Moving Beyond Stasis in Agglomeration Externalities

Exploratory System Dynamics Modelling of Agglomeration Externalities Innovation Performance in Regional Innovation Systems for Research-Informed Decision-Making

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By

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Preface

I developed my thesis within the framework of the MSc. Complex Systems Engineering and Management Graduation Project over the course of 3 months. In it, I investigated how innovation unfolded across European regions, shaped by differing mechanisms of knowledge generation and exchange, whether through specialised or diversified structures. The final goal of this exploratory journey was to build a dynamic understanding of the factors affecting innovation performance in differing agglomeration types to build robust advice for decision-making. Beyond exploring these dynamics, I aimed to simplify our understanding of innovation processes and examine how they might be replicated in an evolving and adaptable way.

This thesis has six parts. The first chapter set the foundations of the thesis and introduced the knowledge gap and research questions. The second chapter dove into those foundations and state-of-the-art literature to define system components and understand the quantitative transactions occurring between the components in EU Regional Innovation Systems (RIS). It used Williamson's 4-Layer Institutional Framework to do so. The result was a System Dynamics model that included the components and interactions quantified with Williamson's 4-Layer Framework. The third chapter focused on the validation and verification of the model behaviour with a set of tests. The fourth chapter described the use of a Sobol global sensitivity analysis and a scenario test to assess quantitative and qualitative significance of the model's parameters. The fifth chapter presented a discussion of the results and comparison with analysed literature to identify essential points to consider for robust decision-making. The final chapter reached the conclusion of the thesis.

Innovation and knowledge generation are essential in today's globalised world. For instance, the northeastern region of Catalonia thrives with a dynamic ecosystem of clusters generating €80 billion in aggregate turnover, while SMEs in northern Italy struggle to achieve economies of scale through coordinated R&D efforts. The regional scale offered a unique lens into processes that also occur on larger scales, serving as a manageable and insightful experimental playground to explore these mechanisms at their root. In this work, I did not attempt to provide exhaustive explanations but rather initiate a line of inquiry that remained underexplored in the field.

Although beyond the direct scope of this thesis, innovation also plays a critical role as a geopolitical tool. Access to technology significantly influences a nation's political, economic, and military power. Considering the EU's continued funding of R&D projects and cybersecurity procurement from a nation engaged in military aggression and civilian persecution, it is worth reflecting on the long-standing implications of innovation dependence. A deeper understanding of innovation mechanisms could empower decision-makers to adopt more responsible and informed choices, recognising the interconnected nature of global innovation systems.

Delft, 14th August, 2025

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Executive Summary

Agglomeration dynamics in Regional Innovation Systems (RIS) are considered important determinants of economic direction and resilience. Yet, existing studies lacked tools to model how agglomeration mechanisms interact dynamically to shape innovation outcomes, specifically MAR and Jacobs externalities. Traditional methodologies, such as regression or case studies, cannot capture feedback loops and causality effects, leaving researchers without actionable insights for innovation development. In this research, I aimed to materialise the mechanics of agglomeration patterns in Regional Innovation Systems to build a dynamic understanding of their effect on innovation performance anchored in the EU regional context. The final aim is to shape research-informed decision-making with the findings of this dynamic study.

To bridge this gap, I created an SD model to simulate agglomeration dynamics in RIS. Modelling agglomeration patterns requires different levels of granularity from traditionally aggregated innovation system modelling. To satisfy this requirement, I drew concepts from a thorough theoretical literature review. I analysed collected theories by making use of Williamson's Institutional model, informing the exploratory aspect of the SD modelling. To verify the model, boundary adequacy, structure verification, dimensional consistency, parameter verification and extreme value tests were accomplished. To validate model behaviour, a replicative data validation, an expert validation and a parameters sweep were realised. The model was parametrised with Ile-de-France and Bretagne data to simulate the interactions between different sectors of Jacobs and MAR RIS to inform system behaviour. Finally, a Sobol sensitivity analysis informed influential system variables with a multivariate parameter variation, subsequently reinforced by a scenario test. These tests have been analysed for both MAR and Jacobs regions.

The results of the modelling informed that the MAR model was more robust to uncertainties. It also showed a faster recovery from shocks than Jacobs regions. Additionally, government funding did not play a significant role in regional knowledge development. It therefore appeared more important that regional sectors developed links with nearby industries, whether in MAR or Jacobs regions, to ensure higher flexibility in periods of uncertainty. Decision-making can therefore examine ways to increase industry proximity in Jacobs regions and firm collaboration in MAR regions. Finally, it highlighted the importance of timing in innovation generation, often overlooked in agglomeration studies.

Beyond the findings, the contribution of this thesis also reflected itself in the modelling, a further conceptual offering to understand the complexity of innovation development. While the data and assumptions are interesting considerations brought by this thesis, the strongpoint stood in the formalisation and pragmatism of field theories through causal relationships in a model. Theoretically, it advanced RIS scholarship by reframing agglomeration as a systemic equilibrium rather than a linear outcome, while methodologically, it demonstrated how conceptual SD can democratise policy design.

The model offered can be further refined, detailed and parametrised in further research to lead to more robust outcomes and more precise data-informed decisions. One key improvement suggested is the inclusion of Agent-Based Modelling to form a hybrid-SD-ABM model. Representing variables at the levels of single agents can support higher flexibility and dynamism, which can be advantageous to represent regions with a start-up landscape more accurately.

***Keywords**: Regional Innovation Systems, Agglomeration Patterns, System Dynamics, MAR externalities, Jacobs externalities, Complex System Modelling.*

Declaration on the use of AI: No generative artificial intelligence (AI) or AI-assisted technologies were utilised in the process of drafting this work with the aim of creating content or concepts. The utilisation of AI was solely for the purpose of enhancing readability and language. This use was subject to stringent human control. Following the integration of AI technologies, the thesis was meticulously reviewed to ensure its coherence. No AI or AI-assisted technologies have been designated as an author or co-author of this thesis. The responsibilities and tasks intrinsic to authorship are a point of awareness in this thesis, which are unique to human performance. Additionally, AI has been used in this project to assist with the debugging of Python code.

Code: The programs, model and connected data are made available at the GitHub repository linked to this thesis
https://github.com/AllegraMelli/AgglomerationExternalitiesThesis/

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I would like to formally recognise two truly exceptional people from my daily life, Margherita and Chjara, for their emotional guidance.

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I would like to thank Balanzs for the full body stretches.

Finally, I would like to thank myself. I had to endure rejection, abandonment, domestic abuse, relocation, separation all while pushing through the ambitious challenge I set for this thesis. I wish someone had told me I'd be doing this by myself. There's reasons that I'm thankful, there's a lot I'm grateful for, but it's different when life hides from you what it has in store. I could have given up when I couldn't find a second supervisor, or when my kick-off was rejected, or when my green light was denied, or when the affiliated company withdrew their support, or when I had to compress three months of research into three weeks. Sleep became a luxury and food tasted like paper, but tough times never last, only tough people do. I pushed through every day, with a galea on my head. I am glad I did.

Her forehead wrinkled at the idea. “No, I didn't outlive Stalin to be depressed.”

-The Emperor of Gladness

1 Introduction

1.1 A Story of Innovation Studies

Over the centuries, humans paved the way for increasingly important developments through their inventive pulses (Fogel, 1999). From fire to flames to lightbulbs, society and the economy slowly developed following this progression of eurekas (Commission on Growth and Development, 2008). After the 18th century, mechanisation revolutionised both agriculture and industry, elevating this evolution to an entire new level (Gaudin, 2009). With the industrial revolution, life expectancy suddenly increased, and so did GDP per capita and the world population (Lee, 2003).

Following the assumption that innovation was the backbone of wealth, Robert Solow showed that once capital and labour contributions are accounted for, the total factor productivity which is driven by innovation explained the bulk of long-run growth (1957). However, given the epimorphic character of innovation, I defined its intended shape in this section by posing the foundation of innovation studies. The concept of innovation introduced by Schumpeter in his 1934 work *The Theory of Economic Development* remains a cornerstone in modern innovation research. He described innovation as the creation of “new combinations” involving production elements, such as developing novel products, implementing new methods of production, entering previously untapped markets, sourcing new raw materials or intermediates, and restructuring industries. Many current definitions still draw heavily from Schumpeter’s framework although possessing drastic variations from their detailed point of view. Recently, Awwad et al (2025) interestingly summarised these dichotomies by describing the different characteristics showing innovation as a fresh idea, scientific breakthrough, or technological advancement that has not yet been realised in practical or commercial terms. Innovation is commonly “a new and better product or service or a more efficient way of producing or delivering it” (World Bank, 2010). Innovation emphasises that Schumpeter’s distinction of innovation over invention means policy must support not only R&D but also commercialisation and diffusion (Yusuf et al. 2008). However, growth has been uneven: rich countries diversified into complex industries, while many developing countries stayed in a narrow range (Fink et al. 2024). This led to a major assumption: the relevance of different innovation types varied with the context (Valdivia & Risser, 2015).

Nonetheless, Solow’s exogenous growth model considered innovation as a given, which did not carry explainability for yet persistent economic difference between locations (Mankiw et al, 1992). Almost haft a century later, Lucas (1988) and Romer (1986, 1990) formulated knowledge as an engine of growth. This would make innovation path-dependent where institutions matter. This new growth theory emphasised that the most lasting drivers of economic expansion were the creation of knowledge and advances in technology (Paul, 1990).

In today’s interconnected world, where scientific and technological breakthroughs spread rapidly, innovation has become a central determinant of a region’s competitive edge (Shi et al., 2020). The “production functions of innovations” are described as the relationship of inputs and outputs linked to knowledge (Antonelli & Colombelli, 2015). Technological innovation underpins a firm’s competitive edge, and the vitality of private enterprises increasingly hinges on the development of new technologies and organisational innovations (Gaubinger et al. 2015, Ferreira et al. 2015, Wolf et al. 2021, 2021, López Fernández & Oliver, 2025). Economists widely agree that technological progress emerges from rich exchanges across industries and technological domains (Bergeron et al., 1998; Hsu et al., 2003; Lin et al., 2006). Clustering an industry in a particular region amplifies these interactions, thereby fostering innovation (Kim et al, 2023). Since Porter introduced the concept of industrial clusters in the 1980s, clusters have been recognised as key drivers of innovation, entrepreneurship, and technological growth, leading many governments to integrate cluster development into economic policy. Yet, the factors influencing cluster impact interact in complex ways, and few studies employed dynamic methods to unravel their impact.

This chapter delved into the foundations of this thesis, as well as its research approach, characterised by its link with the CoSEM program, its research objectives and research questions and an overview of its structure.

1.2 Understanding the Concepts

In the last thirty years, researchers and policymakers have increasingly focused on regions as key areas for innovation and competitiveness within the globalising economy (Asheim, 2003; Saxenian, 1994; Porter, 1990). These investigations shared a common premise that regional agglomerations offer the most conducive environment for an innovation-driven global economy, owing to localised learning processes and knowledge rooted in social interactions (Asheim, 2002; Asheim and Isaksen, 2002; Gertler, 2004). They have highlighted the importance of the regional level in economic development, sometimes prioritising it over the national level (Asheim & Coenen, 2005).

Three concepts from the regional innovation theory framework have gained notable traction in both academic and policy discussions: regional innovation systems (RIS), clusters (Cooke et al., 2004; Porter, 2000), and agglomeration externalities (Moulaert and Sekia, 2003). While these concepts are interrelated, it is essential to recognize that they should not be confused with one another (Asheim & Coenen, 2005).

1.2.1 Regional Innovation Systems and their components

Regional innovation involves producing new ideas, technologies, and practices within a defined region to boost economic growth, competitiveness, and social progress (Capello & Lenzi, 2018). Given the breadth of the concept, it has been introduced and developed by a multitude of authors since 1990 (Bai et al. 2024). Cooke (2008) initially inspired himself from the agglomeration externality theories published by Marshall (1918) and Jacobs (1969) to develop the idea of regional ecosystem competition (Cooke, 1992). This concept has been complemented with the idea of the geographical limitations of local knowledge (Asheim & Isaksen, 2002), of regional proximity between technologies (Boschma, 2005) and of regional policy implications (Tödtling & Trippl, 2005) to evolve into the RIS concept we know today (Bai et al. 2024). These concepts developed the overall idea that a region's innovation capacity depended on its ecosystem, composed of R&D, entrepreneurship, academia–industry collaboration, infrastructure, and supportive, context-specific policies (Etzkowitz & Leydesdorff, 2000; Cooke, 2008). Infrastructure, such as transportation, communication networks, and research facilities, is critical for facilitating knowledge exchange (Edquist, 2011). Shenzhen's transformation from a manufacturing hub to a global innovation centre illustrated this, driven by technology focus, entrepreneurship, and public support (Mogi & Florida, 2003). Effective regional innovation thus requires coordinated efforts across collaboration, infrastructure, entrepreneurship, and policy (Cooke, 2004).

From an innovation-systems perspective, a Regional Innovation System (RIS) comprise the region's knowledge resources, technology, information, and know-how and its actors, including government, core firms, universities, research institutes, and intermediaries (Cooke, et al., 2004; Pino & Ortega, 2018). These actors disseminate and apply knowledge within the region, influenced by market and social conditions, thereby improving the region's knowledge diffusion and innovation performance (Pino & Ortega, 2018; Shang & Zeng, 2017). A central challenge with regional innovations is fostering effective knowledge transfer and collaboration among these diverse actors (Samara et al., 2024).

At EU level, numerous regions and nations adopted the RIS framework to build mission-oriented innovation policies (Mazzucato, 2018, Mazzucato et al. 2020, Schot & Steinmueller, 2018, Diercks et al. 2019). This went beyond simply improving economic growth to aiming to tackle a set of challenges hindering the competitiveness of regional sectors (Isaksen et al. 2022). The RIS framework is critical when studying regional innovation because it defines the boundaries and components of the system to be modelled (Heidenreich, 2025). This framework as such allowed me to consider a whole set of influential regional actors, comprising those outside of innovation-producing firms. To analyse the dynamics of innovation, I defined how these actors are regionally organised and interact in practice. This leads directly to the concept of clusters. Given the broader sector orientation of Regional Innovation Systems (RIS), clusters represent the specific tangible, spatial aspect of RIS within regional sectors (Asheim & Coenen, 2005).

1.2.2 Clusters in Regional Innovation Systems

Within a Regional Innovation System, economic activities are seldom evenly distributed (Moulaert and Sekia, 2003). Rather, they tend to form clusters (Asheim & Coenen, 2005). In essence, RIS and clusters span multiple sectors within the regional economy, as firms and knowledge organisations engage in systematic interactions (Pino & Ortega, 2018). Consequently, it follows that clusters and RIS can, and frequently do, coexist within the same geographical area (Asheim & Coenen, 2005).

Researchers have long examined the economics of industry location and clustering that lead to the success of key regions like the Silicon Valley's rise around Stanford University (Engel, 2015). Many nations have followingly established science and technology parks adjacent to universities aiming to replicate this success (Beaudry & Schiffauerova, 2009). Porter (1990) firstly defined an industrial cluster as a geographically proximate network of suppliers, buyers, related firms, governmental bodies, and support institutions like universities. He argued that a cluster's potency arises from four interlocking determinants arranged in a diamond framework: firm strategy and rivalry, demand conditions, related and supporting industries, and factor conditions.

Hill and Brennan (2000) offered an alternative cluster definition, viewing clusters as systems in which firms and institutions achieve higher profitability and efficiency through innovation spurred by intense local competition and collaboration. They proposed five cluster components: sectoral drivers, technology, labour, customer industries, and suppliers (Hill & Brennan, 2000; Hsu et al., 2003). In today's knowledge-based economy where knowledge and learning are the foremost assets, firms embedded in vibrant clusters enjoy greater innovation rates, largely due to technological knowledge spillovers (Bergeron et al., 1998). Clusters function as engine rooms of the RIS, where intense competition and collaboration spur innovation and increase productivity (Hill & Brennan, 2000). Furthermore, Porter (1998) noted that understanding cluster dynamics helps organisations choose locations strategically, build productive local networks, and cooperate to strengthen the cluster.

Carrie (2000) described clusters as a set of enterprises, with some members spanning multiple sectors. He argued that cluster boundaries often exceed a single industry, linking factories and firms through complementarities in technology, marketing, and customer demand. Key conditions for cluster formation include skilled labour, technological expertise, capital, robust infrastructure, technical foundations (Porter, 1998), academic and research centres (Grillitsch, 2015), and an entrepreneurial culture (Samara et al., 2022). In a globalised economy, clusters can extend their reach worldwide. Carrie (2000) observed that competition is shifting from firms to clusters themselves, pitting regions against one another in a battle for global economic leadership. Therefore, this concept encourages the view of innovation development as moving beyond firm-based relations to cluster-based relations as a potential justification of unequal innovation spurs (Carrie, 2000).

For many industries in a region, innovation is integral to their organisational expertise and competitive positioning (Faria et al., 2020). To leverage this asset, firms engage in innovation transfer (Samara et al., 2024). Lin (2003) found that companies in developing countries with limited R&D budgets gained sustainable advantages through such transfers. By sharing innovations and forging partnerships with complementary organisations, firms solidify clusters and enhance competitiveness. The ultimate aim of clusters is to attain global competitiveness for their member organisations (Lin et al., 2006). Porter (1998) suggested firms boost competitiveness by improving productivity, steering the trajectory of innovation, and fostering new institutional forms. Hence, within the expanded RIS perspective, these concrete cluster interactions add to the model's usefulness and realism.

Recapitulating, modern industries rely on specialised labour divisions and thrive on supply-chain partnerships, with clusters reflecting these interfirm relationships (Lin et al., 2006). In a decision-making context it is crucial to acknowledge the sector specificity of clusters and the more generic sector orientation of RIS (Asheim & Coenen, 2005). The concept of the cluster is vital to my research because it provides the necessary structural and spatial unit of analysis within the broader RIS. It allowed me to move from an abstract map of actors to a concrete map of industrial relationships. While the RIS informed who is in the system, the cluster informed where the critical interactions are happening. However, simply identifying a cluster is insufficient for a complete understanding of the system's dynamics (Pino & Ortega, 2018). To understand why and how these proximate arrangements generate innovation, we examined the underlying economic forces at play. These forces are known as agglomeration externalities.

1.2.3 Agglomeration Externalities in Clusters

Agglomeration externalities refer to the advantages firms obtain by situating themselves near other economic actors, therefore influencing the growth of a cluster and its innovation development (Rosenthal & Strange, 2004). These externalities are the invisible wiring that powers the cluster engine, and they are essential for explaining how clusters contribute to the innovation output of a RIS. Researchers distinguish among two main varieties of these externalities, Marshall–Arrow–Romer (MAR) and Jacobs, which correspond to differing channels for learning and cost structures within regions (Neffke et al., 2011).

Under MAR externalities, companies specialising in the same industry tend to co-locate, thereby stimulating short-run growth through intensified linkages (de Vor, 2011; Henderson, 2003). This "localisation" effect brings three main benefits (Marshall, 1890). Labour-market pooling is enhanced. A dense cluster of firms in one sector draws a workforce possessing the requisite skills, cutting down on recruitment costs and boosting staffing flexibility (Storper & Venables, 2004). Input–output connections are increased in this cluster-centric agglomeration. Industry concentration attracts both suppliers and purchasers, reinforcing supply chains and reducing transaction costs (Duranton & Puga, 2004). Finally, knowledge spillovers take place. Informal exchanges, via employee turnover or social interactions, allow ideas to diffuse among co-located firms, fostering incremental innovation without formal compensation (Breschi & Lissoni, 2003). By focusing on a narrow set of activities, firms can exploit scale economies fully.

In contrast, Jacobs externalities arise when a mix of diverse industries in one locality generates benefits for all (Jacobs, 1969, 1984). Key mechanisms include demand stabilisation, input flexibility and cross-industry knowledge recombination. The first signifies that a broad customer base cushions firms against sector-specific downturns (Glaeser, 2000). Additionally, it gives access to a wide array of locally supplied inputs which enables firms to switch when particular resources become scarce or expensive (Henderson, 1997). Finally, radical innovations often emerge from merging ideas across unrelated fields, so-called "new combinations" or *neue Kombinationen*, which a varied industrial milieu makes more likely (Boschma & Lambooy, 2002). Thus, in a Jacobs-type setting, the collective productivity of a city rises as firms benefit from a rich tapestry of clusters and activities, regardless of their own sector (Dissart, 2003).

The specialisation of a cluster encompasses more than just the effects of industrial specialisation (Kosfeld & Mitze, 2023). When considering the dynamics of supply and demand relationships, it becomes evident that related sector dynamics are more extensive than what is typically indicated by the literature on within-industry MAR externalities (Henderson, 1997). Vertical linkages may play a role in regional clusters due to technological similarities that transcend sectoral boundaries. Consequently, cluster specialisation could also partially encompass Jacobs-type externalities, which can be observed as related variety (Franken et al., 2007).

The extensive body of literature concerning the advantages of cluster agglomerations in relation to innovation typically encompasses two perspectives on the connection between innovation and region (Pino & Ortega, 2018). The first perspective adheres to the Marshallian framework, aiming to discern the benefits of this relationship and its implications for economic development (Iammarino, 2005). Conversely, the second perspective represents a more contemporary line of inquiry, which not only examines the variables associated with the geographical locations of organisations but also considers the characteristics that define their capacity for innovation (Pino & Ortega, 2018). Recently, scholars have highlighted that within the agglomeration externalities framework, geographic embeddedness, regional and local conditions, and the overarching macroeconomic context of the RIS in which the clusters are situated, significantly influence the innovation generation of the region (Ho, 2009, Muscio, 2006). Hence, these three concepts influence each other. While agglomeration externalities allowed me to understand how innovation is generated within the core innovative structure of a cluster, I cannot properly comprehend the regional innovation generation process without considering the local RIS context which they are embedded in.

Inspired by the summative work of Moulaert & Sekia (2003) and the conceptual work of Trippl & Tödtling (2007), Figure 1 illustrates the origin and alignment between the concepts discussed above. As embodied by the funnel structure of my explanation, components are nested within each other and often interact with other systems. As such, both MAR and Jacobs externalities, represented by the white and grey arrows, can exist in a region, or none depending on the components, shown by the black dots. The same goes for clusters, represented by their system boundary, which, without coordination, are simply represented by their single industries. For the scope of this research, Regional Innovation Systems that only showcase MAR externalities are named MAR Regional Agglomerations, and RIS that only showcase Jacobs externalities are named Jacobs Regional Agglomerations. Theories, shown in the white ovals, also build upon each other and nurture the connection between different system views, as illustrated by the dashed arrows. As such, the RIS framework originated from theories that encapsulated findings from Marshall (1890) and Jacobs (1969) and aimed at further expanding them. This is reflected in the system's interlaced interactions.

