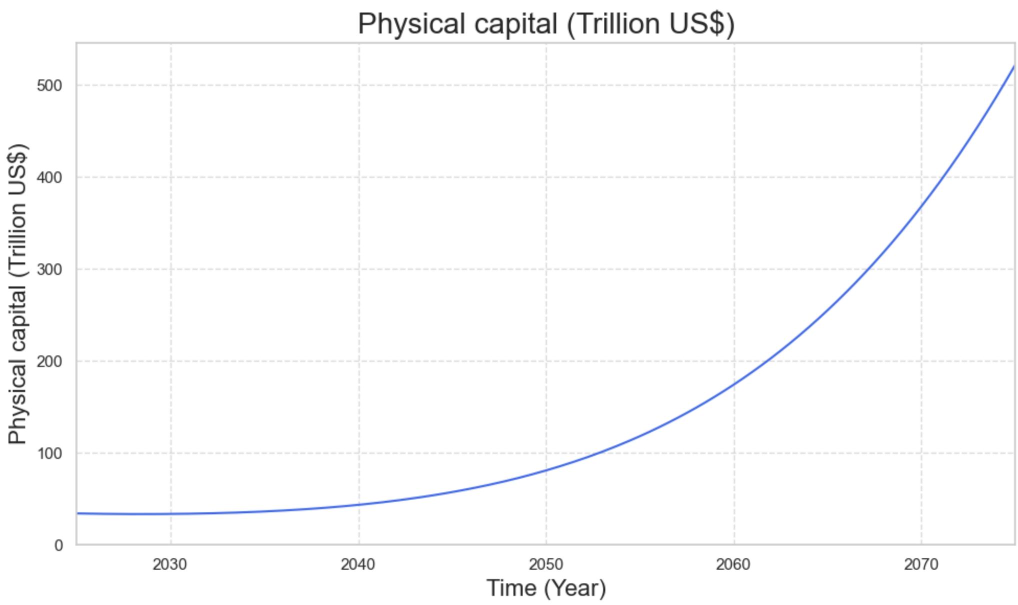

Figure A15: Total physical capital value over time

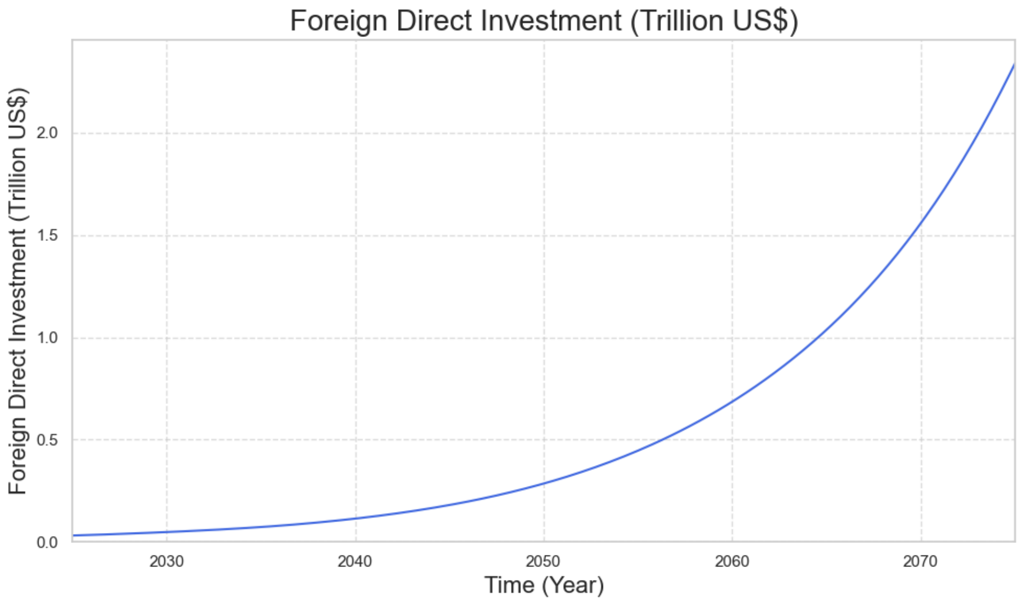

Figure A16: FDI inflow over time

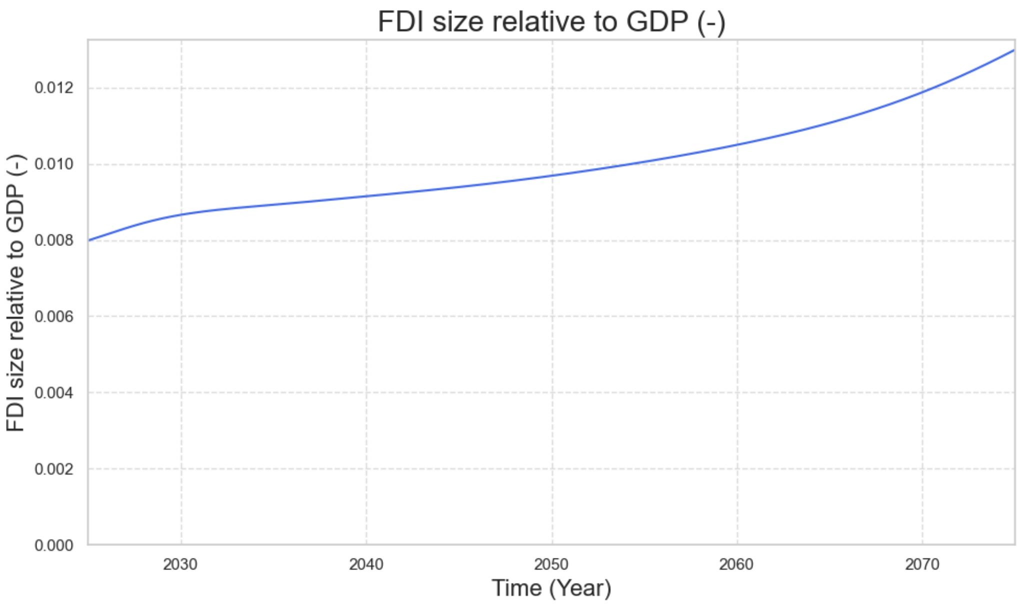

Figure A17: FDI inflow relative to GDP

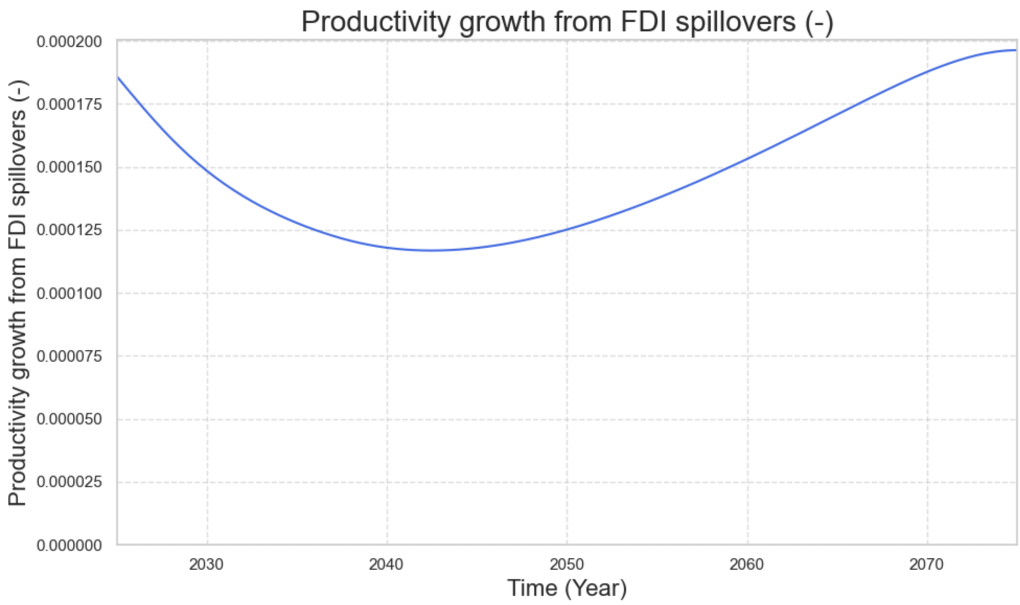

Figure A18: Productivity growth from FDI

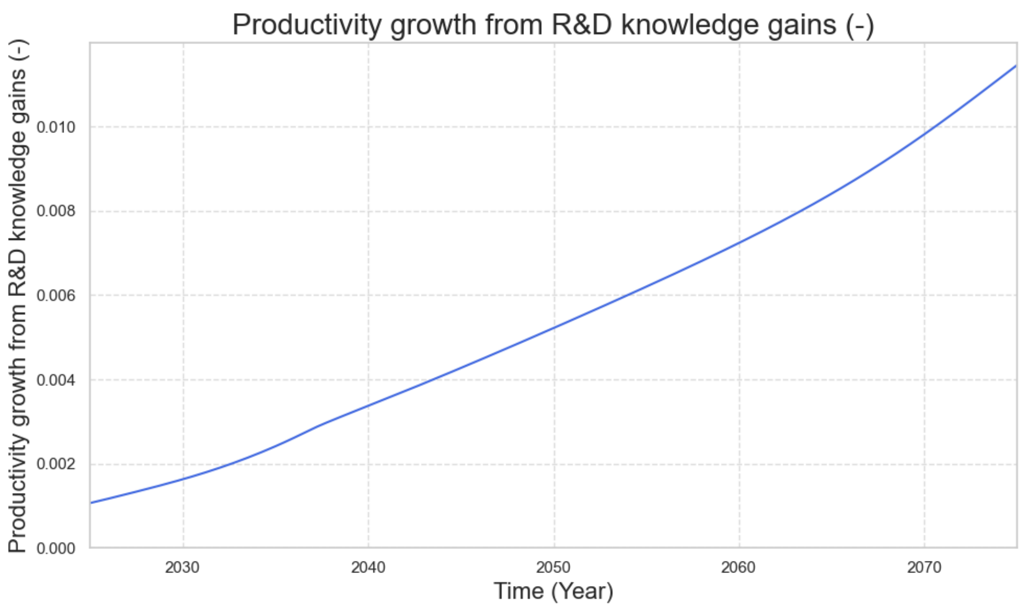

Figure A19: Productivity growth from R&D

A3 Model analysis

Table A3: Sensitivity analysis variables and its ranges

Parameter Name	Lower Bound	Upper Bound
Capital depreciation rate	0.03	0.05
Developed country infrastructure stock net increase rate	0.01	0.03
FDI elasticity to GDP	0.4	0.6
FDI elasticity to GDP Growth	0.5	1
FDI elasticity to HCI	0.5	1
FDI elasticity to infrastructure	0.5	1
FDI spillover elasticity to absorptive capacity	0.3	0.7
FDI spillover elasticity to FDI flow	0.5	0.9
FDI spillover elasticity to TD	0.5	1
FDI spillovers scaling factor	0.002	0.004
HLO depreciation rate	0.005	0.015
Initial capital stock	32	36