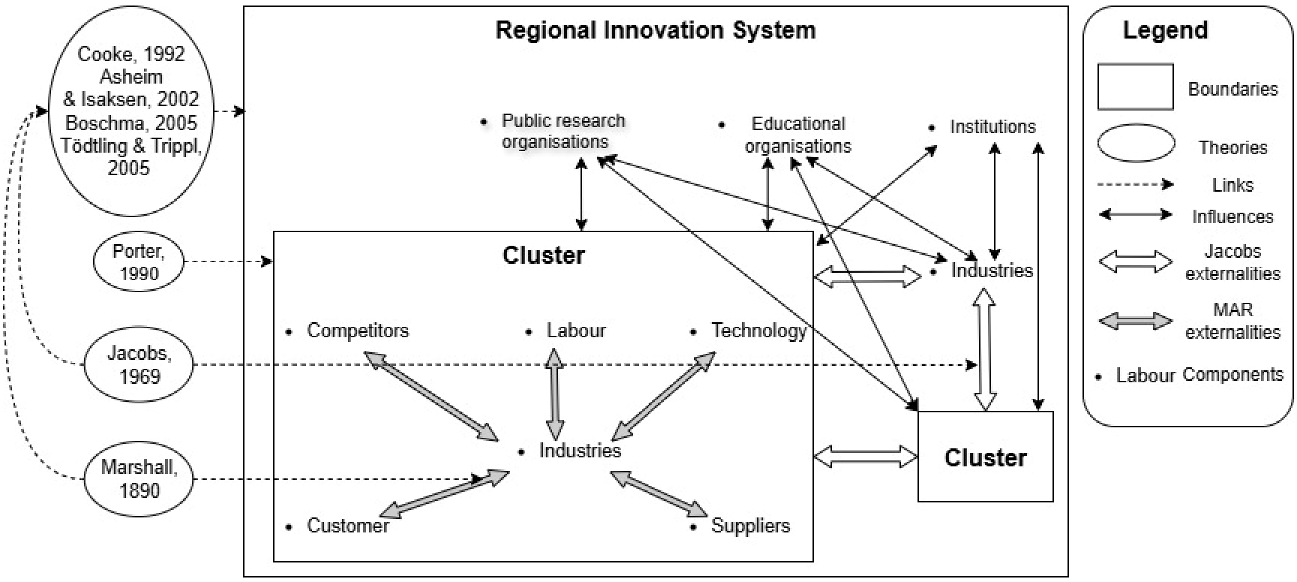

Figure 1: Geographical Innovation Perspectives anchored in geography, superposition of boundaries and theories

1.3 Defining the Knowledge Gap

I determined the knowledge gap by building an oversight of recent state-of-the-art literature. Firstly, I undertook a conceptual summary of agglomeration studies in innovation systems to structure an overview of the methodology employed, and results obtained in agglomeration externalities studies. Secondly, I used the outcomes of the first literature review to lead an analysis of current progress in dynamic modelling of RIS with the specific System Dynamics (SD) method to build a comparative assessment of literature methodologies and results. I adopted a systematic approach for the literature search following the PRISMA 2020 guidelines (Page et al. 2021).

To create the search query, I followed Bramer et al. (2018)'s methodology of determining a focused objective from which to build keywords. While the first review aimed to understand the current methodologies and results of Jacobian and Marshallian interactions in RIS, specifically through system dynamic lenses, the second review's goal was to assess the current progress of SD modelling of agglomeration externalities in RIS. Given the overlap between both goals, for both the first and second literature review, I used Web of Science, Google Scholar and EU

Publications (e.g., JRC), with the query (”regional innovation system*” OR ”RIS”) AND (”diversification” OR “specialisation” OR ”relatedness” OR ”unrelated diversification” OR “MAR” OR “Jacobs” OR “Agglomeration externalities”) AND (”Williamson*” OR “Williamson’s 4 layer”) NOT (”urban planning” OR” climate change”).

After the search, I firstly discarded papers if they were found duplicated across both databases or if they were found in a different language. Secondly, I disregarded records if their title or abstract did not align with the topic of interest of this research. Once I selected reports based on title and abstract, I did another filtering based on whether the research file was accessible. This led to another 13 reports not accessible. The last filtering step realised was based on reading the full documents, starting from the introduction, result and conclusion section, to determine whether the document was of added value to this research. Finally, based on the available studies, a date filtering is done. Only studies more recent than the year 2000 were considered. Appendix A is dedicated to the desk research results. The resulting literature selection process given in Figure 44 in Appendix A stemmed down to a corpus of nineteen papers then analysed in Table 13 and Table 14 of Appendix A for the 10 studies on agglomeration externalities and 9 studies on SD in regional innovation systems respectively.

1.3.1 Agglomeration Externalities in Literature

From the initial 118 search results for MAR and Jacobs agglomeration externalities in RIS, I considered 10 papers as relevant for the level of specificity required for this research after applying the PRISMA method (Page et al. 2021). Table 14 gives their overview.
Authors generally adopted empirical or meta-analytical stances to investigate the relative benefits of MAR specialisation versus Jacobs diversity externalities, often finding context-dependent results. What can be noticed at first is that most papers supported MAR effects for the development of innovation. In Italian provinces, Castellano et al. (2024) found that specialisation outweighs diversification for innovation. Skill complementarity and mobility, especially within macro-areas, magnified the benefits of specialisation. Geographic closeness aided knowledge absorption irrespective of industry composition. Kekezi et al. (2017) found that while both intra-sector MAR spillovers and inter-sector Jacobian spillovers mattered, specialisation also more strongly correlated with innovation. They also highlighted the importance of academic knowledge and its long-distance spillovers (Ponds et al., 2010).

Fan et al. (2023) analysed 230 Chinese regions with spatial econometrics, showing that concentrations of competences and labour productivity drove urban innovation efficiency, alongside controls for infrastructure, industrial mix, consumption, and environmental factors. This also supported the advantage brought by MAR externalities. Nielsen et al. (2021) and Yangjun et al. (2019) empirically compared MAR and Jacobs effects on firm location and green economic efficiency, respectively, revealing that the impact varied by firm ownership and can even be negative for specialisation in certain contexts, such as green economic efficiency in China. This is echoed by de Vor & de Groot (2010), who found that specialisation can hamper employment growth at the industrial site level. In Tunisia and Indonesia respectively, Amara & El Lahga (2015) and Widodo et al. (2015) confirmed that Marshallian effects dominated Jacobian ones in manufacturing, and that peer-group characteristics can exert external influences distinct from a firm’s own traits.

However, reviews often revealed divergent findings on the relevance of MAR or Jacobs forces. Feldman (2000) and Glaeser (2000) both reported mixed empirical evidence. Neffke (2008) noted substantial variability even within U.S. only studies. Differences in measurement, aggregation level, and methodology explained these inconsistencies (Combes et al., 2004; Neffke et al., 2011). Beaudry & Schiffauerova (2008) attributed wide-ranging results not to true variation in agglomeration forces but to measurement and methodological choices. They found that at the 3-digit industry level, MAR and Jacobs effects often blurred, especially when regions were broadly defined. These findings pointed to the fact that variation in determining the factor of regional performance was largely due to the research approach and not to differing factors determining system interactions. The latter aspect remained largely unexplained by academic articles as shown by multiple literature reviews (Feldman, 2002; Glaeser, 2000; Neffke, 2008; Combes et al., 2004; Neffke et al., 2011; Beaudry & Schiffauerova, 2008). De Vor & de Groot (2008) showed that specialisation can hinder growth at the site–industry scale. Authors did not identify specific differences between MAR and Jacobs characteristic districts in Amsterdam's industrial sites. Accessibility such as proximity to highways or ports, was a stronger predictor of expansion irrespective of the agglomeration type.

The meta-analyses by Beaudry and Schiffauerova (2009) and de Groot et al. (2016) synthesised these findings, consistently highlighting that methodological choices such as industrial and geographical aggregation or performance measures, were the primary causes for the inconclusive debate, and even suggesting publication bias towards specialisation in more recent studies. Furthermore, Antonelli and Colombelli (2015) delved into the micro-foundations of knowledge generation. They emphasised the localised character of knowledge externalities and the crucial, complementary role of external knowledge, whether local or inter-regional, for innovation. They reinforced the importance of proximity in knowledge flows. Finally, Bergek et al. (2015) provided a conceptual framework for understanding the geographical context of Innovation Systems centred around technologies. They underscored that elements of such systems are inherently localised and that their boundaries often coincided with territorial limits, which influenced how innovation processes unfold spatially. These papers showed that further investigation is needed to elucidate the dynamics of the regional observations.

A few papers used the uncertainties surrounding agglomeration dynamics to innovate in their line of research. Nielsen et al. (2021) used 387,000 workplace observations to demonstrate that domestic and foreign firms responded differently to MAR and Jacobs forces, with manufacturing especially sensitive to ownership-specific clustering. A significant contribution came from Neffke et al. (2011), who introduced the industry life cycle, demonstrating that MAR externalities increase with industry maturity, while Jacobs externalities are more beneficial for young industries but decline for mature ones. He provided a dynamic perspective to the debate. These two studies introduced external factors in the study of externalities which were not emphasised previously.

Interestingly, Antonelli et al. (2017) gave a different twist to their research. They mapped EU regions by technological variety, ubiquity, and complexity. They argued for policies that assemble diverse, skilled knowledge pools rather than pushing for narrow specialisations. They also reconceived MAR as density-driven advantages and Jacobs as diversity-driven, noting clusters can exhibit both. These studies collectively underscored the need for more nuanced and dynamic approaches. The persistent methodological inconsistencies called for greater standardisation in defining and measuring agglomeration externalities across different scales and industries. The studied authors emphasised that research should further explore the conditions under which specialisation develops, moving beyond simple density measures to analyse the quality and composition of knowledge interactions (Antonelli et al., 2017, Antonelli & Colombelli, 2015). Antonelli et al. (2017) refined the Jacobs argument by emphasising "qualified variety" of knowledge as crucial for innovation, suggesting that not all diversity is equally beneficial. They emphasised that industry life cycle perspective is crucial for understanding the evolving needs of industries and designing adaptive regional innovation policies (Neffke et al., 2011). Moreover, they stressed that integrating the conceptualisation of geographical context within cluster frameworks with empirical studies on agglomeration externalities can provide a more holistic understanding of how spatial factors shape innovation systems (Bergek et al., 2015).

From the literature overview, the lack of dynamic quantitative methodologies in understanding the impact of agglomeration externalities on innovation performance and the under-studied geographical context within MAR and Jacobs research appeared as an evident research gap (Bergek et al., 2015). Hence, I posited the usage of System Dynamics to fill this gap and assess the impact of agglomeration externalities on innovation performance within a regional innovation context for robust decision-making. In the following section, I presented System Dynamics's origin and application to justify its appropriate choice as dynamic quantitative method to bridge the knowledge gap. This being said, to ensure that this research gap existed from a System Dynamics perspective and that SD could be used for this goal, I led a second literature overview with the methodological tool as subject, to assess what the state of System Dynamics modelling for regional agglomeration externalities was and whether progress had already been achieved with this method.

1.3.2 Description of the System Dynamics Method and its historical use

System dynamics, pioneered by Jay W. Forrester at MIT's Sloan School, originated in 1956 when Forrester transitioned from leading MIT Lincoln Laboratory's Computer Division to founding the industrial dynamics program, now known broadly as System Dynamics (SD). SD applies feedback-control principles and simulation to managerial, organisational, and socioeconomic challenges (Roberts, 1978). It promotes a holistic view of organisations, integrating functional areas into a unified quantitative framework for policy design. Advances in control systems, decision-process modelling, simulation, and data processing made SD possible (Forrester, 1961). Roberts (1978) emphasised that organisational behaviour stems from its structure, including policies and traditions, yielding amplification, delays, and feedback akin to engineering systems. Managing such nonlinear systems presents significant challenges, which is why the field of SD was introduced (Forrester, 1961).

Another core SD tenet views organisations through their flow structures, people, materials, money, orders, equipment, and information rather than siloed functions. This flow orientation discourages sub-optimisation and fosters system-wide thinking. Building an SD model begins with mapping the forces sustaining a problem, sketching causal diagrams, then translating them into mathematical form. I showed this approach in the following sections. Models are iteratively tested, critiqued, and refined, deepening understanding alongside model improvement.
Because real-world systems often defy intuition, simulation is indispensable for exploring complex social, economic, and organisational feedback. Roberts (1978) identified four feedback levels: variables, linkages, loops, and systems. Variables change over time, exogenous ones lying outside system influence and endogenous ones shaped within. Feedback loops, which are chains of linkages forming closed paths, can reinforce or counteract changes. They are termed “positive loops” and “negative loops” respectively. SD uses causal-loop diagrams, marking each link as positive or negative, to unravel these dynamic structures and guide further simulation.

A parallel body of work proposes that computational simulations can equip policymakers with a laboratory for experimenting with policy designs, thereby avoiding the time lags and high costs of real-world trial and error (Ghaffarzadegan et al., 2011). Within this realm, system-dynamics (SD) models have proven especially valuable across numerous policy domains. SD excels at revealing the behaviour of complex systems characterised by boundedly rational actors, reinforcing and balancing feedback loops, non-linear interactions, and time delays (Sterman, 2000; Niosi, 2004; Niosi, 2010).

Importantly, SD is framed not as a crystal ball that predicts the future with precision, but as a quantitative “what-if” laboratory that exposes the key drivers and uncertainties shaping possible futures, building insights that are essential for rigorous policy analysis (Ciarli et al., 2016). SD models can be depicted in three complementary ways: causal-loop diagrams to map feedback structures qualitatively; stock-and-flow diagrams to simulate dynamic trajectories; and the underlying differential-equation formulations that govern stocks and flows mathematically (Sterman, 2000).

In SD theory, stocks, shown as rectangles, are the accumulations that result from the net of inflows and outflows, while flows, shown as arrows, are the rates at which those accumulations change (Sterman, 1989). Stocks are computed by integrating net flows over time; flows are described by rate equations that depend on current stocks and parameter values. By treating time as continuous, SD captures events and adjustments at any instant (Samara et al., 2024). For simulation, stock-flow structures are translated into systems of differential equations and executed in specialised software such as PowerSim®, Vensim®, or Stella® (Samara et al., 2023; Katsoras & Geordiadis, 2022).

Building an SD model is inherently iterative. As the researcher refines its representation of reality, the structure, parameters, and assumptions of the stock-and-flow diagram are repeatedly adjusted. These adjustments serve two purposes. First, sensitivity analysis tests whether the model reliably reproduces observed system behaviour under varying assumptions (Ford, 2009; Sterman, 2000). Second, policy-testing experiments manipulate leverage-point parameters to gauge the effects of potential interventions on system outcomes.

A notable strength of SD is its capacity to incorporate "soft" variables that lack precise measurement (Paasi et al., 2023). Because SD prioritizes capturing overarching dynamics rather than statistical exactitude, modelers can include factors defined through stakeholder experience and expert judgment. Validation of these intangible variables occurs via comparison of model behaviour with real-world observations and practitioner insights; the model's credibility rests on fitness for purpose rather than universal empirical validation (Zolfagrahian et al., 2014).

1.3.3 System Dynamics for Regional Innovation Systems Modelling in Literature

From the abundant 83 studies on regional innovation systems, I selected only 9 to analyse them in this literature review, described in Table 13. These 9 papers all satisfied language, topic, recency and full model development and explanation, which was lacking in the other papers. It is necessary to note that a minority of the papers selected did not present any stock and flow models. However, I kept them as they presented a causal loop diagram with consistent support of theoretical concepts. To start, it is interesting to note that the use of system dynamics in innovation system studies had grown with the progressive growth of the domain of innovation system studies itself. This seemed to reflect researchers' opinion of System Dynamics as an appropriate tool to measure innovation development in a system (Samara et al. 2022). Over the past decade, the innovation-systems perspective (e.g. Borras et al., 2011; Edquist, 2011) has become a cornerstone for crafting and evaluating science, technology, and innovation policy. At its core, the innovation-systems approach regarded technological progress as the outcome of a richly interactive, non-linear process in which firms engaged with universities, research institutes, customers, suppliers, financial actors, regulators, and a web of formal rules, at national, regional, and sectoral level, in pursuit of creating and spreading new products, processes, and practices (Uriona & Grobbelaar, 2018). Scholars of innovation ecosystems have urged treating these systems as complex adaptive entities that process information internally and learn in response to external pressures (Phillips & Ritala, 2019). While SD naturally embeds feedback and adaptation, it also requires a defined system boundary; influences outside that boundary must be modelled as static inputs or exogenous drivers (Turner & Baker, 2018). Thus, interpreting SD results demands supplementary knowledge about external forces not captured dynamically.

The reviewed SD literature regularly demonstrated a broad embrace of System Dynamics as a powerful methodology for analysing innovation systems, albeit from varied conceptual angles and at different scales. One of the earliest efforts to represent multi-level socio-technical transitions via simulation was the EU-MATISSE project (Bergman et al., 2008; Köhler et al., 2009; Rotmans et al., 2008). That work combined agent-based modelling with SD elements to reconstruct historical transitions across niches, regimes, and landscapes. While the approach provided valuable heuristic insights into generic transition dynamics, researchers found it challenging to align simulated pathways precisely with historical case narratives. Kim and Choi (2009) adopted a firm-centric view of innovation systems, focusing on the internal dynamics of R&D and innovation processes within a single entity. In contrast, Lin et al. (2006) and Dangelico et al. (2010) expanded the scope to industrial clusters, emphasising multi-dimensional flows and the critical role of knowledge and proximity in driving agglomeration. Walrave and Raven (2016) further broadened the perspective by taking a socio-technical transitions stance, integrating Innovation System functions linked to technology with a multi-level perspective to understand systemic change. More recent contributions by Samara et al. (2022, 2023) and Hou et al. (2024) explicitly modelled Regional Innovation Systems (RIS) and Regional Technology Innovation (RTI), highlighting the transformative impact of digital technologies and addressing critical issues such as regional disparities. Maruccia et al. (2020) pushed the boundaries further by integrating a Quintuple Helix model, thereby emphasising the crucial roles of broader societal and environmental dimensions in the university-government-firm innovation ecosystem. The importance of knowledge was consistently identified as a central driver of innovation and regional growth across all scales of analysis. This appeared valid for knowledge in all its various forms, whether considering creation, accumulation, diffusion or spillovers.

While reinforcing loops are shown to drive growth, several papers simultaneously identified "interference points" or balancing loops that constrain unlimited expansion. Lin et al. (2006) pointed to resource limitations as a key constraint on industrial cluster growth. Dangelico et al. (2010) revealed an inverted U-shaped relationship for proximity, where both too little and too much proximity can lead to suboptimal outcomes like lock-in or decay, in line with Boschma's findings (2005). Walrave and Raven (2016) introduced "regime resistance" as a significant balancing force that can impede the emergence and growth of Technological Innovation Systems.

A key emergent theme from this comparative analysis was that optimal policy interventions are highly context-dependent and stage-specific. All papers have developed SD models for the final purpose of better advising policymaking for technology and innovation and further advance the system's understanding. Zeng et al. (2021) illustrated that the effects of Intellectual Property Rights (IPR) policy varied significantly depending on the development stage of the Regional Innovation system linked to technology. Similarly, Samara et al. (2024) demonstrated that different smart technology priorities are required for distinct Greek regions, based on their initial conditions and development trajectories. Hou et al. (2024) further reinforced this by identifying differentiated optimisation paths for central versus non-central cities in China, underscoring that a "one-size-fits-all" policy approach is ineffective. This collective finding strongly advocated for adaptive and nuanced governance strategies.

Additionally, a strong convergence existed across these studies regarding SD's superior efficacy in capturing dynamic, non-linear, and feedback-rich innovation processes with respect to other analytical methods. All reviewed works leveraged SD's inherent ability to model complex causal relationships and inherent time delays within innovation systems. This same consideration, along with SD's efficacy for policy support, encouraged its use as method for this research's objective. Consequently, SD has been used both to illuminate the intrinsic growth-and-decline dynamics of regional innovation systems (Walrave et al. 2015; Walrave et al., 2011; Davis et al., 2007) and to evaluate potential policies aimed at enhancing system performance.

1.3.4 Knowledge Gap from Combined Literature Reviews

Resuming the previous findings, of all the reviewed studies, no study undertook to decipher interactions of cluster agglomeration mechanisms in regional innovation systems for robust decision making oriented towards innovation performance. Additionally, to date, no research has dynamically modelled how distinct agglomeration configurations shape the performance of regional innovation systems; most work treats agglomeration as a static attribute influencing firm-level outcomes (Neffke et al. 2011). Policy advice for innovation development in agglomerations remained based on static measurements and the factors influencing the performance of regional agglomerations have not been investigated, shedding light on the research gap identified for my thesis. The findings from these two literature reviews were therefore employed to define the research gap as being the lack of dynamic understanding of the behaviour of specialised and diversified agglomerations for decision-making aimed at improving the innovation performance of a region. To bridge this gap, I suggested to create a model of agglomeration dynamics in Regional Innovation Systems by employing System Dynamics. Therefore, my research was amongst others aiming at modelling innovation development with System Dynamics, but the only one aiming to incorporate aspects specific to agglomeration dynamics to do so.

1.4 Link with the CoSEM Master Programme

My research aligns with the objectives of the Complex Systems Engineering and Management program at TU Delft within the ICT specialisation. The study of Regional Innovation Systems agglomerations through system dynamics modelling embodies the program's emphasis on understanding and managing complex, multi-actor systems. My research leverages advanced modelling techniques to simulate the intricate interactions within innovation systems, reflecting the program's focus on quantitative analysis and system thinking and design as required by the Master module (TPM, 2025). I incorporated these elements by conceptualising the topic of focus as an ensemble of systems and system components interacting with each other. Moreover, by addressing a pressing societal and regional economic challenge, my project exemplifies the program's commitment to applying engineering and management principles to solve real-world problems (TU Delft, 2024). In conclusion, my research seeks to contribute to the field of Regional Innovation studies by providing a nuanced understanding of the factors influencing regional agglomeration patterns. Through the development of a system dynamics model, my study aims to offer valuable insights for researchers and stakeholders striving to promote economic development across European regions.

1.5 Objectives and Research Questions

Despite substantial work, studies largely suggested policy-recommendations based on static statistical measurements of agglomeration patterns. They overlooked the evolving, interdependent processes through which clusters strengthen each other, whether through diversification or specialisation and how these dynamics impact innovation outcomes. My study's main contributions lie in applying the SD methodology to explore agglomeration factors shaping innovation performance within the context of a Regional Innovation System and in constructing a dynamic model of regional agglomeration externalities, represented through causal-loop diagrams, to capture these interdependencies.