Initial HLO	325	375
Initial infrastructure stock	3.5	4.5
OECD wage growth rate	0.01	0.03
Output elasticity of capital	0.35	0.45
Primary degree LFPR [Female]	0.35	0.65
Primary degree LFPR [Male]	0.8	0.9
Primary school dropout rate	0.005	0.02
RD relative wage	4	6
RD spillover elasticity to labour force	0.75	0.85
RD spillover elasticity to TFP	0.55	0.65
RD spillovers scaling factor	0.0042	0.0048
Return on teacher investments	0.5e-5	1.5e-5
Secondary degree LFPR [Female]	0.20	0.36
Secondary degree LFPR [Male]	0.7	0.86
Secondary school dropout rate	0.10	0.15
Share of FDI going into other capital	0.05	0.15
Share of FDI into infrastructure	0.15	0.25
Share of graduates able to join RD labour force	0.0075	0.0125
Share of labour in RD cost	0.4	0.5
Teacher quality contribution to HLO	0.2	0.4
Technological frontier TFP growth rate	0.01	0.02
Tertiary degree LFPR [Female]	0.41	0.61
Tertiary degree LFPR [Male]	0.84	0.94
Tertiary education dropout rate	0.2	0.3
Uneducated LFPR [Female]	0.4	0.55
Uneducated LFPR [Male]	0.7	0.9