The observed knowledge gap and defined research scope led to the following main research question:

How do specialisation and diversification agglomeration externalities interact dynamically with components of regional innovation systems to advise decision-making for the improvement of innovation performance in EU NUTS2 regions?

The following are a set of sub-questions that this research answered:

1. Which actors, relations and institutions exert an important function in the development of innovation in MAR and Jacobs regional innovation agglomerations according to field literature and how can they be simulated in a SD model?

2. How closely does the model behaviour align with reality to allow to validate the relationships conceptualised in the model and how does it further inform the theoretical framework on agglomeration externalities in clusters and in regional innovation systems?

3. Which variables from the model have the largest influence on the development of innovations in EU NUTS 2 regions and what would be their implication for decision-making aimed at improving innovation generation in the region?

1.6 Outline

From the previously stated research gap and research questions, the research is divided into three parts, constantly reinforcing and interacting with each other. The research flow diagram depicting the research framework is presented in Figure 45 in the Appendix.

Firstly, to answer sub-question 1, I undertook a literature review, clarifying how different agglomeration characteristics and interactions are defined. Williamson's 4-layer institutional model guided and allowed for the codification of the results of the literature research presented in the previous section. I made the link between the system performance and its characteristics by means of the classification of the results from this literature review. Hence, I first translated the outcome from the desk research and literature review into a four-layer institutional model to then be interpreted into a Causal Loop Diagram and a System Dynamic Stock-Flow Diagram mapping feedback between agglomeration patterns and knowledge generation mechanisms. This method helped identify patterns in the actors and relationships that can be agglomerated under single variables. This method has limitations in the sense that it might generate research bias in the current study of the domain, therefore influencing the robustness of the modelling procedure in the research phase. Translating these mechanisms into mathematical interactions for a system dynamics model allowed to simulate the complex behaviour of Regional Innovation System agglomerations. I used the Vensim modelling software to output a working dynamic model simulating the interactions previously defined in literature. This method might have limitations given the quantitative nature of the modelling technique compared to the mixed nature of the real system's agglomeration patterns. This required different approaches for abstracting qualitative fuzzy variables to simulate in the model for the correct working of the system.

I then undertook a set of model verification tests to ensure that the model correctly generated the system behaviour. I verified the resulting model with boundary adequacy, structure verification, dimensional consistency, parameter verification and extreme value test. After verifying the model, I completed model validation tests to ensure the model generated the correct behaviour. To do so, I firstly assessed the replicative validation of the model, then followed by a parameter sweep. For the replicative validation test, I presented the system dynamics model parametrisation. The model validity was assured through a replicative data test with multiple exogenous variables, an expert interview and a parameter sweep. The steps within the verification and validation method inform each other. Hence, the results of each step are presented after the method and tool has been presented. The limitation of this method could originate from subjective setting of variable values, uncertainty parameters or biased expert questions. To minimise the risks of bias, I based myself on strict methodologies guiding and supporting the validation phase. Additionally, the coded variables were data-informed by being in-line with EU-level socio-economic datasets.

Finally, both a quantitative and qualitative analysis examined which variables considerably changed the stimulation of innovation performance of the RIS. The output of this section of research is a contextual quantitative evaluation of the modification brought by the variation of certain system parameters that lead to a different system performance for the system's knowledge size. Following the quantitative analysis of those parameters, a qualitative analysis introduced shocks in the model. The shocks induced by varying significant parameters and insignificant one are assessed as a scenario test. Like the previous phase, these analyses could be limited by bias. To minimise this risk, the selection of parameters for both these analyses was informed by the previous validation and verification results as well as each other's results, and the scenarios were informed by scenario studies. The Discussion section highlighted the results and the way the model results fit the studied literature and commented on possible model limitations.

2 From Concepts to Model

In the following section, I elaborated on the findings from the literature review to develop a theoretical overview underlining the concepts used in modelling phase. This section took core concepts from the literature review and integrated them to analyse the different mechanisms for knowledge generation in both MAR and Jacobs regions according to Williamson's Institutional Model (Williamson, 2000). The final scope of this section consisted in build an SD model to answer sub-question 1.

2.1 A Comparative Overview of Literature Concepts for MAR and Jacobs Agglomerations

Antonelli et al. (2017) based their research on their previous findings (Antonelli & Colombelli, 2015) to establish that instead of being merely supplementary, the knowledge contributed by other firms and research bodies plays a crucial, inseparable role alongside a company's own internal knowledge stock, both in terms of its magnitude and make-up, and its ongoing R&D endeavours. Because technological knowledge comes in diverse forms, both the quality and quantity of a firm's knowledge reserves matter. When disparate knowledge types are more closely aligned, a firm can more easily absorb outside knowledge and integrate it with its accumulated internal expertise into a knowledge recombination (Boschma & Lambooy, 2002). However, assimilating external know-how incurs real costs, making these external knowledge benefits pecuniary rather than pure externalities. This "ability to recognise the value of new external knowledge, assimilate it and apply it to commercial ends" is coined absorptive capacity (Cohen & Levinthal, 1990). Knowledge may spill freely, but its effective use as an input for creating further innovation demands dedicated resources.

The recombinant perspective from Boschma & Lambooy (2002) highlights two vital inputs for generating fresh technological insights. First, each firm's own knowledge base, characterised by its size, more prominent in MAR regions, and composition, more varied in Jacobs regions, matter. Secondly, the external knowledge stock that complements it, is essential to the firm's inventive activities.

Antonelli et al. (2017) have profiled European regions using three dimensions of their knowledge base: variety, ubiquity, and complexity. Variety reflected how diversified a region's technological capabilities are; ubiquity measured how widespread those specialised technologies are across regions; and complexity provided a composite score indicating a region's capacity to master advanced, rare technologies, which depended on having a critical mass of skilled talent and specialised expertise.

They distinguish between related variety, which is the diversity of products and processes within similar industrial or technological categories, and unrelated variety, which spans across different sectors (Frenken & Boschma, 2007). Empirical work at the regional level shows that having a diverse, yet related set of activities fosters the emergence of new industries (Boschma, 2005; Neffke et al., 2011).

2.1.1 Agglomeration Externalities for Jacobs Regional Innovation Systems

Jacobs-style knowledge externalities arise when a region's knowledge base exhibits organised complexity, offering affordable access to shared, quasi-public knowledge that firms can recombine to spark innovation (Antonelli et al. 2017). When local knowledge components are varied, regular, and related, the cost of absorbing these complementary knowledge items falls, generating positive pecuniary effects (Dissart, 2003). Antonelli et al. (2017) analysed how specialised variety enhances knowledge creation at the regional scale to reveal the impact of Jacobs externalities on innovation.

They emphasised that the relationship between industrial concentration and output often follows an inverted U-shaped curve. Merely increasing the number of activities does not guarantee better innovation if those activities rely solely on commonplace knowledge and skills: in that case, Jacobs externalities remain weak. High variety that includes rare competencies, however, tends to produce strong Jacobs effects. Conversely, a narrow activity set with only ubiquitous knowledge yields low externality benefits, while a small set that includes rare capabilities can generate volatile but potentially groundbreaking innovations, boosting productivity and output when rare combinations arise.

2.1.2 Agglomeration Externalities for MAR Regional Innovation Systems

Marshallian knowledge externalities derive from the accumulated size of a firm's knowledge base, built up over time (Marshall, 1890). This historical endowment influences a firm's long-term capacity to innovate (Neffke et al., 2011). Yet, current R&D investments and the quality of accessible external knowledge pools can modify those effects (Antonelli & Colombelli, 2015). Recognising the deep complementarity between pecuniary externalities from outside knowledge and a firm's internal knowledge stocks and R&D efforts underscores the importance of localised knowledge ecosystems (Marshall, 1890). The density and quality of knowledge held by other firms and networks shape how much a given R&D investment yields in new knowledge.

These two types of agglomeration externalities tell us that, when selecting locations, firms should weigh not only their internal capabilities but also the richness of external knowledge externalities (Aghion & Griffith, 2005). Likewise, policymakers aiming to accelerate technological uptake are urged to prioritise enhancing both the quality and quantity of these external knowledge resources to stimulate higher rates of innovation adoption.

Schumpeterian frameworks highlight a tension amongst these different agglomerations: vigorous rivalry spurs firms to invest in R&D, yet if innovations arrive too rapidly, the payoffs diminish, discouraging further R&D and slowing innovation overall (Schumpeter, 1934). Porter (1990), however, contends that intense local competition within specialised clusters bolsters growth.

To illustrate this with an example from Neffke et al. (2011), let us imagine two equally sized cities, each supporting two industries. In City A, four client firms allow each firm to master specific products for two sectors. City B, by hosting eight client firms, forces each firm to cover four sectors, diluting their specialisation. Consequently, City A's services and by extension its institutions and infrastructure can be more finely tuned to client needs than City B's more generalised offerings. When industry requirements remain stable, this focused support represents a locational strength; its absence can be a liability (Combes et al., 2004; Ooms et al., 2015).

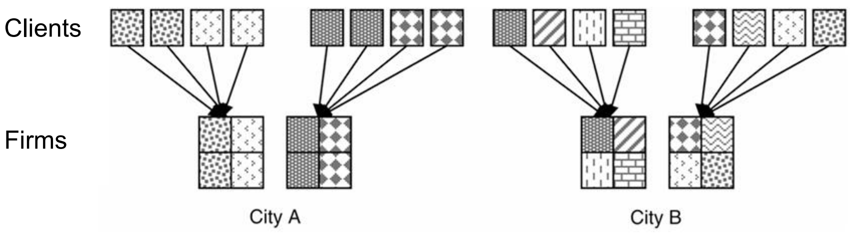

Figure 2: Diversity and focus (Neffke et al. 2011)

Strategic management scholarship has long emphasised that relying solely on cost leadership or differentiation does not suffice for sustained competitive advantage. Instead, firms must focus on generating and managing new knowledge and fostering innovation to maintain their competitiveness (Prahalad & Hamel, 1990). As noted earlier, the rapid development and governance of new knowledge have become pivotal elements in determining the success and growth of both firms and regions, particularly evident in the evolution of technological clusters (Tallman et al., 2004; Iammarino & McCann, 2006). With the current economic scenario varying the openness to globalisation, the behaviour of firms changes to reach the benefits of cost-savings and competitive advantages without needing to invest in specific locations. Nonetheless, a few parameters remain subject to a firm's location, these being knowledge transfer and proximity, with their respective effects (Dangelico et al. 2010).

2.1.3 Knowledge Generation in Firms

The generation of new knowledge arises from two primary learning mechanisms: internal and external. Internal mechanisms include activities like in-house research and development, experiential learning (learning by doing), and adapting through usage (learning by using) (Kaminski et al., 2008). External mechanisms encompass learning strategies such as imitating other actors or interacting with them (Malerba, 1992; Hu & Hsu, 2008). Innovation and knowledge creation typically emerge through the combination of diverse knowledge sources contributed by various stakeholders (Katz & Kahn, 1996). This being said, the transfer of knowledge is often impeded by its tacit nature and unique contextual dependencies (Antonelli, 2000). In this context, the concentration of firms within a geographic area can enhance external learning by facilitating collaboration and information flow (Feldman, 2000; Ghemawat, 2001). Localisation proximity fosters face-to-face interactions, trust-building, and the exchange of tacit knowledge, ultimately strengthening firms' connectedness and responsiveness (McKelvey et al., 2003). A district's capacity to generate and circulate knowledge thus becomes a defining trait that influences its long-term appeal and resilience (Arthur, 1989; Garnsey & Heffernan, 2005; Ibrahim & Fallah, 2005).

2.1.4 Knowledge Generation in Clusters

Within the diverse external learning strategies, two stand out in cluster environments, learning by imitation and learning by interaction (Maskell & Malmberg, 1999). Learning by interaction is defined by Maskell and Malmberg (1999) as the constant sharing of knowledge among complementary organisations, including collaborations between businesses, clients, and research institutions. In contrast, learning by imitation is based on unilateral knowledge flow, where firms absorb information from other actors possessing different expertise levels (Griliches, 1979). This form of learning draws on various knowledge sources such as scientific literature, industry publications, analyses of competitors, supplier and customer feedback, and participation in professional events like trade shows and academic conferences (Maskell & Malmberg, 1999).

These external learning activities are primarily driven by knowledge spillovers. According to Griliches (1979), such spillovers occur when entities work on similar problems and inadvertently benefit from each other’s efforts. Cantwell and Piscitello (2005) identify three key types of knowledge spillovers based on the origin of the knowledge: within the same sector (MAR), across different sectors (Jacobs), and from scientific to technological domain and vice versa. Another distinguishing feature of spillovers is whether they occur intentionally or unintentionally (Torre & Gilly, 2000; Breschi & Lissoni, 2001). Unintentional spillovers can yield both positive and negative outcomes, with the latter emerging due to the competitive nature of knowledge resources (Shaver & Flyers, 2000; Kalnins & Chung, 2004).

2.1.5 Knowledge Generation in Regional Innovation Systems

In addition to geography, other forms of proximity have been recognised as crucial in establishing competitive advantages and facilitating knowledge exchange. While spatial closeness plays a prominent role in enabling communication among economic agents, it is not the only factor that enhances knowledge flow (Boschma, 2005). Knoben and Oerlemans (2006), in their extensive review, categorize proximity into seven distinct dimensions: geographical, organisational, cultural, institutional, cognitive, technological, and social.

From Knoben and Oerlemans (2006), each of these forms of proximity offers unique communicative advantages. Organisational proximity fosters the integration of information and facilitates the combination of distributed knowledge, supporting systemic understanding across firms. Cultural proximity enhances interaction outcomes by enabling shared interpretations and common routines when organisational cultures align. Institutional proximity, which refers to shared norms, rules, and expectations among actors, functions similarly to cultural proximity in facilitating mutual understanding (Edquist, 2011). Cognitive proximity involves the degree of shared knowledge and mental models among organisations, while technological proximity refers to similarities in technical expertise or technological bases. Both types support the absorptive capacity of actors and thus reinforce effective knowledge assimilation and use. Social proximity, grounded in trust, familiarity, and shared experience, also promotes knowledge sharing through interpersonal ties and informal networks (Boschma, 2005).

Despite their advantages, these dimensions of proximity can also pose challenges. When proximity becomes excessive, it can lead to a "lock-in" effect, limiting exposure to new ideas and reducing the diversity of inputs necessary for innovation (Boschma, 2005). This is what is called the "competency trap" (Levitt & March, 1996). Hence, proximity must be managed carefully. According to Antonelli et al. (2017), the benefits derived from proximity follow an inverted U-shaped curve, meaning moderate levels encourage learning and exchange, whereas very high or very low levels can hinder them. Therefore, achieving an optimal level of distance is key to leveraging proximity for effective knowledge transfer and innovation. The interactions referenced above and in the previous chapters are summarised in Table 1.

Table 1: Mechanisms between MAR and Jacobs regions.

Mechanisms	MAR regional characteristics	Jacobs regional characteristics
Definition	Size of a regional knowledge base	Composition of a regional knowledge base
Origin	Originates from the development of the system's own knowledge base.	Originates from the absorption of outside knowledge.
Influences	Is dependent on R&D activities in the system and quality of external knowledge. Influences the absorptive capacity of a firm.	The outside knowledge is only as useful as the system's absorptive capacity is and depends on the absorption costs.
Density	The effect of density and quality of knowledge held by other firms and networks influences the yield of internal R&D investments but can lead to "lock-in" effect	Industrial concentration decreases the positive effects of Jacobs externalities after a certain threshold due to the increase in knowledge ubiquity and "lock-in" effect.
Competition	Competition decreases firm reliance on external knowledge, stimulating the R&D investment of a firm.	Competition increases firm monopoly and increases the absorption costs.
Collaboration	Collaboration increases knowledge spillover, thereby decreasing the pay-off from internal R&D, thereby discouraging further R&D.	Collaboration decreases absorption costs, making knowledge more easily accessible.
Proximity	Proximity can increase competition for work on similar projects and lead to unintended knowledge spillovers. Too little organisational proximity decreases monitoring and increases opportunism.	Proximity can enhance face-to-face interactions, knowledge flow, connectedness and responsiveness. Too much organisational proximity reduces network flexibility and increases lock-in.
Attractiveness	Knowledge generation is an attractive trait bringing more industries in the system.	Knowledge circulation influences the long-term attractiveness of the system.

Knowledge is assumed to be enduring, in such a way that when it is gained, it cannot decay or vanish (Hubert, 1991). Knowledge is however assumed to become obsolete as time progresses and as new knowledge on the same topic gets developed. The timespan of this obsolescence has been seen to vary depending on the sector and can be averaged to 10 years (Griliches, 1979, 1984, Schankerman, 1984).

2.2 Analysis of Regional Agglomeration Dynamics with Williamson's Framework

2.2.1 A Brief Introduction to Williamson's 4-Layer Institutional Framework

Dynamics in Regional Innovation Systems can be analysed in terms of Williamson's four levels of institutions (Williamson, 2000). This model was firstly created in the 1970 by Williamson based on Coase's previous work to analyse legal contracts, more specifically the occurrence of transaction costs and the role of property rights (Coase, 1960; Ménard and Shirley, 2014). However, given its relevancy in a multitude of domains, Williamson expanded it to include the analysis of any institutional transaction (Williamson, 2000). Today the model is widely used for the legal and economic analysis of institutions (Lee & Llyod, 2018).

Institutions can be described as the foundational frameworks within which societies function. These are deliberately created constraints that direct human behaviour (North, 1990: 3). These structures have concrete relational dimensions as they help manage uncertainty regarding others' actions, thereby enabling trust, fostering cooperation, recurrent patterns of social conduct and encouraging both investment and interdependence (Farole et al., 2011: 62; Bathelt & Glückler 2014). Reflecting North's later work, Williamson defines institutions as constructed limitations that organize interactions across political, economic, and societal domains (North, 1991: 97).
Institutions can be classified into formal mechanisms, such as constitutions and legal frameworks, and informal ones, like social customs and cultural traditions. Williamson (2000) categorises institutions into four distinct levels: foundational informal norms, established formal frameworks, governance structures, and operational rules regulating everyday strategic behaviour. When considering regional development policy, institutions play a significant role, either enabling or hindering progress, particularly in relation to issues like preferential treatment of sectors, corruption, rent-seeking, and structural entrenchment (Boschma, 2014; Ederveen et al., 2006; McCann and Ortega-Argilés, 2013; Rodríguez-Pose and Di Cataldo, 2015). For example, Ederveen et al. (2006) examined the impact of EU structural funds on average national economic growth between 1960 and 1995. Their study, using indicators like institutional trust, market openness, and levels of corruption, concluded that institutional quality significantly moderates the effectiveness of such funding.

Given that EU innovation policy often aims to reshape institutions, it is crucial to interrogate the logic underlying policy interventions: what are the institutions targeted for transformation and what mechanisms, both internal and external, drive institutional persistence or change over time?

2.2.2 Layer 1 of Williamson's Institutional Framework

At the foundational level, institutions comprise deep-seated cultural practices, belief systems, religious traditions, and shared societal values (Williamson, 2000). These informal structures often provide unspoken answers to core questions around identity, referred to as ontology, and legitimacy of knowledge, referred to as epistemology, forming the moral and cognitive bedrock for individual and collective behaviour. Such norms contribute to distinguishing various societies and cultures. Since other institutional layers are grounded in and legitimised by these informal foundations, Williamson (2000) referred to this base as "embeddedness". The character of informal institutions shapes what kinds of formal systems are seen as legitimate and how those systems are enacted. This has serious implications when analysing how different societies produce divergent outcomes, even under seemingly similar formal structures. Williamson (2000) contended that these foundational norms change only slowly, over generations, and that transformations are often triggered by significant internal developments or external shocks such as war or urbanisation.

2.2.3 Layer 2 of Williamson's Institutional Framework

The second institutional layer consists of codified rules that define political structures and the distribution of power. This includes constitutions, legal institutions, and administrative frameworks (Williamson, 2000). Peters (2012) refers to these as "meta-rules," underscoring their function in delineating who holds decision-making authority and under what conditions. These rules shape governance institutions by constraining the range of acceptable institutional configurations. According to Williamson (2000), unless disrupted by major external forces such as revolutions, endogenous changes to this layer tend to occur over decades, ranging from 10 to 100 years.

2.2.4 Layer 3 of Williamson's Institutional Framework

The third tier encompasses governance mechanisms, which set the procedural rules for specific policy domains such as education, healthcare, or competition. These mechanisms not only regulate daily interactions among individuals and organisations but also shape policy outcomes. They are nested within and influenced by the broader formal frameworks above them. Institutional change at this governance level typically unfolds over a 1–10-year timespan and may be prompted by either shifts in higher-order formal institutions or dissatisfaction with the performance of current governance arrangements.

2.2.5 Layer 4 of Williamson's Institutional Framework

The fourth and most immediate level of institutions governs the continuous, everyday actions and decisions made by individuals and organisations (Williamson, 2000). These micro-level interactions are shaped by the existing governance structures and help determine the payoffs of various strategies. This level introduces agency into institutional analysis, explaining why actors may achieve different outcomes even within similar institutional contexts. The interplay among these four layers summarised in Table 2 helps explain both institutional inertia and transformation. The stability of institutions is often rooted in the mutual reinforcement between layers: core norms constrain possible changes to formal structures, which in turn set boundaries on policy reform. Moreover, when day-to-day practices yield satisfactory outcomes for key stakeholders, they tend to reinforce the status quo at the governance level.

Table 2: Williamson 4-Layer Institutional Model (Llyod & Lee, 2018).

Level of Analysis	Phenomena	Change (years)	Origin
1. Embeddedness	Informal institutions (customs, religion, norms)	100-1000	Social Theory
2. Institutional	Formal rules of the game (law, rights, constitutions)	10-100	Economics of rights, political science
3. Governance	Play of the game	1-10	Transaction cost economics
4. Resource allocation	Resource flows (prices, quantities, incentives)	Continuous	Neoclassic economics

Finally, from its creation until its modern-day use, this framework demonstrated its completeness in illustrating relational dynamics within a system of study (Llyod & Lee, 2018). While not directly aligned with RIS, this framework can be applied to analyse the interaction of RIS components and transactions such as clusters and agglomeration externalities. I used it in this thesis to underline the agents, institutions and relations highlighted in RIS, cluster and agglomeration externalities literature. The use of this model for SD simulation could help identify not just the relations between different variables but also the exogenous and endogenous variables, the role of shocks and potential variables outside of the system modelled, such as the higher layers of institutions, to account for potentially slower evolutionary dynamics. From the literature review conducted in this study, no paper has shown to be using the 4-Layer model from Williamson to analyse their RIS system. I dare even to say that no published paper in the SD field seems to have adopted this method to inform the construction of their system. I wish however, to put forward the suggestion of incorporating this model due to its hierarchical completion. I hope that the results of this thesis will inform the validity of such a suggestion.