A3.1 Uncertainty Analysis

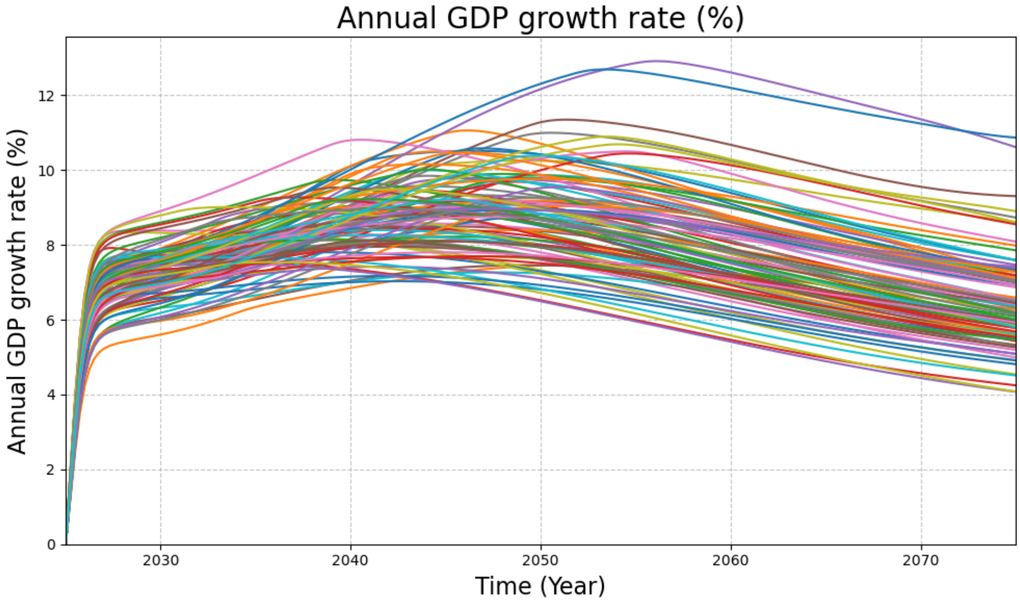

Figure A20: Outcome range of the GDP growth rate

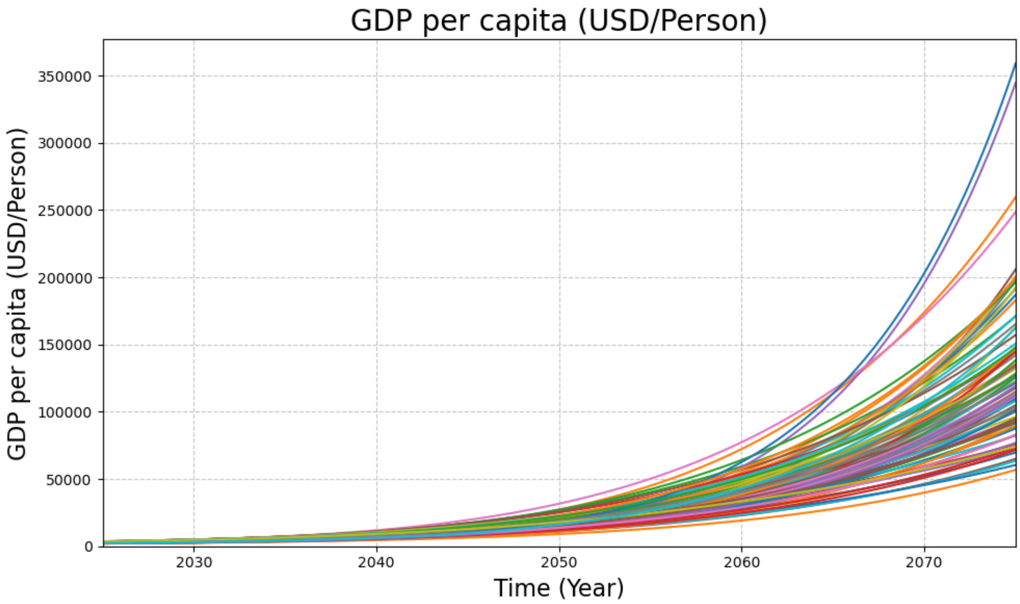

Figure A21: Outcome range of the GDP per capita

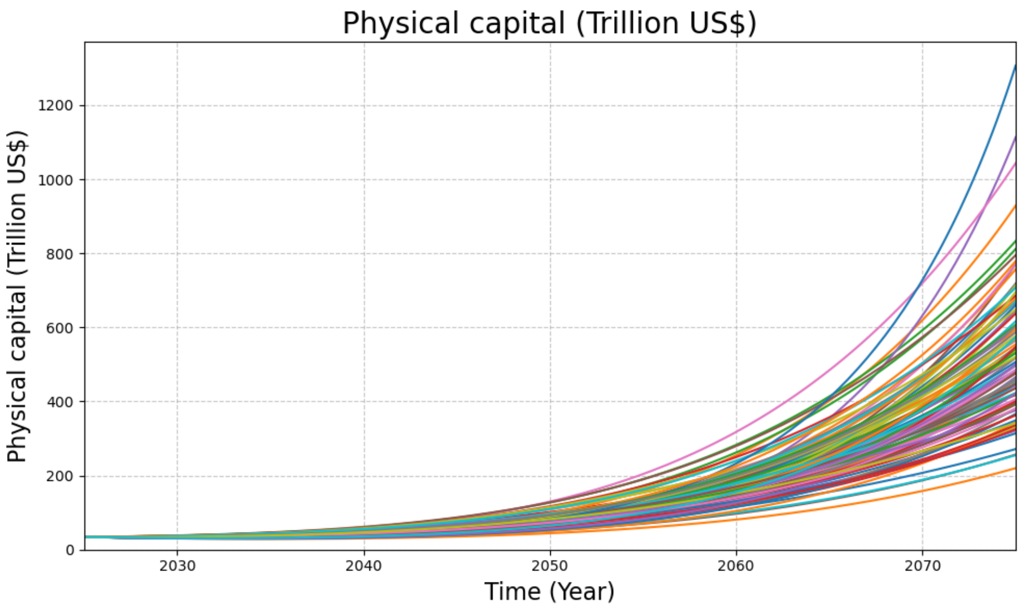

Figure A22: Outcome range of the total capital stock

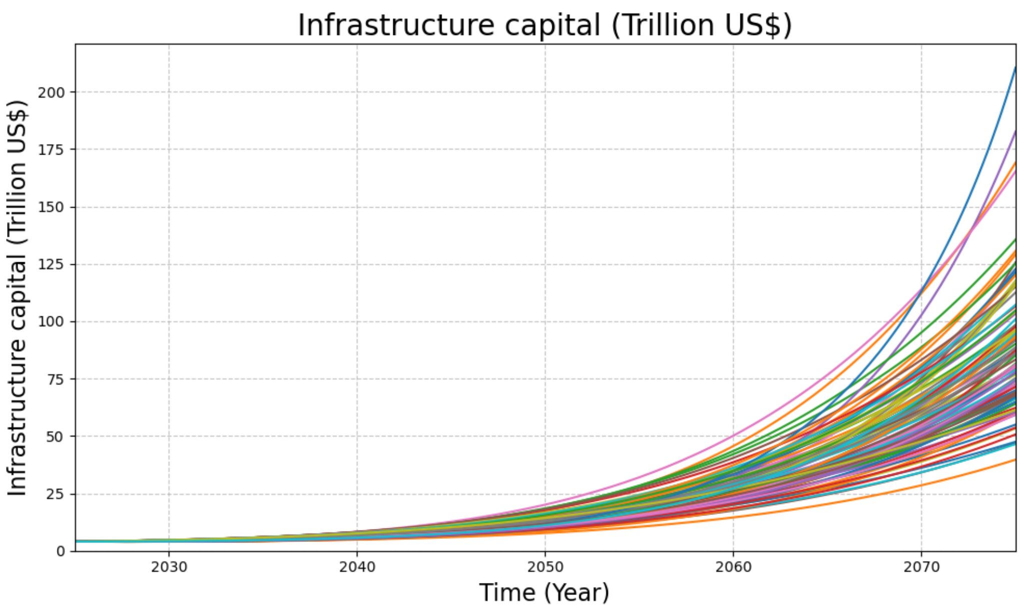

Figure A23: Outcome range of the total infrastructure stock

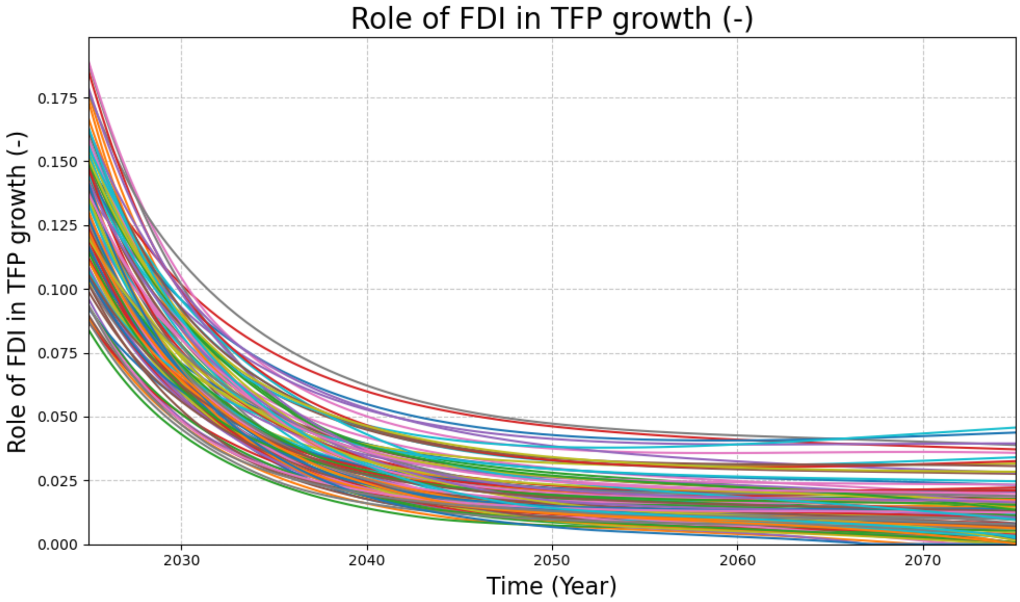

Figure A24: Outcome range of the role of FDI in creating productivity growth

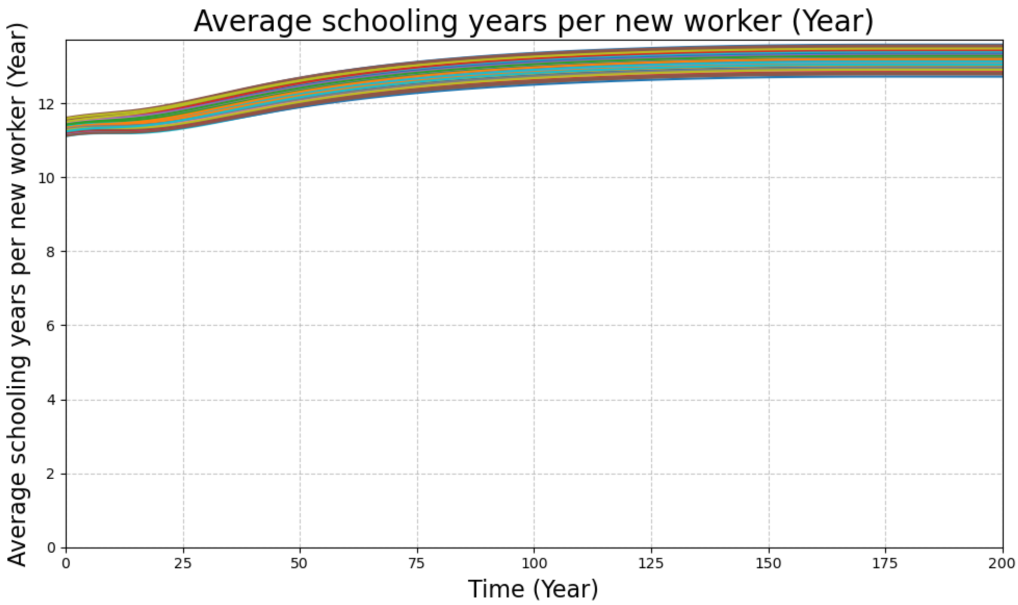

Figure A25: Outcome range of the average number of schooling years per new worker