2.2.6 From Agglomeration Externalities to Institutional Transactions

This section aimed to use the concepts and frameworks presented above to forge an organised understanding of the system interactions that can be translated into a model.
Table 15 in the Appendix is an expanded table detailing MAR and Jacobs agglomeration mechanisms across all four layers of Williamson's institutional model, drawing upon the findings from the reviewed literature. It illustrates how the mechanisms of MAR and Jacobs agglomerations permeate all four layers of Williamson's institutional model, from deep-seated cultural norms to daily resource allocation decisions. The literature reveals that the debate between specialisation and diversity is not a simple "either/or" but rather a complex interplay influenced by various contextual factors. The first apparent finding is that actors are centred around three groups: firms, government entities, and public research and university centres. Hence, a sector is followingly defined as the combination of government, industry and public research and academia all dedicated to a knowledge generation activity within a specific industry. Inter-sectoral links would therefore be defined and the overall collaboration between all these three actors with all three other actors of a different sector.

2.2.7 Layer 4 Transactions of RIS Agglomerations

At Layer 4 (Resource Allocation and Employment), the continuous, micro-level interactions within a regional innovation system directly reflects the cumulative effects of the higher layers. This layer represents where the tangible benefits pertaining to specific clusters, such as knowledge spillovers, labour market pooling, reduced transaction costs, and costs pertaining to regional ecosystem, such as congestion, lock-in, negative environmental impacts of both specialisation and diversity are realised, influencing firms' daily decisions on prices, quantities, and incentive alignment.

Translating this into an SD model, several key flows and stocks became apparent. Knowledge spillovers, a central mechanism for both MAR and Jacobs (Kekezi et al. 2017, Breschi & Lissoni, 2003, Aghion & Griffith, 2005, Katz & Kahn, 1996), can be modelled as flows of knowledge between sectors. These spillovers are influenced by the knowledge-sharing activities between the public and private domains, as well as the knowledge assets generated by specialised labour (Antonelli et al. 2017, Antonelli & Colombelli, 2015, Edquist, 2011, Boschma, 2005). For instance, in a MAR region a highly specialised automotive manufacturing hub might experience rapid efficiency gains due to continuous knowledge exchange among engineers and easy hiring of specialised labour, which reduces costs. However, a sudden shift in global demand towards electric vehicles could lead to mass unemployment and a severe economic downturn due to the lack of transferable skills and a diversified industrial base.

Conversely, a city with a diverse economy aligning with Jacobs externalities, including strong design, software, and manufacturing sectors, could see new product innovations emerge from the recombination of ideas across these fields (Boschma & Lambooy, 2002, Dissart, 2003). When one industry faces a downturn, workers might more easily transition to other sectors, and firms could find alternative suppliers, leading to greater economic resilience (Jacobs, 1969, 1984).

Communication across diverse sectors directly influences knowledge spillover rates. This knowledge exchange is often contingent on the "proximity" between sectors, as highlighted by Boschma (2015). The "attractiveness" of a sector, driven by its capacity for innovation generation, influences collaboration with other sectors, depending on their relatedness (Dangelico et al., 2008). This attractiveness also draws foreign investment into the industry's expenditure, further reinforcing the budget available for R&D and human resources. For example, Yangjun et al. (2019) found that specialised agglomeration of producer services in some Chinese regions inhibited green economic efficiency and had negative spatial spillovers, while diversified agglomeration enhanced local green economic efficiency. This illustrated a scenario where the continuous resource allocation decisions at Level 4, influenced by the type of agglomeration, lead to divergent environmental outcomes. Combined knowledge size, human flows and financial capital allowed to represent the external learning function as well as considering that absorptive capacity is dependent on the absorbing firm’s resources (Cohen & Levinthal, 1990).

I considered the specialised workforce as a flow entering a sector based on available employment opportunities (Lin et al. 2006). As these additional human resources integrate into a sector's workforce, they introduce diverse knowledge from their geographical regions and educational backgrounds, contributing not only to knowledge generation but also to knowledge spillover, which then fuels innovation, quantified as the sector’s total knowledge size. The sale of these innovations generates revenues, creating a reinforcing feedback loop where product sales and revenues influence a sector's capacity to grow, hire more personnel, or allocate a larger budget to R&D (Uriona & Grobbelaar, 2018). Hence, the internal knowledge generation presented by Kaminski et al (2008) can be quantified in the modelling through human capital and financial flows.

Concretely, this layer showed the lower-level flows between firms and public knowledge producing entities by placing emphasis on human capital, knowledge stock and financial resources. It therefore quantified the agglomeration externalities taking place within clusters.

2.2.8 Layer 3 Transactions of RIS Agglomerations

Layer 3 (Governance), operating at a more tactical level, involved the "rules of the game" for specific policy domains applicable to the clusters and institutions of the regional innovation system. Specialised industry associations and vertical MAR collaborations contrasted with cross-sectoral Jacobs-type innovation platforms and active "orchestration" of diverse ecosystems (Ponds et al. 2010). The effectiveness of these governance structures depended on their alignment with the lower layers and their ability to adapt (Cooke, 2004).

Layer 3 introduced mechanisms that directly influence the flows and stocks identified in Level 4. The supply of skilled labour is an output of the university system within each sector. Universities can be modelled as having an intake capacity for a segment of the population, with a time delay representing the average education period of 6 years. After this period, the educated workforce seeks employment in their specialised sector. A percentage of graduates may also remain in academia, reinforcing the stock of academics and increasing the likelihood of communication and knowledge spillover with the private industry. There is a delay of around one-year to hire qualified workers, meant to represent the job search, candidacy and hiring procedure time. Once hired, workers undergo a one-year training period, representing a delay before they fully contribute to the productivity of the knowledge generation mechanism. Collaboration between universities and industry can be modelled based on a "co-innovation factor," such as a co-publishing factor per sector. While the model aggregates private actors under a "sector" sub-model, collaboration mechanisms within private firms in the same industry are implicitly captured by assuming that all knowledge within a sector contributes to its overall innovation.

This layer was critical for understanding how "the rules of the game" for specific policy domains shape interactions (Capello & Lenzi, 2018). For example, a powerful industry association in a specialised manufacturing cluster might lobby against policies that support emerging, unrelated industries, fearing competition for resources or a dilution of their influence. This governance mechanism, while beneficial for the specialised sector, could inadvertently create a "lock-in" effect, hindering the region's overall adaptability (Antonelli et al. 2017, Levitt & March, 1996). Conversely, a regional innovation agency actively "orchestrating" a diverse innovation ecosystem (Jacobs) by setting up platforms that connect biotech startups with AI developers and healthcare providers could lead to novel digital health solutions. This proactive governance fosters cross-sectoral collaboration and resource sharing, enabling the emergence of new industries and increasing regional resilience (Capello & Lenzi, 2018).

Finally, in the model, collaboration between different sectors are not detailed to the extent of Layer 3 in Table 15 given the simplifying assumption previously made that external learning mechanisms happen for all actors in sectors equally. These factors are nonetheless to some degree influenced by the institutions at Layer 2. Layer 3 conceptually anchored itself at a broader level than layer 4. By targeting the public-private research alignment, it positioned itself across agglomeration externality theory, cluster and RIS theory. This layer explicitly defined the set of actors present in the model beyond their simple flows.

2.2.9 Layer 2 Transactions of RIS Agglomerations

Moving to Layer 2 (Institutional Environment), formal rules and legal frameworks implemented in the regional innovation system either reinforced the cultural and normative predispositions of the region, such as industry-specific regulations for MAR, or broad competition laws for Jacobs, or attempted to steer them (Williamson, 2000). The impact of IPR protection, for instance, can vary, potentially supporting specialised innovation but also hindering broader knowledge diffusion if too restrictive. Layer 2 was crucial for establishing the direct link between formal policies, legal rights, and the development of MAR and Jacobs agglomerations (Boschma, 2014; Ederveen et al., 2006; McCann and Ortega-Argilés, 2013; Rodríguez-Pose and Di Cataldo, 2015). While changes at this level are typically slow (10-100 years), their impact on the environment and Layer 4 flows is significant, influencing the resource efficiency of the system (Llyod & Lee, 2018).

For instance, property rights and laws can be modelled as factors that directly influence collaboration rates between sectors. They also implicitly affect competition dynamics. For example, when a region becomes crowded with firms, market saturation and strong competition can deter new entrants (Dangelico et al., 2010). In an SD model, this can be simplified by assuming that an increase in workers within a sector leads to a reduced budget for additional workers until sales allow for expansion. This simplification can also represent scenarios of market domination by a few large firms, where competition for workers becomes intense, influencing the industry's attractiveness (Shaver & Flyers, 2000, Kalnins & Chung, 2004).

Labour laws can be aggregated into an "Industry Attractiveness" factor, which influences the inflow of workers and graduates into the skilled workforce. The labour laws can be said to influence the quality of life of people entering the industry and are therefore proxied by R&D expenditure per capita in the sector over the total R&D expenditure per capita of the system. Similarly, these formal institutions influenced a sector's openness to inter-sectoral collaboration and knowledge spillover. This openness, along with knowledge relatedness between sectors, affected the absorption costs of knowledge spillovers, further influenced by sector attractiveness. For example, a MAR region with strict environmental regulations tailored for its dominant chemical industry might inadvertently create high barriers for new cleaner industries that do not fit the existing regulatory boundaries, thus reinforcing specialisation, and thereby lock-in (Lewitt & March 1996). Conversely, a national policy promoting open-source software development in a Jacobs region could lead to a flourishing ecosystem of diverse tech startups and collaborations across various application domains, even if the region initially lacked a specific tech specialisation. Government R&D grants and funding, as formal policy instruments, can directly influence the funding for public R&D, thereby increasing the number of skilled workers entering academia and public research institutes, and can also boost private R&D by allocating specific budgets to certain sectors. These variables offer a comprehensive way to translate qualitative observations from the institutional environment into quantifiable model parameters.

The profound influence of policy and government on innovation generation in a region is specific of RIS scholarship (Ponds et al. 2010). While the transactions in Layer 2 are interlaced with the value of transactions happening in Layer 3 and Layer 4, they specifically belong to the RIS conceptualisation of innovation systems. This stressed how essential RIS conceptualisation is for the accurate representation of interactions between smaller nested sub-systems, in this case clusters and agglomerations.

2.2.10 Layer 1 Transactions of RIS Agglomerations

Finally, at Layer 1 (Embeddedness), norms and culture played a foundational role in a region's historical development. The foundational cultural and cognitive norms shape a region's predisposition towards either deep specialisation or broad diversity (Edquist, 2011, Boschma, 2005). A culture valuing deep expertise might foster MAR-type clusters, while one that encourages cross-pollination of ideas and risk-taking is more conducive to Jacobs-type innovation.

Given the very slow pace of change at this foundational level (100-1000 years), these deeply embedded predispositions are generally considered exogenous and constant within the typical time horizon of a System Dynamics model, which usually focuses on shorter-to-medium term dynamics (1-100 years). Therefore, while acknowledged as critical underlying factors, their direct evolutionary modelling is often outside the scope of such simulations.

However, their influence can be represented through initial conditions or sensitivity analyses. For instance, a MAR region with a deeply embedded tradition in heavy industry might struggle to transition to a knowledge-based economy due to cultural resistance to new types of work or learning, even if formal policies are in place. This cultural inertia could manifest as a lower initial "Sector Attractiveness" for diversified sectors in the model. Conversely, a Jacobs region with a strong historical tradition of diverse craftsmanship and open guilds might more easily adapt to new technologies by recombining skills, such as the transition from traditional printing to digital media in a city with a diverse creative sector. This inherent cultural openness could be reflected in a higher initial "Inter-industry Knowledge Spillover" rate in the model.

The analysis from Layer 1 embedded cultural and normative contexts and important players in the transactions of regional agglomerations, once again emphasising the need to merge RIS scholarship with theories on agglomeration externalities. Normative influences permeate through every actor in the system of study, showcasing how Layer 1 influences the sub-layers of the regional model while its change is very slow.

2.2.11 From Institutional Transactions to Agglomeration Externalities in RIS

By merging these findings with the concept overview given in Figure 1, I created Figure 3. Figure 3 grouped the findings from Williamson's 4-layer model analysis with the RIS, cluster and agglomeration externalities concepts. With this section, I showed not only how Williamson's model broke down conceptually complex theories into concrete system interaction, but also how it is possible to use those interactions to complement theoretical understanding. Building up on the need identified by Bergek et al. 2015 and Antonelli et al. 2017 to include the geographical context of clusters with agglomeration externalities, I integrated the results from the institutional analysis with RIS and cluster theory to provide further depth to the academic debate on agglomeration externalities. Both regions exhibited the same system boundaries in terms of institutional layers. Concretely, this means they are created out of the same building blocks. However, a first difference between MAR and Jacobs agglomeration externalities laid in the presence of components. The private knowledge generation and knowledge exchange functions in a MAR system are defined over the same sub-system given its intra-sectorial spillovers (Marshall, 1890). Jacob's sectors however showed only knowledge generation as being an internal function, while knowledge exchange is hosted between sub-systems, representative of the inter-sectorial spillovers (Jacobs, 1969).

Additionally, while they are both composed of the same building blocks, the number of components in the Jacobs region is far higher, since the private knowledge generation component is divided for every sector present in this region instead of being gathered in a cluster. This representation seems appropriate given that, due to their diversified economies, Jacobs regions showcase a majority of inter-sector exchanges rather than MAR intra-sector exchanges. Hence, each sector present in a Jacobs region showcases a link to a public knowledge generation and exchange sub-system based on its industry. The transactions for a Jacobs region are therefore more diverse than for a MAR region. For the latter, they are centred around its core cluster, which already provides a measure of cognitive alignment between industries in this cluster. This conceptual difference supports the idea that Jacobs regions need more coordination efforts than MAR regions to be performant (Cooke, 2004).

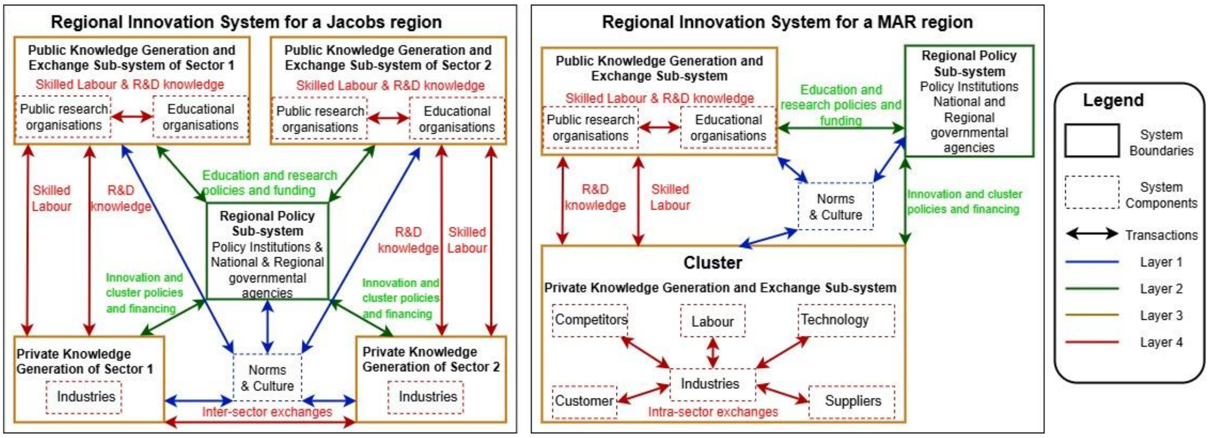

Figure 3: Comparative conceptual overview of the transactions occurring in Jacobs and MAR Regional Innovation Systems based on their institutional layer from Williamson (2000).

The modelling needs to reflect the structural difference in the diversity of components and in the different values of their transactions. Layer 1 transactions have not been labelled as norms and culture are conceptually the same across all sectors in a region. This align both evolutionary economic theories with the 4-Layer institutional model on the idea that although norms showcase little change over time and per component, they are still of importance in RIS (Edquist, 2011, Boschma, 2005, Trippl & Tödtling, 2007, Williamson, 2000). As such, Layer 1 components are environmental variables representing the regional culture in which sectors are.

Layer 2 components are the layers of interest for decision-making, while Layers 3 and 4 form the structure and flows of our system. All transactions should be present in the SD model to ensure alignment with literature and reality.

This multi-layered perspective underscores the need to move beyond agglomeration externalities in cluster flows and consider the deep institutional, formal, and governance structures influencing a region's innovation dynamics.

2.3 From Institutional Transactions to System Dynamics Modelling of Concepts

2.3.1 Model Structure

I created the model based on the dynamics identified through Williamson's framework. The Causal Loop Diagram in Figure 4 presents the dynamics in an aggregated view from a sector perspective, showcasing all sub-systems identified with Williamson's framework. The sector perspective does not differentiate whether the knowledge generation is in one industry or multiple. In this sense, it aggregates all human and capital flows as well as interactions for that sector irrespective of the industry. The CLD presents three reinforcing loops which put into play the defined dynamics from Williamson's Institutional Layer 4. The findings from Layer 1, 2 and 3 are included in the loop through the exogenous variables, agglomerated respectively under "Cognitive Proximity in the Sector", "Government Funding" and "Knowledge Spillover from Academic and Public Research in the Same Sector".

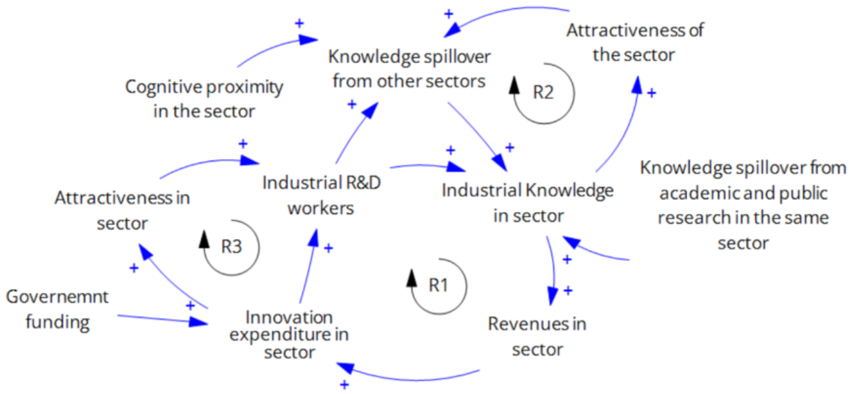

Figure 4: Causal Loop Diagram of the Innovation generation within a sector in a NUTS2 region

R1 is a reinforcing loop illustrating the effect of cluster knowledge directly on the sector's economic performance. As such, a higher knowledge size increases innovations in a sector, which in turn increase the sales of that sector either through improved processes lowering the product cost or though product innovation leading to the fulfilment of an unmet need (Uriona & Grobbelaar, 2018). The sales increase the revenue generated which in turn allows for a higher innovation expenditure in the sector, which translates into an increased workforce through higher hiring process (Dangelico et al. 2010). The increased R&D workforce in the sector in turn contributes to higher knowledge generation, therefore reinforcing the effect noticed in loop R1 (Lin et al. 2006). This represents the transactions occurring at Layer 4 of Wiliamson's model. Given the broader RIS scope, I added the government funding and knowledge spillover from academic and public institutions, which I considered as positively impacting the innovation expenditure in the sector, as representative of Layer 3 and Layer 2. Hence, this first loop already considers the human, knowledge and financial capital transactions identified through Williamson's model.

R2 is the reinforced effect of sector attractiveness on knowledge spillover. It signifies that a sector with a higher industrial knowledge increases the attractiveness of the sector over other sectors. This leads to higher knowledge spillovers from those sectors into the sector of interest, therefore increasing its size repetitively (Dangelico et al. 2010). The knowledge spillovers shared are however dependant on the cognitive proximity between that sector and the other sectors in the region (Frenken & Boschma, 2007). While emphasising on Layer 4, this loop also places the institutional transactions from Layer 2 and Layer 1 in the cognitive spillover factor of the CLD.

Finally, I added a reinforcing loop R3 for the attractiveness in the sector, which is connected to the hiring process in such a way that an attractive sector leads to a higher hiring in that sector, therefore increasing the sector researchers generating knowledge (Lin et al. 2006). This increased knowledge increases innovation which positively affects sales. As for R1, higher sales lead to higher R&D spending, which increases the attractiveness in the sector. Researchers that are well-funded in that sector will want to stay and new researchers will want to enter, therefore increasing the hiring in the sector. This is a central transaction described in Layer 3, setting the scene for sector competition and regional research culture.

The advantage of aggregating per sector is that this CLD can be applied to both MAR and Jacobs regions as it is not dependant on the agglomeration externality but is rather modular, Thus it can be replicated for every sector or cluster of interest. By externalising the knowledge exchange function in its own loop, this simple CLD can be connected with the other sectors' CLD through the spillover causality links. Additionally, it allows for further or less granularity based on the innovation perspective. Given the focus on agglomeration clusters in my research, the sector perspective is optimal as MAR and Jacobs externalities are differentiated through their inter-sectorial and intra-sectorial links. However, if these results are considered interesting to model cluster flows, they could make use of the CLD by differentiating it on an industry basis instead of a sectorial one.

Finally, in order to ensure model alignment with theory, the model is divided into four main sub-models based on the transactions identified through Williamson's framework, which are each described in the following sections. These models represent three types of knowledge generation functions in line with Cantwell & Piscitello (2005), within the industry, across industries and from academia to private enterprise. As such, this model assumes that internal learning and external learning are the only learning mechanisms for knowledge generation in the model, as supported by Kaminski et al., (2008), Malerba (1992), Hu & Hsu (2008), Katz & Kahn (1996), Antonelli (2000), Feldman (2000); Ghemawat, (2001), McKelvey et al. (2003) and Maskell & Malmberg (1999). All the exogenous variables are identified in the model Figure 5, Figure 6, Figure 7 and Figure 8 by their orange colour while initial variables are distinguished by their blue colour. All of them are summarised in Table 16. All variables directly linked to government activities are identified by Times New Roman Font.