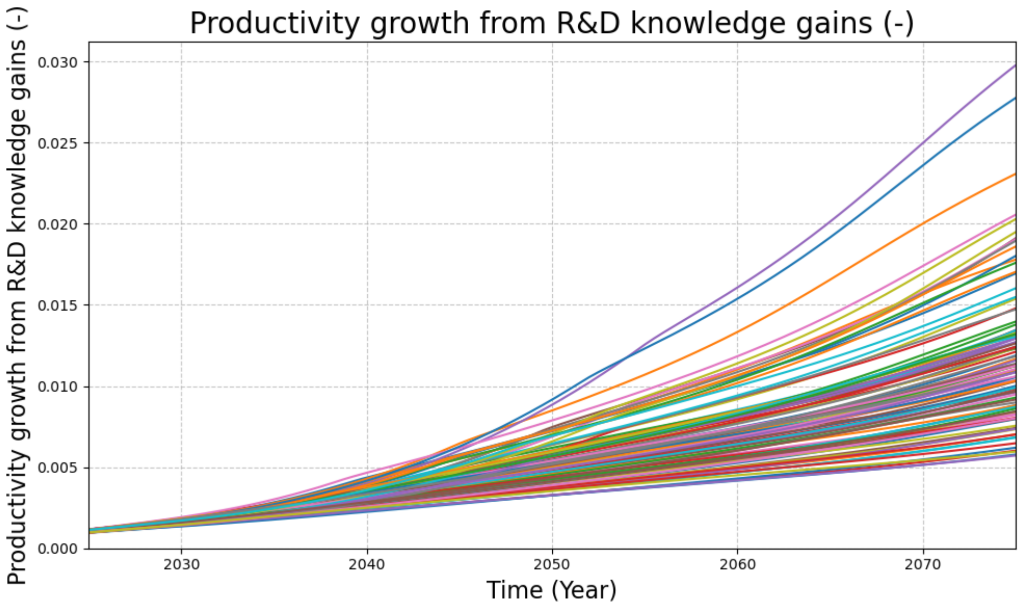

Figure A26: Outcome range of productivity growth from R&D

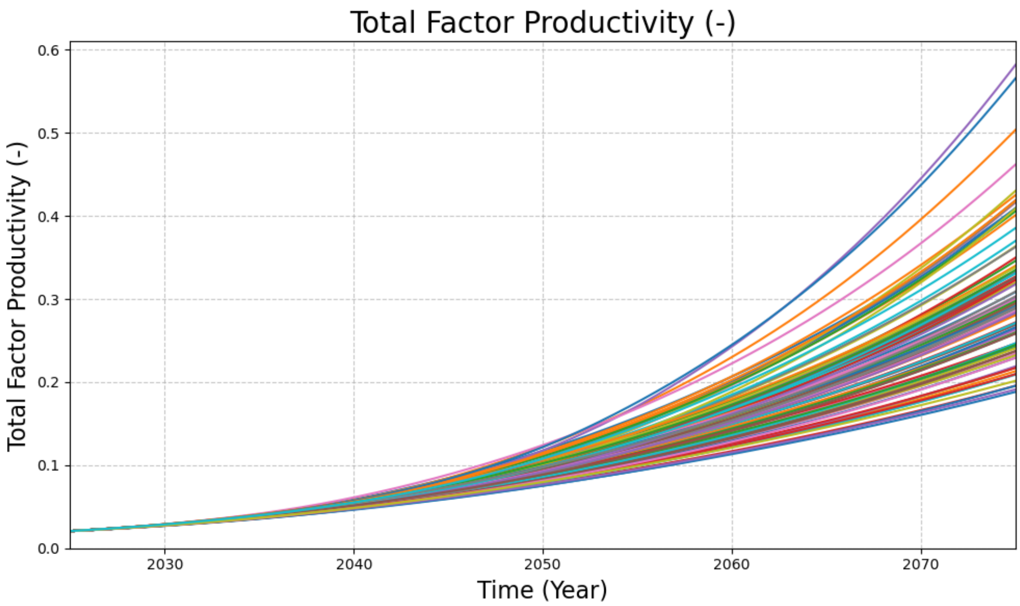

Figure A27: Outcome range of total factor productivity

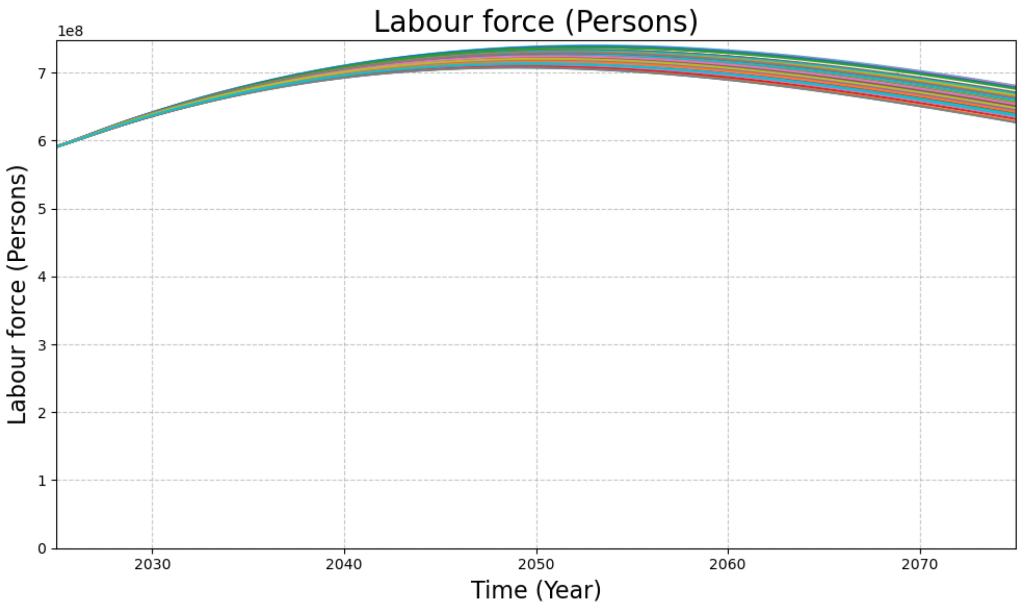

Figure A28: Outcome range of the total labour force size

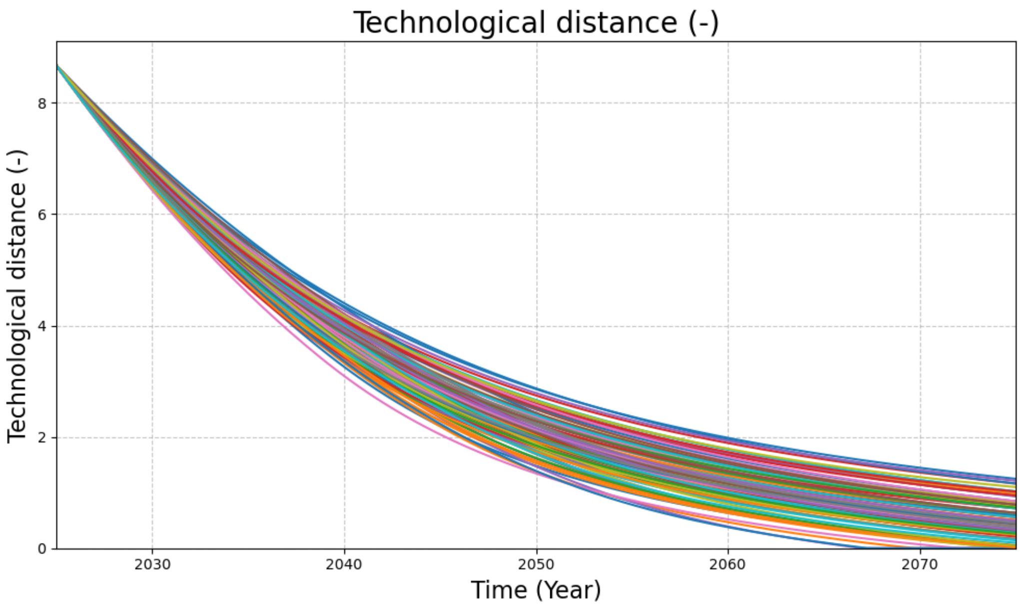

Figure A29: Outcome range of the technological distance

Table A4: Results of PRIM analysis on the base run

Variable	Lower Limit	Upper Limit	QP (min)	QP (max)
Output elasticity of capital	0.300005	0.355435	–	0.000000e+00
RD relative wage	3.500086	4.934027	–	2.82e-187
Secondary school dropout rate	0.040000	0.192829	–	2.93e-01
Tertiary education dropout rate	0.200002	0.297387	–	3.10e-01
HLO depreciation rate	0.005000	0.014826	–	3.86e-01
OECD wage growth rate	0.010000	0.029809	–	4.23e-01
Technological frontier TFP growth rate	0.010000	0.024879	–	4.30e-01
RD spillovers scaling factor	0.004122	0.004600	5.07e-69	–
Share of graduates able to join RD labour force	0.008440	0.012500	2.74e-12	–
Share of labour in RD cost	0.408133	0.500000	1.42e-02	–
Tertiary degree LFPR [Female]	0.501989	0.599999	3.68e-01	–
Share of FDI into infrastructure	0.251052	0.348601	4.57e-01	4.27e-01
Coverage: 0.370534				
Density: 0.877377				
Box ID: 304				
Cases of Interest: 1338				
Threshold used: 0.5				
Peeling coefficient: 0.01				