2.3.2 Private Knowledge Generation sub-model

This sub-model represents the interactions happening under the Private Knowledge Generation Layer 3 of Williamson's model and aims to emulate how knowledge gets generated at sector-level from transactions in Layer 4. In line with Kaminski et al. 2008, I designed an internal knowledge generation function within a cluster in the model using human capital and economic capital transforming ideas into knowledge (Lin et al. 2006). Upon entry into the private R&D workforce of sector i, graduates become potential R&D staff available for hiring. The hiring process is modelled by comparing the firm's economic hiring capacity with its existing R&D headcount as shown in Figure 5. Specifically, sector i's annual revenue is allocated to two broad uses: retained earnings (*Profit*) and operating expenditures (*Commercial Expenditure)*, of which a portion is earmarked for research and development (*R&D expenditure in sector* i) (Hartmann, 2003). *R&D expenditure in sector* i comprises both personnel costs, salaries and benefits for researchers, and capital costs, such as laboratory equipment and other research assets. Each sector exhibits a characteristic innovation cost per researcher (*Innovation Expenditure per person employed in innovation sector* i), reflecting regional variations in wage levels and asset prices (Meo and Usmani, 2014). The maximum number of researchers that can be supported is thus given by:

$$Human\ Capital\ Need\ in\ R\&D_i = \frac{R\&D\ expenditure_i}{Innovation\ Expenditure\ per\ person\ employed\ in\ Innovation\ in\ Sector_i} \quad (1)$$

I then defined the hiring requirement variable ($Hires_i$) as the difference between the Human Capital Need in R&D in the sector and the current R&D workforce ($Workforce\ employed\ in\ knowledge\ intensive\ activities_i$):

$$Hires_i = Human\ Capital\ Need\ in\ R\&D_i - Workforce\ employed\ in\ knowledge\ intensive\ activities_i \quad (2)$$

If $Hires_i$ is positive, that number of positions is opened; if negative, hiring ceases ($Hires_i = 0$), and the R&D workforce declines over time according to a sector-specific attrition rate.

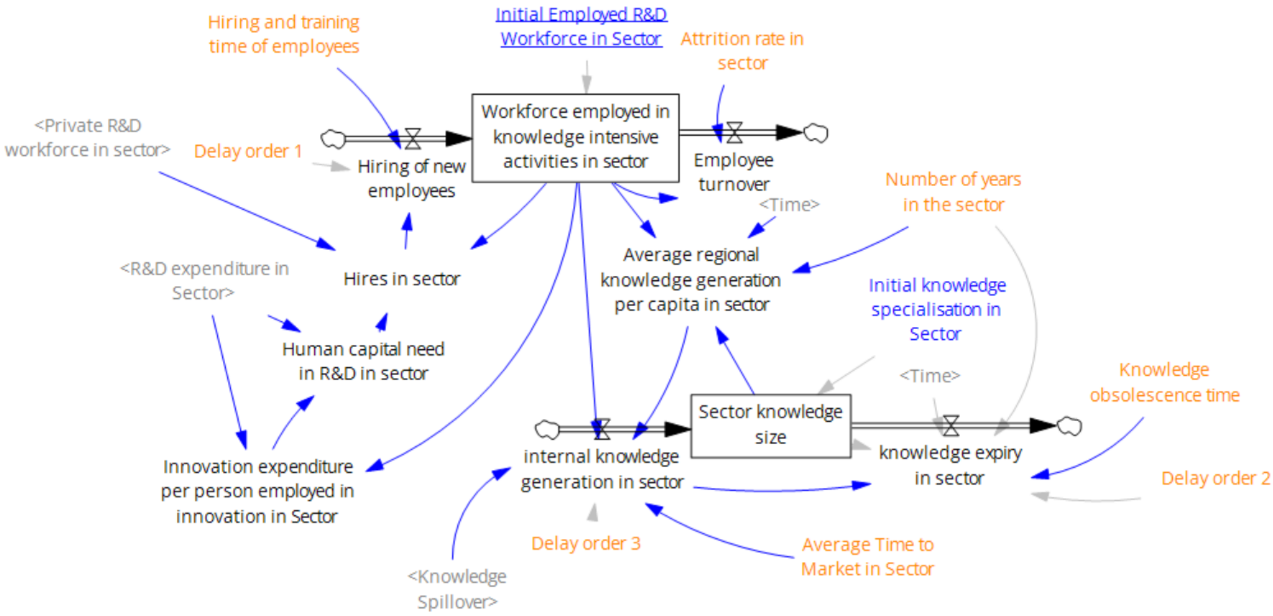

Figure 5: Knowledge development sub-model for the regional system.

All newly hired researchers contribute to the firm's innovation capital only after a gestation delay of two years representing the time required for recruitment, onboarding, and attainment of full productivity (Dangelico et al. 2010). I quantified each researcher's annual knowledge-generation capacity ($Average\ regional\ Knowledge\ Generation_{researcher_i}$) by dividing the total patents filed by sector i over the simulation time starting from the previous decade in years and by the initial R&D headcount in that sector:

$$Average\ regional\ Knowledge\ Generation_{researcher_i} = \frac{\sum_{t-10}^{t-1} Patents_{i,t}}{\text{Years} \times \text{Workforce}_{i,t}} \quad 3$$

This yields a per-researcher patenting rate, which, when applied to the cohort of hires, forecasts the number of new patents generated per year per researcher. If the workforce increases faster than the patents, the knowledge generation per researcher decreases, therefore simulating the crowdedness effect mentioned by Lin et al. (2006) and Dangelico et al. (2010). This ensures that the sector's appeal plays a role in the capacity to create knowledge (Arthur, 1989, Garnsey & Heffernam, 2005, Ibrahim & Fallah, 2005). To account for the lag between invention and commercialisation, I incorporate a sector-specific time-to-market delay (*Average Time to Market in sector* i) (Belay, 2011). For instance, pharmaceutical products typically incur longer development and regulatory testing intervals than information-technology innovations, which often reach market readiness within one year. This also means that if the cluster was to hire an increased amount of people their knowledge generation per person would decrease as the denominator in Equation 3 would increase faster than the nominator. Upon maturity, newly generated patents augment the sector's cumulative knowledge stock, which decays exponentially with an average obsolescence time (*Knowledge Obsolescence Time*) of five years (Griliches, 1979, 1984, Schankerman, 1984).

In this formulation, I assumed a one-to-one mapping between patents and commercially viable product or process innovations; every patent contributes fully to the expansion of the practical knowledge base. Additionally, I assumed that internal knowledge generation is solely based on the workforce's capacity to generate knowledge. I did not explicitly consider infrastructures or capital in the knowledge generation function. I did however internalise them from the innovation expenditure per person employed in innovation in the sector. This means that if a firm needs a high capital for knowledge generation, it reflects it in the amount it spends for the number of researchers it has. This parsimonious treatment captures the essential dynamics of knowledge creation, diffusion, and attrition within sectoral R&D systems.

2.3.3 Economic Cycle sub-model

The economic cycle sub-model aims to embody the Layer 4 interactions that allow a firm to generate economic resources to keep producing knowledge. With this sub-model, I created the bridge between knowledge and financial capital flows analysed in Layer 4 of Williamson's model. The completion of each private knowledge-generation cycle should yield measurable financial returns for the sectors represented in Figure 6. Innovations, independently of whether they are embodied in new products or improved processes, either reduce unit production costs or enhance profit margins, thereby monetising the accumulated knowledge stock (*Industry Knowledge size*) (Kim & Choi, 2009).

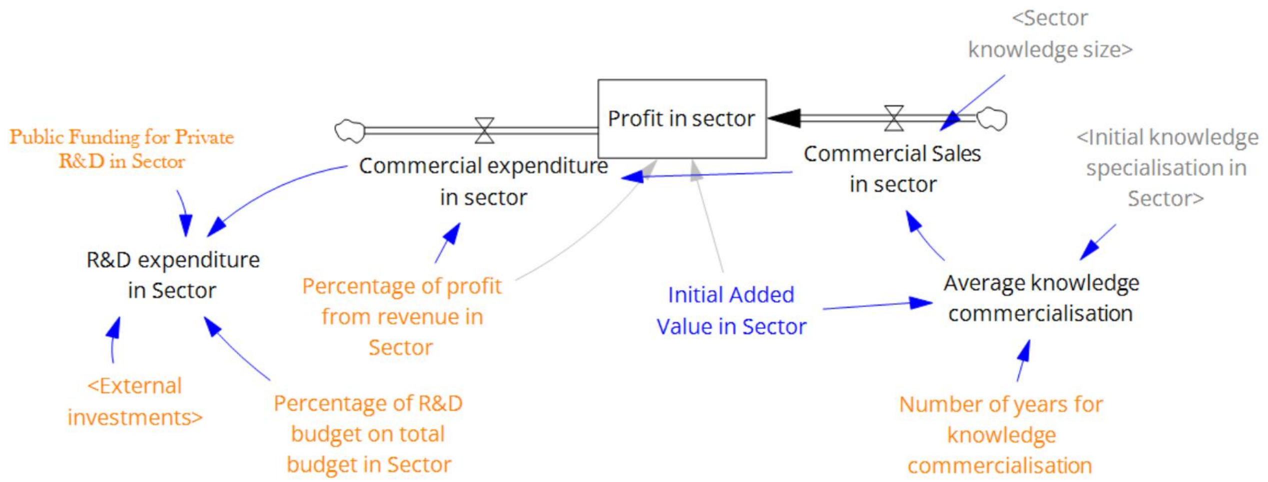

Figure 6: Economic sub-model in Regional Innovation System

I formalised this monetisation as knowledge commercialisation (*Average knowledge commercialisation*), defined as the additional revenue directly attributable to knowledge production defining the commercial sales from the sector (Blundell et al. 1999, Belenzon and Patacconi, 2013). Mathematically, it can be expressed as:

$$Commercial\ Sales_i \ = \ \text{Knowledge}\ size_i \ \times \ Knowledge\ Commercialisation_i \qquad 4$$

Here, $Knowledge\ Commercialisation_i$ denotes the average incremental sales generated per unit of knowledge in sector *i*. The resulting commercial sales ($Commercial\ Sales_i$) produce profit over time, represented as a cumulative profit flow (*Profit*):

$$Profit_i \ = \int_0^T \big(Commercial\ Sales_i(t) \ - \ Commercial\ Expenditure_i(t)\big)\ dt \qquad 5$$

where $Commercial\ Expenditure_i(t)$ is sector *i*'s commercial expenditure, encompassing recurring costs, such as marketing, distribution, and general administration, required to sustain and expand business operations (McConnell and Muscarella, 1985). I assume a constant ratio between profit and commercial expenditure each year (*Percentage of profit from revenue in Sector i)*. The decrease in knowledge generation from Equation 3 would therefore lead to the decrease of commercialised knowledge, therefore leading to less R&D budget for the employed workforce. Decreasing the amount of innovation expenses for the sector would decrease the attractiveness of the sector compared to other sectors, which represents a competition factor between firms to attract new talent (Schumpeter, 1934).

A fixed fraction of commercial expenditure, combined with any public funding for private R&D and external investments, is then redirected into the sector's R&D budget. The R&D expenditure in sector encompasses the proportion of commercial expenses allocated to R&D in sector *i* according to a fixed percentage (*Percentage of R&D budget on total budget in Sector).* As established earlier, the total R&D expenditure directly determines the sector's capacity to hire researchers (see the "Hires" variable in Section 2.3.2). Thus, the financial outcomes of knowledge generation feed back into human capital recruitment, closing the firm's innovation–finance–employment loop of the Causal Loop Diagram and the internal knowledge generation function of firms within sectors.

In this sub-model, I did not explicitly formulate demand for the knowledge generated, assuming that it will lead to sales either locally or internationally. I also assumed price stability of the knowledge generated, by defining it with the added value of the sector at the initial stage over the number of initial patents in the knowledge base. In a realistic setting, fluctuations and competition would alter the price of the knowledge generated. However, this being beyond the modelling scope, I simplified it to a stable market situation within the sector.

2.3.4 Socio-demographic sub-model

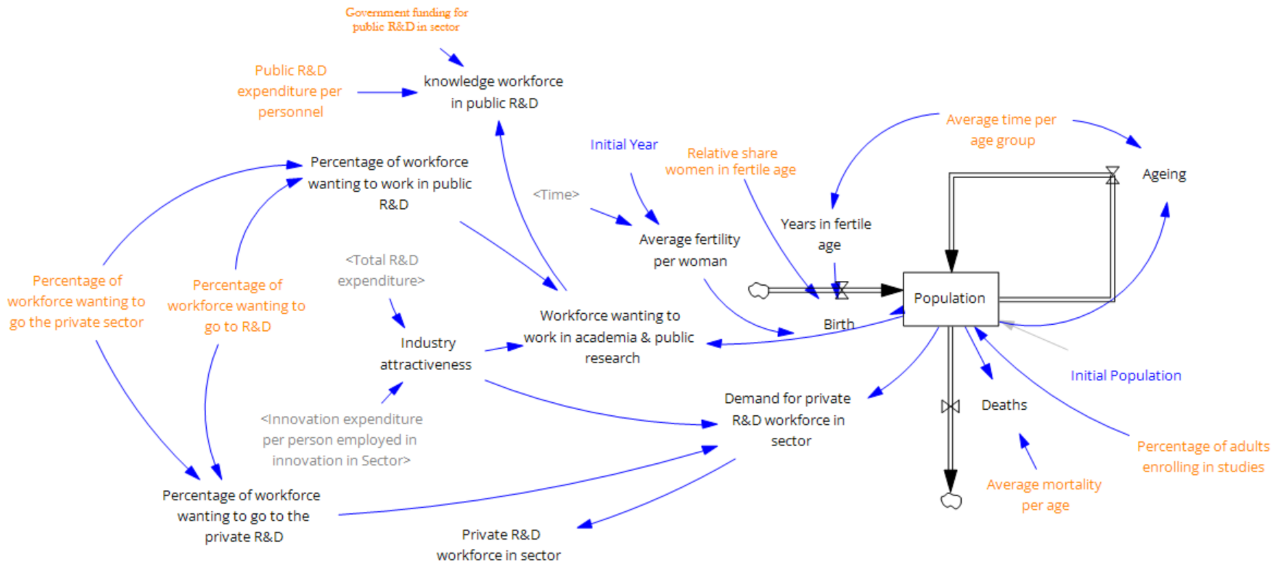

Figure 7: Population sub-model for the regional system.

To ensure that experimental outputs accurately reflect regional conditions, the model incorporates detailed socio-demographic processes, depicted in Figure 7. In this sub-model, I elaborated the interactions of Layer 3 and Layer 2 of Williamson's model. I bridged the private knowledge generation function to the academic resources of Layer 3 and policy transactions influencing them of Layer 2 within the regional context. Births are generated each period by identifying the number of women in fertile age in the population and multiplying them by their average fertility rate as an exogenous parameter. Rather than treating the population as a single undifferentiated group, individuals are allocated into three age-structured stocks according to their typical economic roles and fertility.

The first stock, termed "Children," comprises ages zero to eighteen as it is assumed in this model that individuals younger than 18 will not have children; members of this group undergo mandatory education and do not enter the labour force. Upon reaching age eighteen, individuals move into the "Young Adults" stock, aged eighteen to twenty-four. A proportion of these young adults elect to continue formal education and thus enter the "Students" stock, while the remainder joins the workforce directly. The separation of the "Young Adults" cohort acknowledges that the decision to pursue further study versus immediate employment varies with cultural and geographic factors. Only those individuals who pursue formal post-secondary programs are included in the "Students" stock. It excludes persons who bypass further education, on the assumption that they do not enter research and development roles and thus do not contribute directly to knowledge generation. The entry flow into the "Student" stock (*Students*) equals the fraction of eighteen-year-olds who enrol in higher-education courses, based on regional enrolment rates. The student stock is composed of students in all studies that are directly of interest to the cluster in the region. This allows to consider the whole regional innovation system and not uniquely the technological cluster in it (Capello & Lenzi, 2018). Hence, modelling the system as an ensemble of institutions and academic entities allows to reflect the need for system coordination for regional performance (Cooke, 2004). After completing their studies, of an average duration of 6 years, graduates exit the *Students* stock and join the "Graduates Seeking Employment" stock

(*Graduates per Age*). This cohort is subject to the same age-specific mortality rate as the general population, resulting in annual attrition. After age twenty-four, individuals transition into a working adults stock, aged twenty-five to forty-five. In this context the term workforce encompasses all persons legally available for work, either employed or actively seeking employment, between ages eighteen and sixty-five.

Upon entering *Workforce from studies*, individuals distribute between private versus public research aspirations. Regionally determined exogenous parameters specify the proportions aiming for private-sector R&D and public-sector research, respectively. For example, if a proportion of 0.2 chemical engineering graduates exhibit a willingness to enter the public sector and 0.80 to enter the private sector, then 20 percent target government laboratories and 80 percent seek employment in industry, motivated by compensation differentials or job availability. Within each category, only a subset of these aspirants secure R&D positions; the remainder transition into non-R&D roles such as managerial or advisory functions. These two filtered flows constitute the input variables “demand for private R&D workforce in sector i” and “demand for public R&D workforce”. This allows to include clusters in the institutional ecosystem characteristic of RIS (Capello & Lenzi, 2018). As such, not just clusters but also regions will need coordination to achieve performance (Cooke, 2004). In this sub-model, I assumed that the number of graduates wanting to go to R&D or the public or private sector are fixed. However, in reality, these rates might vary per sector. I also assumed that students that haven’t completed higher education in the studies linked to the sector will not be able to secure R&D position in that sector once they graduated, as the level of specialisation needed for the position is very high. In reality though, it is possible for individuals to redirect their professional career further away from their studies following the job market. However, I simplified this situation in the model.

Next, each group is allocated across industry sectors according to sectoral attractiveness. This is proxied by the ratio of innovation expenditure per researcher in sector i to total regional innovation expenditure. Innovation expenditure comprises all current costs, such as total R&D payroll and operating expenses, and capital costs, such as acquisition of research equipment, normalised by the number of researchers (Link, 1982). A higher innovation expenditure per researcher in sector i signals advanced research infrastructure or elevated researcher compensation, thereby increasing sector i’s appeal. For instance, although chemical engineers might be drawn to Oil and Gas for higher salaries, the pharmaceutical sector’s greater equipment investment could render it more attractive to R&D-oriented graduates.

Finally, the variables “Private R&D workforce in sector i” and “Knowledge workforce in public R&D” aggregate the sector-specific flows across all educational programs. In the private context, “Private R&D workforce in sector i” sums all graduates entering sector i’s R&D roles, chemical engineers entering Chemical or Pharmaceutical industries, for example. Similarly, “Knowledge workforce in public R&D” aggregates public-sector research positions across disciplines. The public-sector capacity is constrained by government R&D funding and public R&D expenditure per researcher, which together set an upper limit on the number of sustainable public research appointments. As with other workforce stocks, both “Private R&D workforce in sector i” and “Knowledge workforce in public R&D” age and shrink according to the mortality rate. This sorting creates the base resources in the “Public knowledge generation and exchange sub-model” for the knowledge flows and skilled personnel transactions in Layer 4 of Williamson’s model, between this sub-model and the “Private knowledge generation (and exchange) sub-model”.

Between age forty-five and sixty-five adults are not considered fertile any longer but are still available for employment or employed. At age sixty-five, individuals retire and exit the labour market. All five population stocks, Children, Young Adults, Students, Adults in the Workforce, and Adults after Retirement are subject to mortality; a uniform age-specific death rate reduces each stock accordingly. For the oldest cohort, further attrition follows average life expectancy in the model’s base year.

2.3.5 Knowledge Exchange sub-model

The knowledge spillovers of MAR and Jacobs regions from Williamson's Layer 4 interactions need to be depicted. Hence, the final component of the model is the knowledge-spillover sub-model, represented by Figure 8, which captures the transfer of insights between co-located industries, essential for both MAR regions (Marshall, 1890, de Vor, 2011, Henderson, 2003, Breschi & Lissoni, 2003) and Jacobs regions (Jacobs, 1969, 1984, Boschma & Lambooy, 2002, Dissart, 2003, Antonelli et al. 2017). As established in Section 2.1.1, regional agglomerations foster firm-industry clusters characterised by inter-firm collaboration and knowledge diffusion (Antonelli & Colombelli, 2015). This corresponds to the sector's external knowledge generation function (Malerba, 1992, Hu & Hsu, 2008).

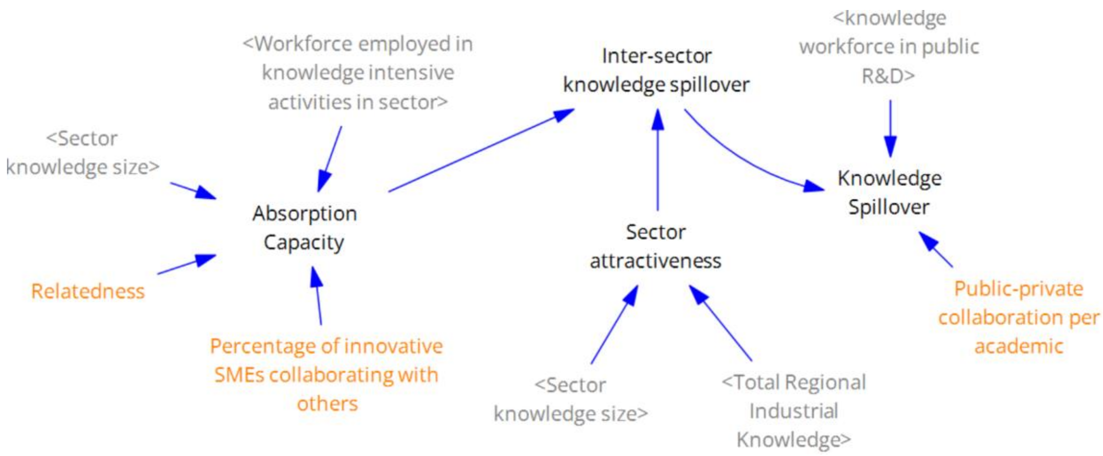

Figure 8: Knowledge Spillover in Regional Innovation System

The region's collaborative culture is quantified by the proportion of innovative SMEs engaged in partnerships with peer SMEs (*Percentage of innovative SMEs collaborating with others*). This proxy is introduced given the important role of institutional and cultural proximity within a region (Edquist, 2011, Boschma, 2005). In this sub-model, I assumed the institutional and cultural proximity to be the same across all firms in the region following Layer 1 of Williamson's 4-layer model analysis. A higher collaborative culture therefore reduces the sector's knowledge absorption cost (*Absorption Rate*). This aims to reflect the important role of abundant external knowledge for innovation (Aghion & Griffith, 2005, Katz & Kahn, 1996).