Table A5: Results of PRIM analysis on the basic policy

Variable	Lower Limit	Upper Limit	QP (min)	QP (max)
Output elasticity of capital	0.300006	0.348638	–	0.000000e+00
RD relative wage	3.500043	5.146428	–	1.62e-116
Capital depreciation rate	0.035000	0.061781	–	1.66e-02
Secondary school dropout rate	0.040002	0.197243	–	3.92e-01
Tertiary education dropout rate	0.200002	0.299408	–	3.93e-01
Tertiary degree LFPR [Female]	0.500002	0.598488	–	4.23e-01
Return on teacher investments	0.000005	0.000015	–	4.61e-01
RD spillovers scaling factor	0.004071	0.004600	2.34e-45	–
Share of graduates able to join RD labour force	0.008461	0.012500	1.46e-07	–
Share of labour in RD cost	0.405883	0.499998	1.21e-01	–
Primary degree LFPR [Female]	0.254390	0.347973	2.92e-01	3.60e-01
Uneducated LFPR [Male]	0.650880	0.700000	3.86e-01	–
Uneducated LFPR [Female]	0.200276	0.249506	3.93e-01	3.93e-01
Secondary degree LFPR [Male]	0.801108	0.899997	3.96e-01	–
Primary degree LFPR [Male]	0.700189	0.799997	4.33e-01	–
Share of FDI into infrastructure	0.250474	0.350000	4.42e-01	–
FDI spillover elasticity to FDI flow	0.051229	0.149999	4.80e-01	–
Tertiary degree LFPR [Male]	0.851006	0.950000	4.93e-01	–
Technological frontier TFP growth rate	0.010035	0.025000	4.97e-01	–
Coverage: 0.304256				
Density: 0.911802				
Box ID: 353				
Cases of Interest: 1437				
Threshold used: 0.5				
Peeling coefficient: 0.01				