Furthermore, the difficulty of absorbing knowledge from sector *j* into sector *i* depends on their technological proximity, or relatedness (*Relatedness*) (Frenken & Boschma, 2007). Sectors with high relatedness require less effort to interpret and integrate each other's intellectual outputs, while low-relatedness pairs incur higher knowledge absorption costs. Formally, the effective absorption cost from sector *j* into sector *i* is defined as:

$$Absorption\ Rate_{i,j} = Relatedness_{i,j} \times Knowledge\ Size_j \times Percentage\ of\ SMEs\ collaborating\ with\ others \qquad 6$$

where the Knowledge Size denotes the knowledge stock of sector *j* (measured in cumulative patents). To define it concretely, knowledge is assumed to be shared by employees as defined in section 2.2.6, for which flows of agents and human resources determine how much knowledge is shared. The total cross-sector spillover into sector *i* at time *t* is then the sum of all incoming flows, weighted by the sender's available human conduits and sector attractiveness:

$$Inter-sector\ Knowledge\ Spillover_{\mathrm{i,t}} = \sum_{\mathrm{j \neq i}} \left(Absorption\ Rate_{i,j} \times \frac{R\&D\ Employees_{\mathrm{j,t}}}{R\&D\ Employees_{i,t}}\right) \times \frac{Knowledge\ size_{i,t}}{\sum_k Knowledge\ size_{k,t}} \qquad 7$$

where the number of R&D employees in *sector j* at time *t* over the number of R&D employees in sector *i* at time *t,* embodies firm *i*'s possible absorption capacity from *j*'s human conduits. This formulation reflects that even if sector *j* possesses abundant knowledge, a small workforce limits the volume of knowledge potentially transmitted to *i*. Conversely, a larger number of R&D employees in *sector j* at time *t* amplifies spillover. The above mechanisms aim to reproduce the idea that the geographical concentration of firms and individuals enhance external learning (Feldman, 2000; Ghemawat, 2001, McKelvey et al., 2003).

In addition to private-sector exchanges, public research also contributes to spillovers (Ponds et al. 2010). The region's public–private collaboration intensity is proxied using the public–private collaboration index per million inhabitants from the Regional Innovation Scoreboard, multiplied by total regional population (European Commission, 2023). Dividing this aggregate by the initial count of public researchers (*Initial researchers in the region*) yields a per-public-researcher collaboration propensity (*Public-private collaboration per academic*):

$$Public\ Private\ collaboration_{pub} = \frac{Public\ Private\ collaboration_{Person} \times \mathrm{Population}}{R\&D\ Employees_{\mathrm{pub}}^{\mathrm{init}}} \quad 8$$

The annual knowledge inflow from public to private R&D for sector *i* at time *t* is then:

$$\mathrm{Public\ Spill}_{\mathrm{i,t}} = Public\ Private\ collaboration_{pub} \times R\&D\ Employees_{\mathrm{pub,t}} \quad 9$$

where the current public-sector researcher headcount ($R\&D\ Employees_{pub,t}$) is multiplied with the public-private collaboration per public-sector researcher ($Public\ Private\ collaboration_{pub}$).This completes the representation of inter-sectoral and public-to-private knowledge flows within the model, which comes to add to the knowledge generation function of the model.

In this section, I defined an integrated view of agglomeration externalities within their system. MAR and Jacobs mechanisms often coexist and interact, reinforcing the idea that regional innovation systems are hybrid configurations. This supports contemporary thinking in innovation ecosystems (Granstrand & Holgersson, 2020) that embrace both scale-based and diversity-based spillovers. These agglomerations have been anchored in their geographical context by including factors belonging to universities and government. The latter are often mentioned in RIS literature and in cluster research as being essential for innovation development (Etzkowitz & Leydesdorff, 2000; Cooke, 2008).

Following the model construction, I verified and validated the model's behaviour. The following section presents the validation and verification steps. This is done to ensure that the correct model behaviour is represented correctly. The mathematically structure of the model is shown in Appendix C with the list of its equations and units.

3 Model Validation and Verification

Once the model created, I needed to ensure that the "model-land" is aligned with reality through a series of verification and validation tests. "Model-land" is a simplified, abstract space where models are evaluated against each other (Thompson & Smith, 2019). Real-world decisions require models to be tested against actual outcomes, not just theoretical consistency.

This section aims to answer sub-question 2. As part of the modelling verification and validation steps in Systems Dynamics simulations. I performed a set of verification tests, including boundary adequacy assessment, structure verification, dimensional consistency, parameter verification and extreme conditions test. After performing stress tests representing extreme conditions scenarios, I realised a replicative validation to ensure the output data shape corresponded to some extent to real world data. Additionally, I further presented the model CLD, the SFD and the results to a field expert for expert validation. Once that was ascertained, I undertook a further validation step with an uncertainty analysis to identify if exogenous parameter representing a degree of uncertainty were strongly influencing the model behaviour. These parameters are informed by literature and by the expert validation. I completed the parameter sweep with the EMA workbench in Python (Kwakkel, 2017). The results allowed me to determine whether there are parameters to which the model might exhibit very sensitive behaviour, and which carefully need to be catered for when testing the model.

3.1 Model Verification

Model testing comprises both verification and validation processes aimed at identifying and correcting errors and refining the model to enhance confidence in its applicability. Verification addresses whether the model's implementation faithfully represents its design, while validation assesses the extent to which the model fulfils its intended purpose, typically in consultation with stakeholders or end users (Pruyt, 2013). Validation and verification can take multiple forms. Structural verification examines whether the model's architecture and boundary definitions align with theoretical and empirical knowledge (Pruyt, 2013). Identifying the suitable structure that governs the 'correct' behaviour is a complex, multidimensional process involving problem representation, logical frameworks, and mathematical as well as causal relationships. Forrester and Senge (1980) examined several tests employed for the structural validation of a system dynamics model, presented in Figure 9 in a non-exhaustive list. After the model creation, a sequence of diagnostic evaluations was performed based on this list.

Boundary adequacy:	whether the important concepts and structures for addressing the policy issues are endogenous to the model?
Structure verification:	whether the model structure is consistent with relevant descriptive knowledge of the system being modeled?
Dimensional consistency:	whether each equation in the model dimensionally corresponds to the real system?
Parameter verification:	whether the parameters in the model are consistent with relevant descriptive and numerical knowledge of the system?
Extreme conditions:	whether the model exhibits a logical behavior when selected parameters are assigned extreme values?

Figure 9: Structural validation methods presented by Forrester (Qudrat-Ullah and Seong, 2010).

During verification, I employed debugging techniques to resolve issues flagged by the modelling software and to detect subtler logical inconsistencies. This included inverting signs in equations when simulated outcomes conflicted with theoretical expectations, introducing accumulator variables to avoid algebraic loops in feedback structures, and safeguarding against numerical overflow by using conditional operators such as zero-if-divided-by-zero (ZIDZ), value-if-divided-by-zero (XIDZ), and explicit maximum and minimum functions or conditional constructs. I adjusted flow equations to prevent state variables from falling below zero. I confirmed fractional totals summed to unity, and I checked units for dimensional consistency. Finally, I performed a stress test representing extreme parameter implementations.

3.2 Boundary Adequacy

I firstly ensured boundary adequacy by constructing causal loops and subsystem boundaries drawing on a thorough literature review of concepts and a multi layered analysis of their interaction. Most feedback loops depicted in Figure 4 were incorporated endogenously at the exception of the cognitive proximity between sectors, which was represented exogenously using the relatedness concept from Boschma (2015). The division between exogenous and endogenous parameters in shown in Figure 10.

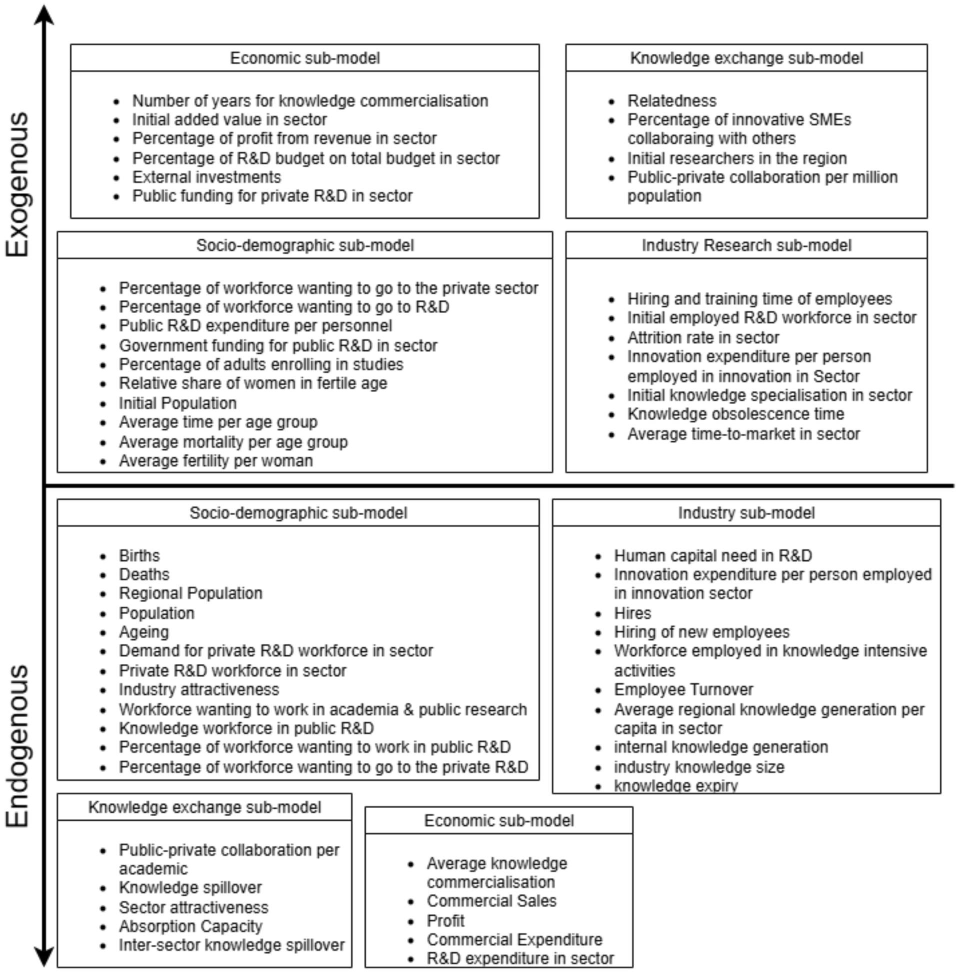

Figure 10: Endogenous-Exogenous variable distribution per sub-model (Qudrat-Ullah & Seong, 2010).

Certain components of the model were implemented with discrete rather than continuous representations, such as the government expenditure per sector in both the private and public industry (Pruyt, 2013). While a fully continuous treatment would be ideal, the regional-scale focus of this work necessitated retaining some discrete elements to maintain data accuracy. Examples include fixed values for regional birth rates and percentages of the workforce transitioning to private or public research roles. These parameters were left unchanged in the absence of more detailed measurement and given that their influence on aggregate outcomes proved limited. Nevertheless, future iterations should revisit these discrete features, replacing them with continuous formulations as more comprehensive data become available.

3.3 Structure Verification

The verification of structural integrity is crucial to the comprehensive validation process. In conducting the structural verification of the model, I employed a dual approach. Initially, during the model's construction, parameters were created based on their existence in specific regional data or, in its absence, existing knowledge regarding the real system. The sub-models or frameworks from established models within the domain also used existing concepts and literature. The conceptual representation of the SD diagram is illustrated through a causal loop diagram, as shown in Figure 4. Consequently, the causal relationships established in the model, which were informed by the available knowledge of the real system, offered a form of 'empirical' structural validation (Qudrat-Ullah and Seong, 2010). The selected sub-models from the existing models in the domain provided a 'theoretical' structural validation for the model (Forrester and Senge, 1980).

3.4 Dimensional Consistency

The dimensional consistency test necessitates that every mathematical equation within the model be evaluated to ensure that the measurement units of all variables and constants involved are dimensionally consistent. The dimensional consistency of each mathematical equation was automatically assessed with the Vensim Unit Check function, certifying the consistency every variable inserted with its neighbours.

3.5 Parameter Verification

The values allocated to the model's parameters are derived from established knowledge, making them consistent with current system theory. Using Wililamson's model for parameter creation ensured the parameter's conceptual validity as well as its quantification. Furthermore, the use of proxies for "soft" variables allows for a quantification based on numerical data.

Finally, the unit check and model check assured that all units were aligned and no base model value was below 0 when reality does not allow it to. The original use of Williamson's Institutional Layer for the quantitative structure of the model ensures structure verification and parameter verification. As a further step in the model verification, I undertook an extreme value test to ensure the behavioural consistency of the model is maintained even when subject to extreme parameter variation.

3.6 Extreme Value Test

Beyond debugging and model fixing ensuring that the unit checks and model checks are fully satisfactory, the model verification is asserted with an extreme value test. The testing technique looks at changing the parameter values of certain variables of interest to see whether the model response to the input is maintained (Pickands, 1975, Anderson, 1970, Dietrich 2002, Drees et al. 2004). For instance, the model can be tested when defining an extreme condition such as setting the Average Female fertility to an exceedingly low value (such as 0), which in reality effectively translates to "no birth" of the regional population. I can then analyse the behaviour produced by the model accordingly.

Table 3 describes all the parameters undergoing the extreme value test per sub-model and the rational model response to that parameter's change. Every parameter is tested with a sample of values within minimum and maximum boundaries. The minimum boundaries correspond to a 100% to 99% decrease in the parameter value while the maximum boundaries correspond to a 1000% to 1100% increase in the parameter values within the boundaries of reality. This means that a proportion or percentage will not have a value higher than 100% even if a 1000% increase of it would go beyond that. These intervals are then the boundaries of the variable values within which the model samples.

I used Latin Hypercube Sampling (LHS) to sample over extreme value ranges (Kwakkel, 2017). LHS is a statistical technique utilised for sampling a near-random set of values for the number of inputs derived from a distribution with multidimensional characteristics (McKay et al. 1979). This approach modifies the uncertainty range of each input by dividing it into equal probability sets. The sampling then selects random values from these sets and combines them to form a matrix. This technique enhances the coverage of the input space in comparison to conventional random sampling techniques such as random sampling or stratified sampling (He et al. 2021). Furthermore, the LHS space-filling experimental design is characterised by a relatively low computational cost (El Garroussi et al. 2019). Even though more advanced methods for random sampling exist, given the previous findings, I deemed appropriate the use of this method for my research. The sampling over the extreme value ranges is applied to both MAR and Jacobs regions such that all parameters representing high variation are applied contemporarily and all the parameters representing low values are tested contemporarily. The behaviour of the model is assessed in terms of workforce employed in R&D and knowledge size.

Table 3: Extreme Values tested per population sub-model and parameter with supporting explanation.

Sub-model	Variable	Expected behaviour for high value	Expected behaviour for low value
Socio-demographic sub-model	Relative share women in fertile age	It will lead to higher births, hence higher workforce availability.	It will lead to lower births, hence lower workforce availability.
	Average mortality per age	When it is increased, the workforce will decrease, leading to less workers.	The elderly population should keep increasing. The other population subscripts will also increase but not significantly given the already low death rate. This is expected to have little to no impact on the R&D workforce or the knowledge generation.
	Initial Population	It would increase the R&D workforce availability.	It would decrease the R&D workforce availability.
	Percentage of adults enrolling in studies	It will lead to higher R&D workforce availability.	It will lead to lower R&D workforce availability.
	Percentage of workforce wanting to go to the private sector	It will lead to higher private R&D workforce availability but higher public R&D researcher availability.	It will lead to lower private R&D workforce availability but higher public R&D researcher availability.
	Percentage of workforce wanting to go to R&D	It will lead to higher R&D workforce availability.	It will lead to lower R&D workforce availability.
	Public R&D expenditure per personnel	It will lead to lower public R&D researchers depending on the capacity.	It will lead to higher public R&D researchers if there is capacity.
	Government funding for public R&D in sector	It would increase the capacity for public R&D employees, which could increase the knowledge spillovers from the public sector if the students interested in public R&D are high.	It would decrease the capacity for public R&D employees, which could increase the knowledge spillovers from the public sector if the students interested in public R&D are high.
	Initial researchers in the region	It will increase the knowledge spillover per researcher.	It will decrease the knowledge spillover per researcher.
Industry sub-model	Initial employed R&D workforce in sector	The knowledge generated will be high at the start of the simulation.	The knowledge generated will be low high at the start of the simulation.
	Attrition rate in sector	The R&D employees should decrease rapidly.	The stock of R&D employees in the model should remain constant.
	Average time to Market in sector	It would lead to a slower knowledge generation as products will need more time to get finished, which will lead to a slower increase in knowledge size.	Products will get done more quickly, leading to a higher increase in knowledge size
	Hiring and training time	The knowledge generation of R&D workforce will take longer.	Employees will be able to contribute to the knowledge generation immediately.

	Initial Knowledge specialisation	It will increase the knowledge size stock but the returns from that knowledge might be lower because the average knowledge commercialisation might decrease.	It will decrease the knowledge size stock but the returns from that knowledge might be higher because the average knowledge commercialisation might increase.
	Knowledge Obsolescence Time	It will maintain the knowledge in the stock for longer	It will lead to a quicker knowledge expiry rate, decreasing the knowledge in stock.
Economic Cycle	Initial Added value in sector	It would increase the R&D budget, allowing to hire more workforce during the start time	It would decrease the R&D budget, restricting the possibility to hire workforce at the initial time
	Percentage of profit from revenue in sector	It will decrease the available funding for R&D	It will increase the available funding for R&D
	Percentage of R&D budget on total budget in Sector	It will increase the available funding for R&D	It will decrease the available funding for R&D
	Number of years for knowledge commercialisation	It will decrease the economic value of knowledge generated, leading to less returns from knowledge, decreasing the R&D budget.	It will increase the economic value of knowledge generated, increasing the returns from knowledge.
	External Investments	It will increase R&D expenditure, increasing the number of hires and the knowledge generation.	It will decrease R&D expenditure, lowering the number of hires and the knowledge generation.
	Public Funding for Private R&D in Sector	It will increase R&D expenditure, increasing the number of hires and the knowledge generation.	It will decrease R&D expenditure, lowering the number of hires and the knowledge generation.
Knowledge exchange sub-model	Percentage of SMEs collaborating with others	It will increase the knowledge spillover from other industries.	It will decrease the knowledge spillover from other industries.
	Relatedness	It will increase the knowledge spillover from other industries.	It will decrease the knowledge spillover from other industries.

3.7 Extreme Value Testing Results

The extreme value testing examined whether the model maintains realistic boundaries and performance when being subject to extreme changes for different parameter between MAR and Jacobs agglomerations. I completed this test by changing every parameter of interest of the model to extreme values contemporarily and analysing model response. The measured response parameters are the R&D workforce employed per sector and the industry knowledge size. I selected these parameters as they can give insight into the system's innovation performance. As such, this analysis assesses at the impact of extreme values on the system's R&D workforce per sector and industry knowledge size per sector. The outputs of both the low extreme value test and high extreme value test have been plotted in the same graph figure to allow for easier comparison. The code for the Extreme Value test is reported in the GitHub repository for both MAR and Jacobs regional models in the Extreme Value Tests folder (Melli, 2025).

Figure 11 and Figure 13 represent the model output in terms of private R&D workforce and industry knowledge for the *telecommunication* and *manufacturing of communication equipment* sectors in the MAR region respectively. Figure 14 is an adjusted scale of the model behaviour view for the knowledge size for extremely low values in the MAR region. It allows for a better view of the model behaviour and output distribution over extremely low value scenarios. The purple curves represent run outputs in timeseries for parameters with extreme high values, while the blue curve shows the runs simulated with extremely low parameters. The Jacobs region results are graphed in the same way such that both extremely high and low scenarios are plotted contemporarily. Figure 12 presents the results for the Jacobs region for the *manufacturing of measurement instruments of navigation and watchmaking*, *editing audiovisual and diffusion*, *manufacturing of communication equipment* and *production and distribution of gas vapour and AC* sectors in terms of private R&D workforce while Figure 15 represents the knowledge in the sector for the same sectors. I placed the remainder of the sector graphs in Figure 46 and Figure 47 in Appendix B. Appendix B presents the additional material used for the validation and verification tests in more detail, such as sector specific figures or data tables. Figure 46 and Figure 47 represent the results of the *pharmaceutical industry*, *chemical* *industry*, *automotive industry*, *ICT information and services, aerospace construction and engineering* and *specialistic technical and scientific activities*.

From Figure 11 and Figure 13, the MAR regional model does not present any growth when extremely low values are inserted as the blue curves for both the R&D workforce and the knowledge size seem stable at a value around 0. On the other hand, the scenario with high values shows changes in every case, either represented by rapid decline for R&D workforce or by growth of internal knowledge size. The density plots were omitted in the knowledge workforce graphs given that they measure the distribution of the final output. Since that output appears to be very low no matter the scenario, the density graphs are cluttered around 0 without providing valuable information on the overall behaviour of the curves. Figure 13 and Figure 14 show the blue curve representing the knowledge size for extremely low values in the MAR region being extremely low during the whole simulation run. Additionally, as can be seen from the density plot, the growth is stagnant at the end of 20 years of simulation, with a slow decrease or increase in the upper and lower boundaries of the curve respectively.

3.7.1 Analysis of R&D Workforce subject to Extreme Value Test

1. Analysis of the results of Extreme Value Testing on the MAR Model R&D Workforce

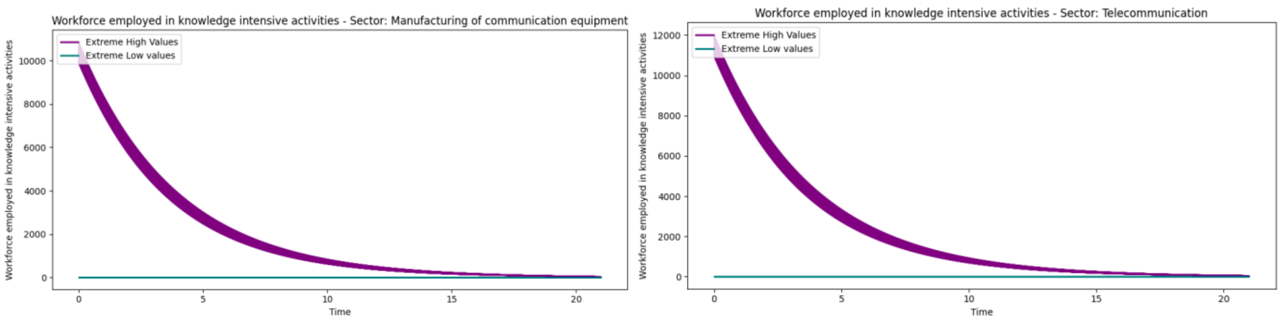

Figure 11: Extreme value test response for employed R&D workforce size from the changes in the MAR region

I apply a similar reasoning when looking at the model behaviour in terms of R&D workforce subject to high extreme outputs. The second significant observation is that workforce subject to extremely high values decreases independently of the sector. As can be seen from the plot, the R&D workforce has initially very high values, which are introduced through the extreme value test captured in Table 3. Even though the R&D workforce is initially very high, the extremely high value test also introduces a very high attrition rate and a very high hiring and training time (20 to 22 years), implying that the workforce that leaves does not get hired quickly enough to compensate for the loss of personnel.