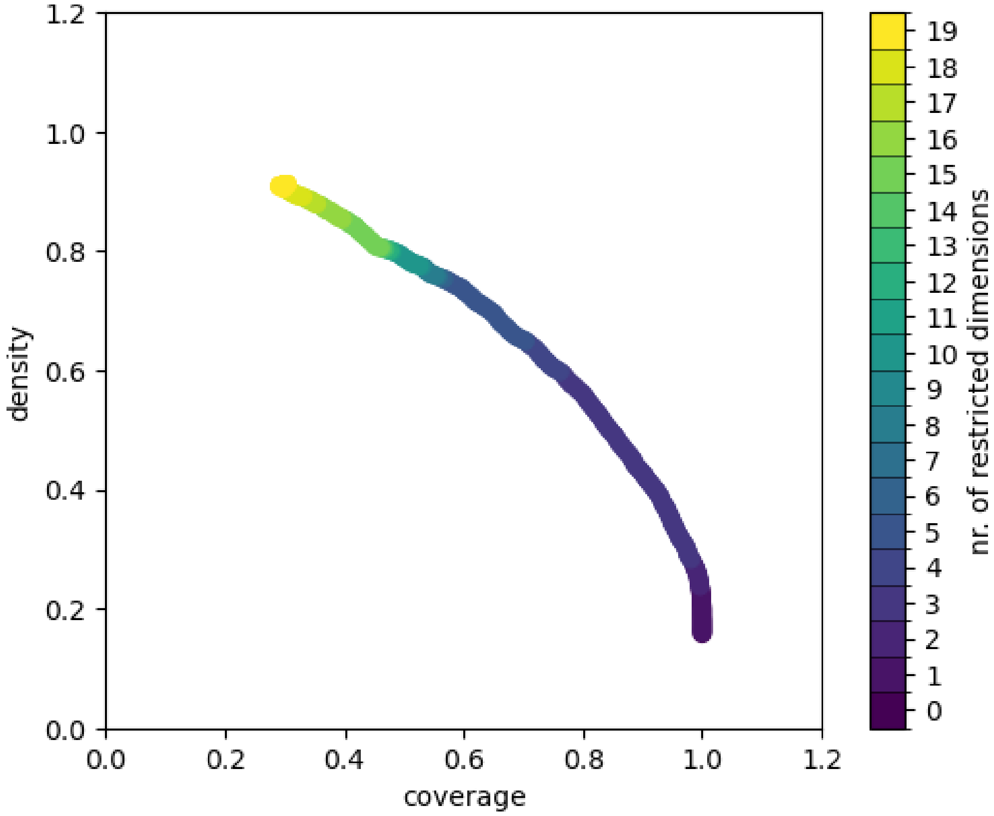

Figure A30: PRIM plot on the enrolment policy

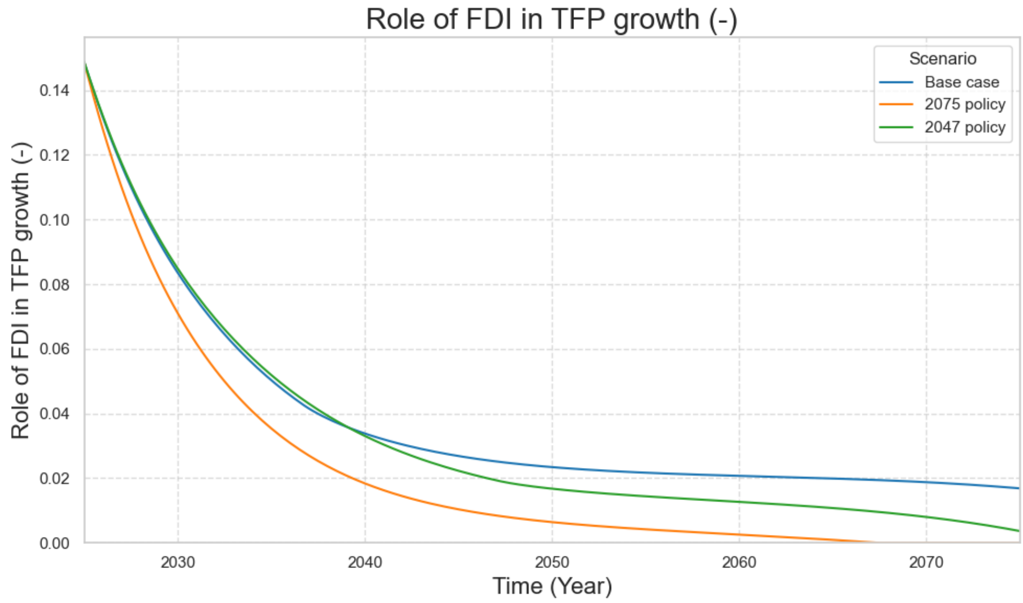

Figure A31: The role of FDI for each budget allocation policy

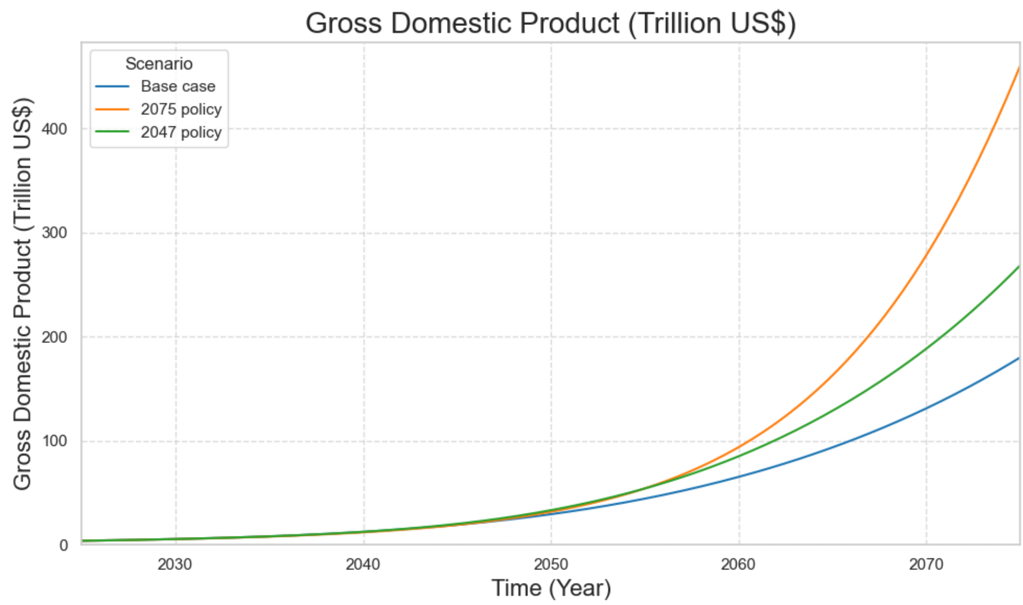

Figure A32: GDP for each budget allocation policy

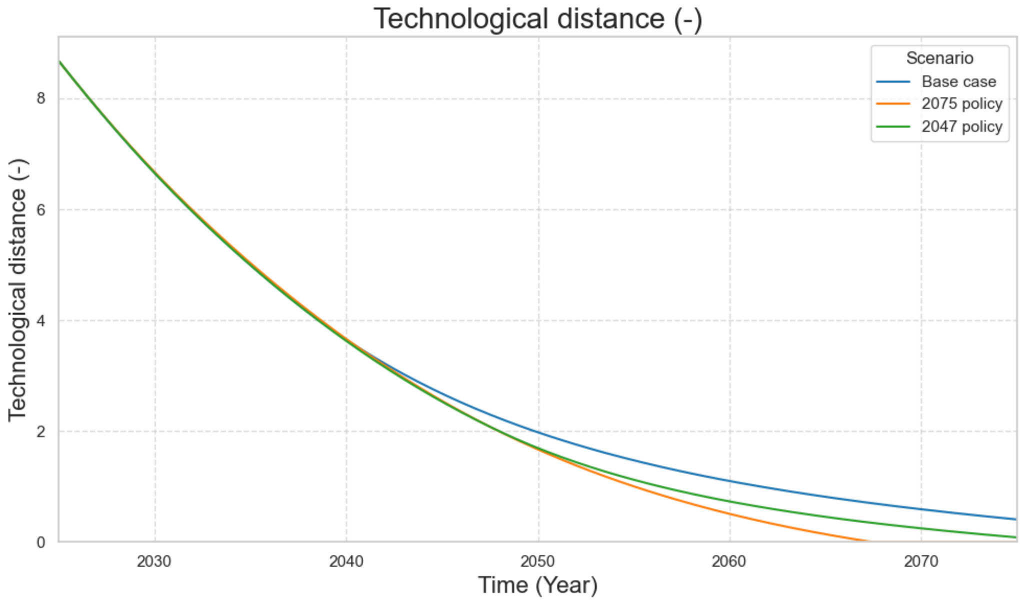

Figure A33: Technological distance for each budget allocation policy