When looking at the implications from the model dynamics presented in Table 3, the behaviour of the respective purple and blue curve seem in line with the modelling. In runs with extremely low parameter values, the workforce remains low given that the relative share of women in the sector and the initial population are low while the fertility rate does not change. This leads to a stagnation in the number of births, not allowing the population to grow in the span of 20 years of simulation. However, the mortality rate is also given an extremely low value, meaning that the population will not decrease considerably in the span of 20 years. On top of that, there are low number of student enrolment rates in the sectors of interest and low percentage of workforce wanting to go to the private sector. This leads to very little workforce available for R&D, so little workforce gets hired to do research in the sectors in the region according to model dynamics. However, given the low attrition rate, very little workforce also leaves the sectors in the model, leading to a low stagnating R&D workforce in the private sector, accurately represented with the blue curve.

2. Analysis of the results of Extreme Value Testing on the Jacobs Model R&D Workforce

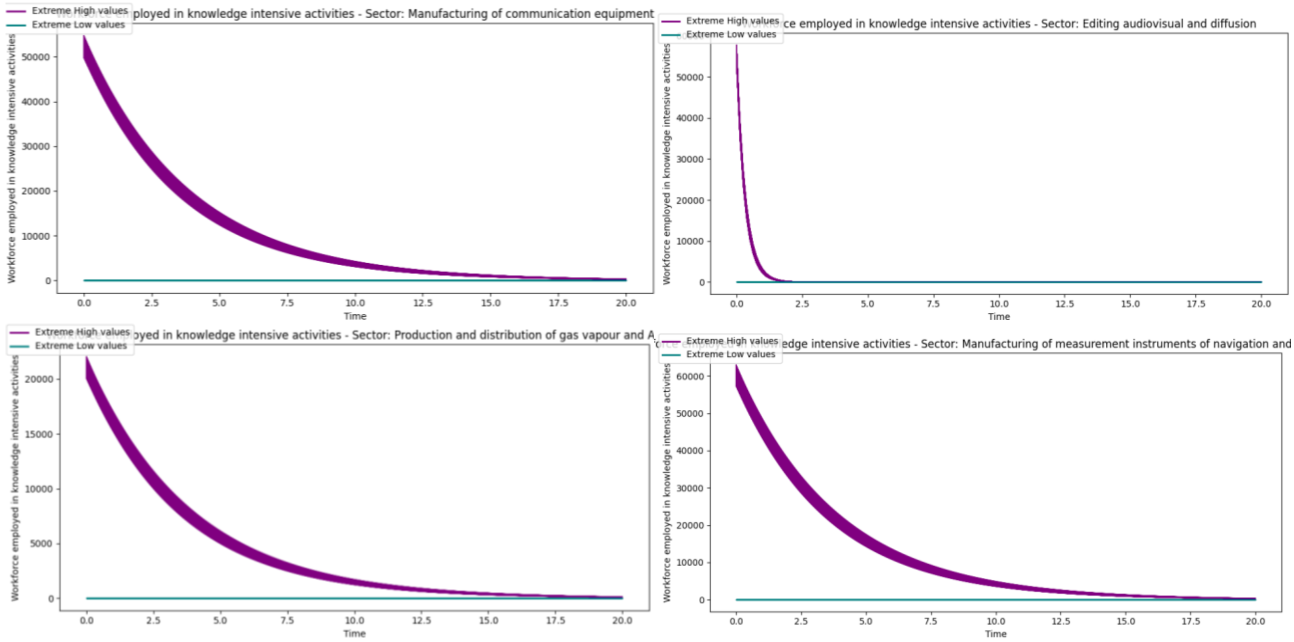

Figure 12: Extreme value test response for employed R&D workforce size from the changes in the Jacobs region. The sectors presented are Manufacturing of measurement instruments of navigation and watchmaking, Editing audiovisual and diffusion, Manufacturing of communication equipment, Production and distribution of gas vapour and AC.

The same findings for R&D workforce for each sector in the MAR region independent of the sector as for the Jacobs region, both represented by stagnating, low cyan curves in Figure 12. Given their similarity, the outputs of Figure 11 and Figure 12 allow me to make these assumptions on model behaviour for both the MAR regional model and the Jacobs regional model, showing that they are both responsive to extreme changes in model inputs in ways that are in line with the conceptual effect of that variation on the model. A key difference stands in the editing, audiovisual and diffusion sector, that shows a decrease more accentuated than the other sectors. This sector has the highest attrition rate amongst the industries, with a values varying between 99% and 100% of the sector's R&D employed workforce. Hence, it is assumed that the high attrition rate in that sector opposite to the long hiring and training time is responsible for the sector exponentially losing employees.

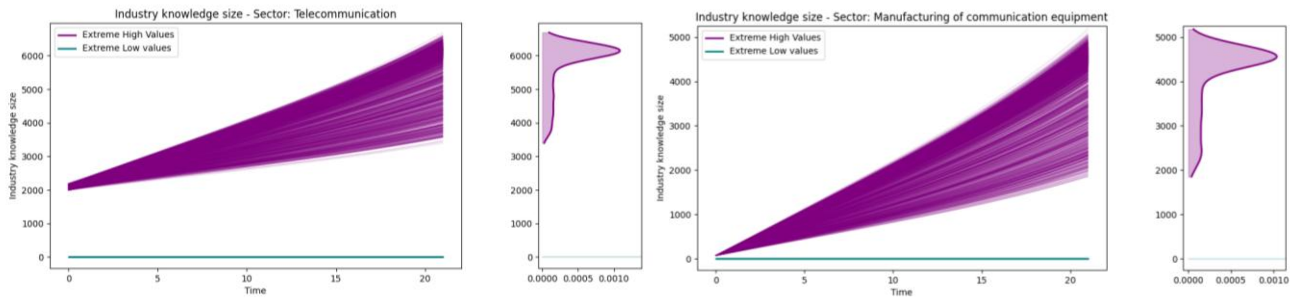

Figure 13: Extreme value test response for knowledge size from the changes in the MAR region

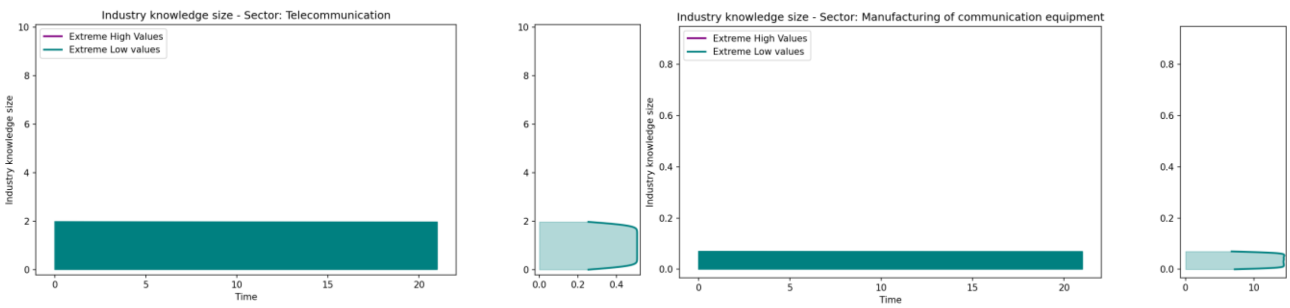

Figure 14: Zoomed-in view of the knowledge size output of the extremely low scenarios over the model run time for MAR region

3.7.2 Analysis of the Industry Knowledge Size subject to Extreme Value Test

1. Analysis of the results of Extremely Low Value Testing on the MAR Model Knowledge Size

Figure 13 and Figure 15 shows the alignment of the knowledge size dynamics to the employed R&D workforce results. The cyan curve representing knowledge generation at very low values seems low and stable for the entirety of the run time. This is supported by the density plot in Figure 14, which shows an outcome distribution that is uniform and equal for most of the outcomes, with a slight centring at the end of the simulation run. This dynamic being in line with the results from the previous variable, R&D workforce, likely stems from its behaviour.

As R&D workforce does not change, the knowledge generation also remains stable if the knowledge generation per researcher does not increase proportionally. Additionally, with very low knowledge obsolescence time (0 to 0.1 years) and low average time to market of knowledge, the knowledge generated cannot grow. It would be generated instantly and would expire as soon as it is generated.
The slight increase and decrease at the edges of the marginal curve in the knowledge output density plot of Figure 13 might come from different dominant loops depending on the initial conditions. For instance, I have established that knowledge obsolescence time is very short so the decrease in knowledge can happen faster that it is generated, leading to a progressively decreasing curve. However, it is also possible that very little workers have a higher knowledge generation capacity allowing to offset the high obsolescence time. Looking at the loop formulation for knowledge innovation, a set of *workers w* produces knowledge at time *t* based on the average knowledge generation per researcher *g* at that same time *t*. *Knowledge generation per researcher* at time *t* is itself defined as $g(t) = \frac{p(t-1)}{w(t)}$ with *p(t)* being the *number of patents* at time *t.* Hence, if the workers decrease but the number of patents stays the same, the knowledge generation factor will increase. Given that the knowledge generation factor increases, the knowledge generated by the workforce will increase, therefore counterbalancing the knowledge expiry, and surpassing it.

2. Analysis of the results of Extremely Low Value Testing on the Jacobs Model Knowledge Size

Comparing Figure 13 and Figure 14 with Figure 15 and Figure 16, the model response to extremely low inputs is overall the same for both MAR and Jacobs regions modelled.

Nonetheless, Figure 16 shows a run in the production and distribution of gas sector that significantly deviates from this set of behaviours, skewing the distribution of the model outputs for that sector compared with the remaining 9. It showcases an exponential increase in the knowledge size around the start time of the run, with a peak reached around time *t=2.5* and a slow decrease until the end of the simulation. The distinct behaviour observed in this sector is likely attributable to the dominance of the previously defined feedback loop, arising from the differing parametrisation. The initial workforce in the production and distribution of gas sector is the lowest of all ten sectors and is sampled within the interval [0; 20]. However, this sector still has an average sized knowledge base, which is sampled in the interval [0; 4.91] for the extremely low value test. This gives it a relatively higher *knowledge generation per researcher g* than the other sectors, as less workers can generate a relatively higher number of patents. Nonetheless, given the stable workforce in the sector in Jacobs region present in Figure 12, $g(t) = \frac{p(t-1)}{w(t)}$ would not increase from the decrease in the denominator $w(t)$. It therefore would increase as $p(t-1)$ is higher. $p(t)$ is defined as $p(t) = \int_0^t i(t) - e(t)dt$, where $e(t)$ is the knowledge expiry at time *t* and $i(t)$ is the innovation generation function defined as $i(t) = w(t) * g(t) + k(t)$. The latter would imply that $p(t)$ is itself influenced by $g(t)$ and $w(t)$, meaning that a stable $g(t)$ and $w(t)$ would not drive a change in $i(t)$ which would continuously proportionally increase $p(t)$. However, $p(t)$ is also influenced by the *knowledge spillover* $k(t)$. This implies that, given that the other conditions $g(t)$ and $w(t)$ are stable and proportionally influenced by each other, they cannot be the drivers of change in the $g(t) = \frac{p(t-1)}{w(t)}$ function, therefore in the knowledge generation loop, $k(t)$ then has to be the factor of influence leading to a spike in the extreme value test response of the blue curve in the production and distribution of gas sector. If the knowledge received by the related sectors and by the institutional research is high enough, it can increase $p(t-1)$ which would then drive up $g(t) = \frac{p(t-1)}{w(t)}$ as further knowledge gets spilled over by other sectors and accumulates.

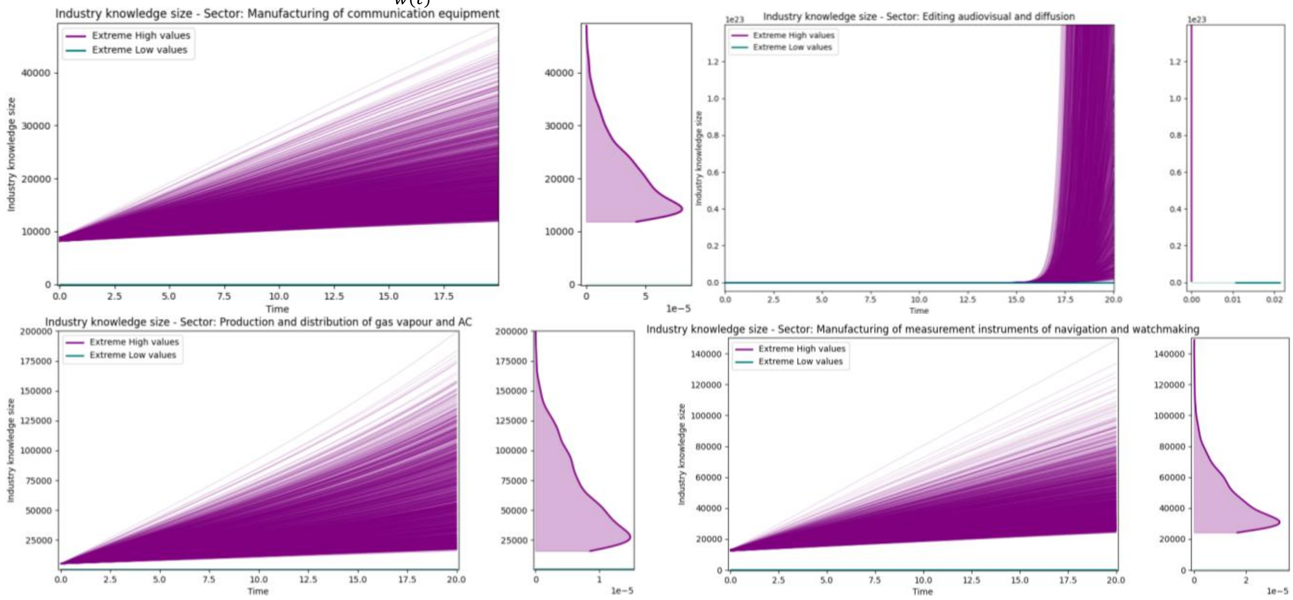

Figure 15: Extreme value test response for internal knowledge size from the changes in the Jacobs region. The sectors presented are Manufacturing of measurement instruments of navigation and watchmaking, Editing audiovisual and diffusion, Manufacturing of communication equipment, Production and distribution of gas vapour and AC.

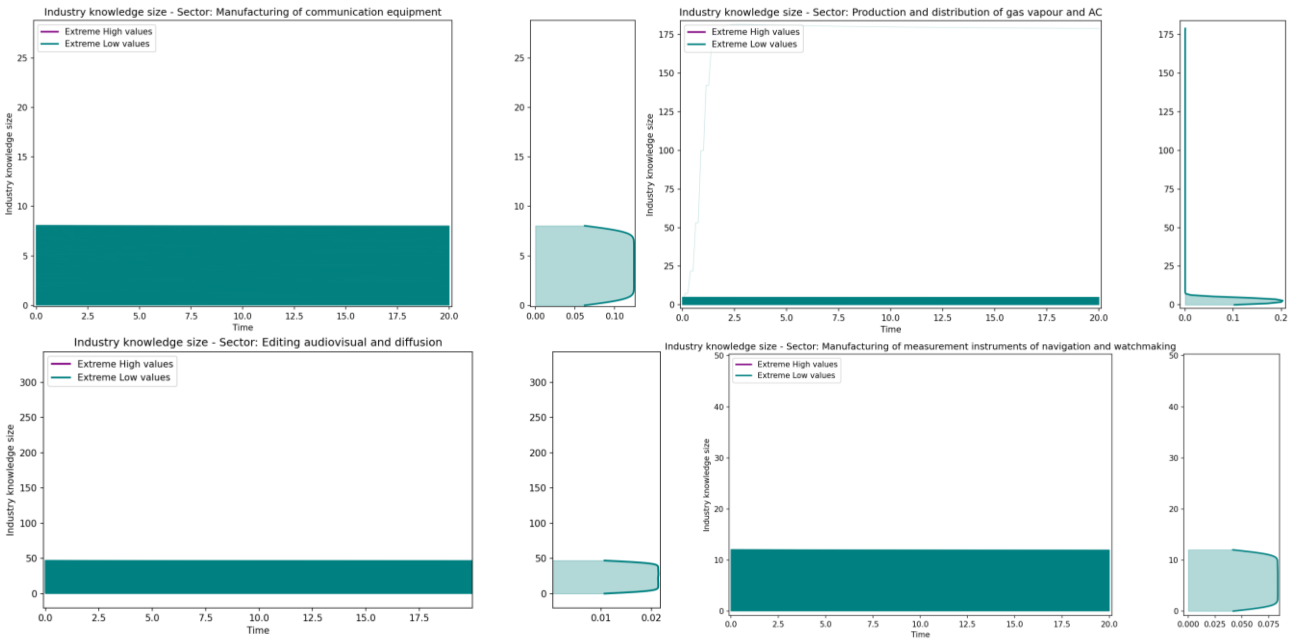

Figure 16: Zoomed-in view of the knowledge size output of the extremely low scenarios over the model run time for MAR region. The sectors presented are Manufacturing of measurement instruments of navigation and watchmaking, Editing audiovisual and diffusion, Manufacturing of communication equipment, Production and distribution of gas vapour and AC.

In this case the knowledge obsolescence time is so small that knowledge generated instantly expires, making $i(t) \approx e(t)$, hence $p(t) = \int_0^t i(t) - e(t)dt = 0$. This also means that for this accumulation to happen, there needs to be a big enough time step between the knowledge generation and the knowledge expiry to allow for accumulation. This shows that although the knowledge spillover $k(t)$ appears to be significant for the model results, the difference between the average time to market and the knowledge obsolescence time has to be big enough to allow for accumulation.

However, this is not an infinite phenomenon. As the proportion of $p(t)$ becomes increasingly big compared to changes in $k(t)$, the effect of $k(t)$ on $p(t)$ will decrease, leading to a slower increase of $g(t) = \frac{p(t-1)}{w(t)}$. If we now also consider that the other sectors in the Jacobs region from Figure 15 and Figure 47 have a decreasing knowledge size, $k(t)$ will decrease for the production and distribution of gas sector, also leading to a decrease in $p(t)$, therefore a proportional decrease in $g(t)$. This is in line with the observations from the plot in Figure 16. Finally, it reflects the sensitivity of the model to initial parameters and to inter-sector relations as drivers of growth.

3. Analysis of the results of Extremely High Value Testing on the Models Knowledge Size

When observing the results of industry knowledge size per sector subject to high extreme variables shown in Figure 13 and Figure 15, the purple curves for every sector in both regions show growth. The infallible growth of sectors over time when subject to high input variables can be attributed to the high initial knowledge size, that is then shared with other sectors through $k(t)$. Given the high external inputs, the sectors experience a very high average time to market that delays the entrance and usage of that knowledge in the industry knowledge size. However, the high knowledge obsolescence time between 100 and 110 years increases the time delay before knowledge expires, allowing for knowledge to get accumulated.

Comparing the results of Figure 13 with Figure 15, the sectors in MAR region, the density plots in Jacobs sectors are wider than MAR sectors are. However, MAR density distribution plots peak towards the upper boundary of their curve while Jacobs density distribution plots peak on the lower boundary side. Hence, MAR sectors seem to have a smaller range of possible outputs, but more concentrated towards the higher boundary than Jacobs's. Considering that the only difference between both models stands in the number of sectors that compose them, therefore also in the number of interactions with each sector, this infallible difference in distribution must be due to the different sector interaction in both models. This might imply that the sectors in the MAR model are more reliant on each other's interactions for performance than sectors in Jacobs regional model. On the opposite hand, in Jacobs regions, sectors are more dependent on their own initial values, with the possibility of having really increased performance if the neighbouring sectors are having a strong performance.

Finally, I would like to draw the reader's attention on the in-sector differences in both models. As mentioned previously, industry knowledge size subject to high extreme values shows growth no matter the sector. The shape of that growth is different for sectors between the two regional variations of the model, but also for sectors in each regional variation of the model. From Figure 15, the editing, diffusion and production sector shows exponential growth when its initial parameters are set to extremely high values. This growth has the same shape as the individual run analysed from the production and distribution of gas sector, suggesting that it would tap into the same loop. The editing and audiovisual sector has very similar characteristics to the production and distribution of gas sector. It has the lowest relatedness score out of the sectors in Jacobs's model, just like the latter, but it is strongly connected to a key sector in the region: the ICT sector.

The ICT sector has the highest relatedness and number of connections with the other sectors in the region, gaining key knowledge from multiple interactions with other sectors in the region. Conceptually, the editing and audiovisual sector would then be able to leverage this accumulated knowledge but would not be able to share it back into the system given its low relatedness score with the other sectors. The initial knowledge specialisation in this sector has similar value to the initial employed R&D workforce in this sector, making $g(0) = \frac{p(0)}{w(0)} \approx 1$. The long knowledge expiry time makes the knowledge conceptually eternal (knowledge expiry $e(t) = 0$). Given the absence of a significant outflow in these simulation scenarios, the industry knowledge size can be generalised as

$$p(t) = \int_0^t i(t)dt = p(t-1) + i(t). \quad 10$$

We are going to show that this equation then increases by its size at the previous time step.