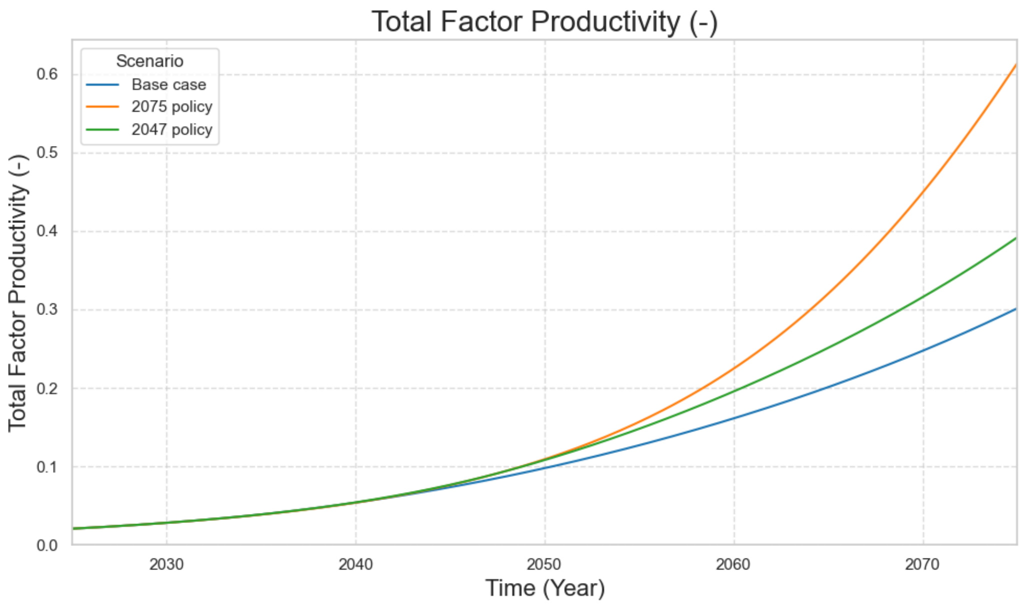

Figure A34: Total factor productivity for each budget allocation policy

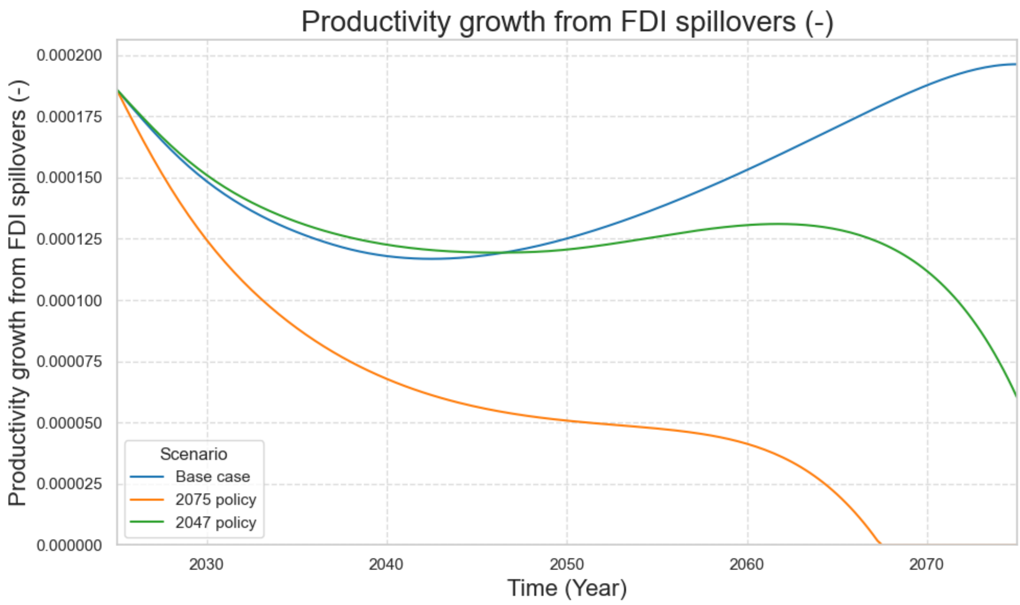

Figure A35: Productivity growth from FDI knowledge spillovers for each budget allocation policy

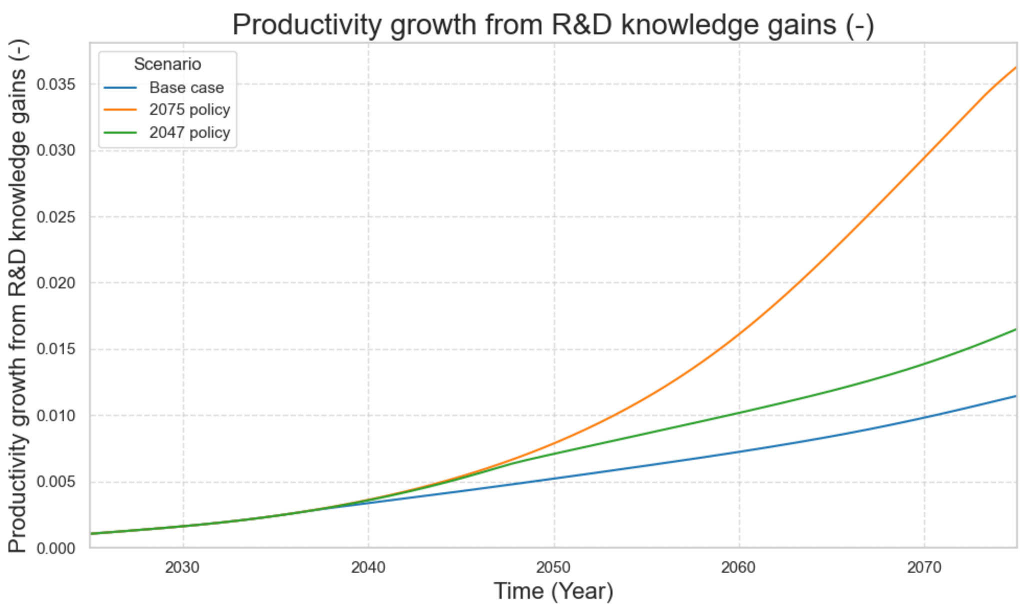

Figure A36: Productivity growth from R&D knowledge gains for each budget allocation policy