Following from $g(1) = \frac{p(0)}{w(1)}$,

$$p(1) = i(1) + p(0) = p(0) + w(1) * g(1) + k(1) = p(0) + w(1) * \frac{p(0)}{w(1)} + k(1) = 2p(0) + k(1) \quad 11$$

This would mean that at the second iteration

$$p(2) = p(1) + w(2) * g(2) + k(2) = p(1) + w(2) * \frac{p(1)}{w(2)} + k(2) = 2p(1) + k(2) \quad 12$$

By generalising these expressions, we get:

$$p(t) = p(t-1) + w(t) * g(t) + k(t) = p(t-1) + w(t) * \frac{p(t-1)}{w(t)} + k(t) = 2p(t-1) + k(t) \quad 13$$

Hence, we can generally express $p(t)$ as

$$p(t) = 2p(t-1) + k(t) \quad 14$$

The mathematical expression in Equation 14 shows how the influence of the patent generation sector weighs on two main variables, the previous knowledge size and the knowledge spillover. If we assume $k(t)$ to be insignificant, then $p(t) \approx 2p(t-1)$ which would simplify to $p(t) = p(0) * 2^{2t}$. When $t = 20$, corresponding to the end time of the simulation, if we take the upper boundary of the initial knowledge specialisation of the editing audiovisual and diffusion sector as starting value $p(0) = 52030$, we would get a result proximal to $p(20) \approx 5.7^{16}$, which would then be the upper limit of the final plot outputs. However, given that some of the final outputs appear beyond a value of 1^{23}, it is very likely that most of the influence comes from $k(t)$. Hence, the audiovisual sector is in the privileged position of benefitting from larger knowledge spillover to boost its initial knowledge generation.
Beyond a strong inter-sectorial connection with a "broker" in the network emphasised by high parametrisation of the collaboration between SMEs, this sector is also the one with the lowest average time to market, which means that its delay before the concept becomes a patent is the shortest amongst the 10 sectors. This also leads the sector to see the fastest knowledge accumulation between all industries. While most sectors have an average time to market varying between 50 to 110 years for the extremely high parametrisation simulation, the editing and audio vision sector varies between 20 to 22 years of average time to market. This is reflected in the graph by a very rapid knowledge growth. It is then very likely that there is a threshold between initial knowledge size, knowledge spillover and average time to market that would lead to this dominant behaviour from the knowledge generation loop.

Finally, sectors in MAR region do not present differences between each other in the industry knowledge output distribution. In fact, looking at the purple curves in Figure 13, even though the sectors have very different initial values, the range of the distribution of their final outcomes is very similar. This is likely due to the emphasis on knowledge exchange brought by the model. Given the high percentage of collaboration that is simulated in the runs with extremely high values and the high alignment between sectors, the would be able to exchange very high knowledge shares in a continuous way. Nonetheless, given the high average time to market of 100 to 110 years, these sectors do not show exponential growth. The very high alignment of their final internal knowledge outcomes is emphasising once more the interdependence between sectors simulated by the model for the knowledge growth.

Overall, during the extreme value test, the model results demonstrated strong alignment with the structure design of the model. Beyond showcasing robustness when implementing extreme values in the parametrisation across sectors, it brought forward insights on the underlying dynamics in such a way as to reflect the intended relationships when creating the model structure. This is particularly relevant for its demographic realism, labour-driven architecture, and local spillover mechanisms. The test further allowed to analyse sector-specific divergences, such as the knowledge generation loop or the average time to market effect underlining the importance of tailoring functional forms and validating calibration using sector-specific data. Hence, in the following section, I dedicated myself to ensuring that the values obtained through a base model run showcase a behaviour that is coinciding with empirical data.

3.7.3 Key Analytical Insights

Lastly, in this section I brought forward how I bridged literature findings on regional agglomeration dynamics with System Dynamics to build a verified model that represents general scientific consensus from literature, answering sub-question 1. In the context of MAR and Jacobs-type regional innovation agglomerations, I defined key actors as firms, research institutions, universities and government bodies. By pinpointing their relationship form literature, I was able to implement them in a System Dynamics model through feedback loops representing knowledge flows, investment in R&D, institutional support, and firm behaviour.

Based on the detailed analysis provided, the extreme value testing revealed several key themes about the model's behaviour and the dynamics of regional innovation systems it simulates.

The primary finding is that the model is robust and behaves logically even when pushed to its limits. It doesn't break or produce nonsensical results. Instead, its outputs under extreme conditions are consistent with its underlying structure. Low-value scenarios lead to predictable stagnation, as low demographic inputs and low mobility prevent the R&D workforce from growing. High-value scenarios lead to predictable trade-offs, such as a declining workforce caused by high attrition rates overwhelming long hiring times.

A major finding is the powerful influence of competing time delays within the system. The model's behaviour is often determined by which delay is dominant. Workforce dynamics are governed by the race between the hiring and training time and the workforce attrition rate. Knowledge accumulation is governed by the balance between the average time to market and the knowledge obsolescence time. Sectors with a short time-to-market can accumulate knowledge exponentially.

The tests highlighted a fundamental difference in the systemic structure of the two regional models. MAR regions behave as tightly coupled, interdependent systems. High collaboration and alignment cause all sectors to perform similarly, with their fates closely linked. Jacobs regions behave as more loosely coupled networks where sectors are more independent and reliant on their own initial conditions. However, they can receive significant performance boosts from knowledge spillovers from successful neighbours.

Finally, the extreme value analysis revealed that under specific conditions, knowledge spillovers $k(t)$ can become the single most powerful driver, creating dominant reinforcing feedback loops. This was seen in two key instances. A sector with a very low initial workforce but average knowledge experienced a spike in knowledge growth, driven entirely by spillovers from other sectors. A sector with a strong connection to a key "broker" industry (ICT) and a very short time-to-market saw explosive, exponential growth, demonstrating how privileged network positions can create massive advantages.

The integration of field literature into a formal SD model demonstrates that innovation in regional agglomerations is a function of multi-actor interactions, institutional layering, and feedback dynamics. The model confirms that MAR regions benefit from internal specialisation and dense intra-sectoral ties (Marshall, 1890; Arrow, 1962; Romer, 1986). Additionally, in line with literature, Jacobs regions thrive on cognitive proximity and inter-sectoral diversity (Jacobs, 1969; Boschma & Lambooy, 2002). System Dynamics therefore seems to offer a robust framework to simulate these complex interactions and inform policy design. Having completed the verification tests, I then assessed the model's validity through a series of validation tests in order to understand whether it accurately replicates real world behaviour.

3.8 Model Set-Up

This section presents the parametrisation of the model for both the replicative tests and the behavioural assessments of the model. I set up the model for two EU NUTS2 regions, one presenting Jacobs-type agglomerations and a second presenting MAR-type agglomerations. This led to the representation and testing of two different models for both a specialised region and a diversified one. The models were set up with two different time intervals in each. The time interval 2001 until 2021 are used for a historical validation of the model. The exploration of model behaviour was also done for 20 years starting from 2001. The model uses Euler integration with a time step of 0.0625. Euler integration posits that the rates calculated at a specific moment remain constant throughout the duration of the time interval (TIME STEP). Generally, this assumption is unlikely to hold true, which accounts for the limited accuracy of Euler integration. The error incurred when employing Euler integration is directly proportional to the square of the TIME STEP for each integration step and proportional to the TIME STEP across the entire simulation. To enhance the accuracy of the integration, one can reduce the TIME STEP. While Euler integration may not be the most effective method for obtaining precise solutions to differential equations, it is suitable for numerous business and social models where the line between difference and differential equations is often indistinct.

3.8.1 Model Parametrisation

I chose the region of Bretagne and Ile-de-France as representatives of Jacobs and MAR regions in the EU at NUTS2 level, which allows for specific use-case parametrisation of the model. I conducted a comprehensive validation exercise using longitudinal data from the Île-de-France and Bretagne region for a single focal sector prevalent in both regions for the validation of the models for Ile-de-France region from 2001 to 2022 and MAR region Bretagne from 2001 to 2011 given the lack of data for the following 2012-2022 decade.

The regional focus on Ile-de-France as an appropriate representation of a Jacobs region is justified by its diversified clusters and high density. Ile-de-France, which includes the nation’s capital Paris, is a good example of a region benefiting from Jacobs externalities. The latter arise from diversity and cross-industry knowledge spillovers (Jacobs, 1969). The region's economic diversity, high urban density, and concentration of creative and service sectors foster innovation through interactions across different industries. Jacobs externalities are particularly strong in metropolitan areas where varied firms and institutions coexist, enabling learning and idea recombination (van der Panne, 2004). This is supported both by extensive prior research on Paris’s economic evolution (Weisz, 1994; Gilli, 2005; Merk et al., 2011), on Île-de-France specifically (Gómez-Tello et al., 2022; Bergamini, 2020), and on the French economy more broadly (Daviet & Monge, 2010; Ott & Ronde, 2018). These studies furnish critical benchmarks for interpreting our model outcomes and present Ile-de-France as a standard regional location to empirically study innovation development in Europe. Moreover, France provides rich, harmonised datasets, particularly from the National Institute of Statistics and Economic Studies (INSEE, 2020), which greatly facilitate parameter estimation.

As Ile-de-France is chosen as a Jacobs region, Bretagne is chosen as a MAR region. Literature on specific MAR regions in France is sparse. As such, national databases have been used to identify a significant MAR region in France. Bretagne appeared as an optimal choice given that it is driven by specialisation within a single industry. The region has a strong presence in telecommunications sectors, with clusters of similar firms that benefit from localised knowledge spillovers, labour pooling, and supplier networks. Its focus on the telecommunication industry and the manufacturing of communication equipment industry receiving more than 80% of the total R&D spending of the region (INSEE, 2021). MAR externalities are more pronounced in regions with industrial homogeneity, where firms in the same sector share innovations and practices (van der Panne, 2004). This option has been validated by studying the results of the Regional Innovation Scoreboard (European Commission, 2023). The latter creates a benchmark across European regions that serves appropriately the function of allowing comparison. This scoreboard which labelled the Bretagne region as a strong innovator with a robust industrial structure. The region therefore appears as a representative choice to simulate an EU MAR region.
Table 16 presents the model’s exogenous parameters at the regional, sectoral, and academic levels, with definitions and data sources. The parameter values for Ile-de-France’s multiple sectors and studies are presented in Table 21 and Table 22.

In order to include the clusters and their knowledge generation mechanisms in the regional context, I collected data on the region. The regional level statistics are made available by the National Institute of Statistics and Economic

Studies (INSEE, 2020). The latter makes available the population proportions from 1958 until 2025 per region and age-range. The age ranges being more granular, they were aggregated to fit the model ranges. This allowed the setting of the base value for 2001 and the time-bound comparison of population data points. The same institute also stores the complete folder of each national region, with key information of multiple domains of regional consideration, including female fertility rates. These are stored in yearly time series, therefore inserted as LOOKUP table functions in the model as shown in Table 20. This is to ensure a higher model fit given the change of parameters that can have a potentially significant impact on the model. The death rates are inserted separately for each age group given the significant statistical difference between both. The INSEE was also useful to provide the added value per sector (INSEE, 2021b). This added value was given at national level, divided into 88 economic sectors. Each economic sector's added value was represented in at regional level through literature of the region's contribution in that sector proportionate to the national added value. France's national investment bank estimated those numbers at 17% for Ile-de-France and 5% for Bretagne (LeLab Bpi France, 2025, 2025b). Given these numbers, I assumed that 17% of the national added value was directly obtained from Ile-de-France and 5% was gotten from Bretagne. Given this simplification, the real value of added value per sector might be different from the estimated with a shallow level of uncertainty of 20%.

Some key regional statistics originate from the Regional Innovation Scoreboard database (European Commission, 2023). These include the percentage of innovative SMEs collaborating with each other and the number of private-public co-publications per million inhabitants. These measures are used as proxies for regional collaboration between sectors and with the public domain respectively.
The collaboration of innovative SMEs with other entities reflects the number of SMEs engaged in innovation cooperation activities, specifically those that have established any cooperation agreements regarding innovation with other businesses or institutions, relative to the total number of SMEs database (European Commission, 2023). This metric assesses the extent of SMEs' participation in innovation cooperation. The development of complex innovations frequently relies on the capacity of enterprises to access a variety of information and knowledge sources or to work together in the innovation development process. This indicator evaluates the exchange of knowledge between public research institutions and businesses, as well as among businesses themselves. Regional data from CIS 2014-2020 have been gathered from the National Statistical Offices (NSOs) through multiple data requests as part of the preparation for previous editions of the RIS and have been used to compute this metric.
Public-private co-publications refer to the count of scientific publications that include at least one co-author located outside the country, relative to the total population (European Commission, 2023). This metric reflects the collaborative research efforts and active partnerships between researchers in the business sector and those in the public sector, culminating in academic publications. The data used originates from Scopus and is computed by Science Metrix (Elsevier) under a contract with the European Commission.

I then collected sectorial-level data to parametrise the characteristics of the different clusters in the region. Most sectorial data originate from OPEN DATA MENESR database (MESR, 2024). This platform is a governmental archive made available by the French Ministry of Education on higher education and research statistics. This archive contains the regional spendings of private sectors in million euros as well as the number of researchers in full-time occupation per sector based on the NAF rev. 2 classification from 2001 until 2022 (MESR, 2024). The initial values of the start year of the model were used as initial parameter values.
The same platform also makes available higher education registrations per region and per study. From these parameters, it is possible to compute the program attendance rate by understanding the yearly proportion of graduates over the total population aged 18-24. The OPEN DATA MENESR portal also provides amount of public funding per sector and of external investments for a time series of 2001 until 2022. This is provided only on a national level and has therefore to be extrapolated for the regional level. The extrapolation is based on the proportion of public expenditure per commercial expenditure per sector. The variation of this proportion remains very stable over every commercial expenditure amount. Public funding for private R&D is therefore introduced as a percentage of the total commercial expenditure per sector. The external investment is kept in euro (€). Given that these measures

have been extrapolated from national-level data, they might present some low level variations with reality, showing a shallow uncertainty.
In a similar way, the percentage of R&D budget over the total commercial expenditure is obtained by dividing the commercial expenditure amounts in the dataset by the R&D expenditure amounts. This proportion is also seen as quite stable over time and was therefore kept as a constant value for each sector.

No direct measure of sectorial attrition rate is available, so extrapolation calculations from employment destruction numbers were necessary to obtain it. The Dares research institute published a report on the expected leaves at the end of employment and at the destruction and creation of new posts per region (DARES, 2023). This forecasting based itself on past trends to determine the proportion of jobs that would be left unfilled for the period 2019-2030. These were given in thousands of people and represented an overall percentage of posts not being fulfilled during the period. That number was divided over the span of their 11-year forecast to estimate an average yearly number of departures and job destructions. Finally, that number was divided by what was expected to be the total number of job positions in that sector per year. The equations are represented followingly.

$$Total\ jobs = \frac{Leaves + Emigration + Job\ Destruction - Recruitment * 100}{Unfilled\ jobs\ (\%)} \quad (15)$$

$$Yearly\ average\ attrition\ rate = \frac{Leaves + Emigration + Job\ Destruction}{Total\ jobs} * \frac{1}{Forecasted\ years} \quad (16)$$

This method ensures that the sector attrition rate is as proximal to reality as it is possible without being able to make use of detailed historical data. As such, the attrition rate could still have a +/-20% uncertainty. The limitation comes with the uncertainty of using these statistics for data of the past given the likely changes that occurred over two decades from the initial collection year of 2001.

The Regional Innovation System view requires the model to consider also characteristics of the academic and public domain, which are presented in the Educational Sub-model of the model. The OPEN DATA MENESR platform offers a dataset detailing the number of researchers and R&D expenses per public research institute over a timeframe of 2001 until 2014. The government funding for R&D per sector was therefore obtained with the amounts in millions detailed in this database as a LOOKUP due to its varying rate and importance in determining the number of researchers in full time staff in the system. The public R&D expenditure per researcher was obtained by dividing the R&D expenditure in the public research institutes by the number of R&D researchers. This variable was also entered as a LOOKUP variable. This should ensure a one-to-one fit between the data and the model.

Literature also played a key role in determining the value of certain variables. Knowledge obsolescence was based on Griliches (1979, 1984) and Schankerman (1984) for patents in industrial sectors due to the lack of data in this domain. This was estimated to be 10 years independently of the sector. Given the date of the literature being 40 or more years ago and the uneven progress of each sector, knowledge obsolescence might have an uncertainty in its parametrisation of +/- 20%, meaning that knowledge today could become obsolete more quickly due to the advanced knowledge generation function in European societies. The average time to market per sector was also estimated from literature and was given a varying value depending on the sector given the different technological complexity and knowledge development of certain industries (Belay et al. 2022). These estimates remain very accurate for most industries but could have an uncertainty range of +/- 20% depending on the location of a certain sector. For instance, taking the pharmaceutical sector in France, it must undergo clinical trials according to the European Medicines Agency or the French National Agency for the Safety of Medicines and Health Products (European Medicines Agency, 2023, ANSM, 2024), which might be different depending on the drug complexity. This would mean that the approval of the product for market sale could vary between 8 to 12 years depending on the product, taking 10 as the average for the base scenario. This example for the pharmaceutical industry in applicable to the other sectors respectively.

Finally, the number of patents were examined for each case of the period 2001 to 2022. Since knowledge obsolescence was given a time of 10 years, patents until 10 years prior the start of the simulation were considered as valuable assets to generate revenue from. These were identified from the National French Patenting Institute through their search function (INPI, 2024). The search was done per year, to determine the patent generation, starting from 2001 until 2022 for each sector in the validation phase. The patents were filtered by location of patent application to aim to differentiate between Ile-de-France patents, Bretagne patents and patents from other regions. Each patent search was done according to a group of CIB patent codes corresponding to each sector. Table 18 presents the CIB search queries for each sector. The patent search is done across French (FR), European (EP) and International patenting (WO) offices. I assured that the manual connection between patents and sectors ensured completeness. However, some patents might be registered over other databases, specific codes might not be present in Table 18 or not be submitted in their region despite the centre of research being located there. Hence, there is a shallow uncertainty of 20% with this measure.

According to INSEE (2020), the ten branches accounting for eighty percent of Île-de-France's R&D expenditure are, in descending order:

- Automotive Industry.
- Pharmaceuticals Industry.
- Information and Communications Technology.
- Aerospace Industry.
- Specialised Technical and Scientific Services.
- Manufacturing of Scientific Instruments.
- Chemical Industry.
- Publishing and Audiovisual Sector.
- Communications Equipment Manufacturing.
- Gas, Steam, and Air Conditioning Supply.

For Bretagne, these are two, listed as follow:

- Telecommunications.
- Communications Equipment Manufacturing.

In the Vensim implementation, these sectors are indexed by subscript s, for instance $Knowledge\ size_s$, $R\&D\ Employees_s$. The relatedness between these industries has been coded with the method used in Boschma et al. (2014, 2015). The incidence matrix between industries has been built based on the count of industry occurrence in the same grouping in the Nomenclature d'activités française (NAF) Rev. 2 classification. The NAF rev. 2 classification is the French equivalent of the NACE rev. 2 from the European Union. Just like the latter, NAF rev. 2 serves the purpose of statistically classifying economic activities. This classification has been in use since January 1, 2008, where it offered a renewed update on the categorisation of businesses and organisations according to their economic activity (*Classification | Insee*, 2016, *NAF: French Classification of Activities - Nomenclature D'activités Française*, 2015). Several hierarchical levels are used to classify businesses:

- Sections correspond to the highest level and are represented by a single letter, for instance A for Agriculture, forestry, and fishing.
- Divisions are represented by two-digit codes and belong to each section, such as 01 for Crop and animal production, hunting, and related service activities.
- Groups are a class lower, represented by three-digit codes, such as 01.1 for Growing of non-perennial crops.
- Finally, classes are represented by four-digit codes, such as 01.11 for Growing of cereals (except rice), leguminous crops, and oil seeds.

The classification system is designed to group together activities that are similar (INSEE, 2020). In fact, sectors within the same group typically involve similar types of work. For example, the group "Growing of non-perennial crops" includes various types of crop production that share common agricultural practices. Additionally, the sectors produce similar products or offer similar services. For instance, the group "Manufacture of beverages" includes the production of different types of drinks, such as soft drinks, alcoholic beverages, and bottled water. Finally, the sectors use similar raw materials, equipment, and technologies. For example, the group "Mining of metal ores" includes activities that involve extracting different types of metal ores from the earth.

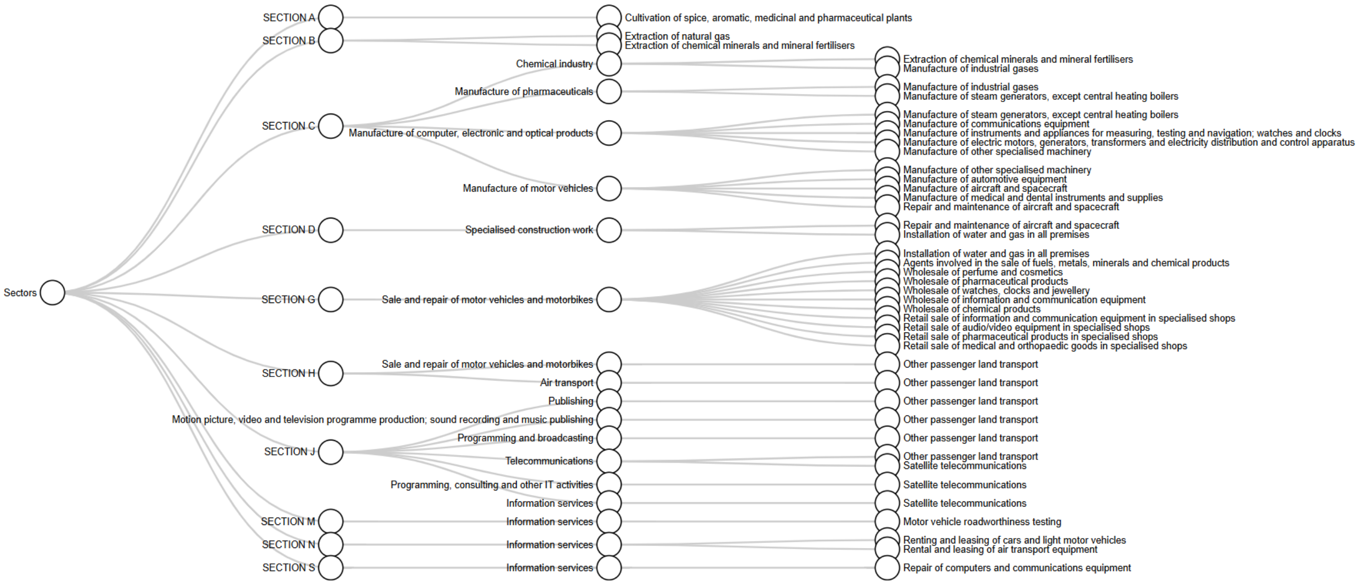

Figure 17: Hierarchical grouping of economic activities linked to prominent sectors in Ile-de-France.

Table 4: Incidence matrix between prominent sectors in Ile-de-France. The sectors are coded from I1 to I10 respectively as Pharmaceutical Industry, Chemical industry, Automotive industry, ICT information and services, Aerospace construction and engineering, Specialistic Technical and scientific activities, Manufacturing of measurement instruments of navigation and Watchmaking, Editing audiovisual and diffusion, Manufacturing of communication equipment, Production and distribution of gas vapour and AC

		I2	I3	I4	I5	I6	I7	I8	I9	I10
I1	0	11	1	4	3	0	3	0	2	0
I2	11	0	1	2	1	0	3	0	2	4
I3	1	1	0	2	4	4	1	0	0	0
I4	4	2	2	0	3	1	2	10	6	0
I5	3	1	4	3	0	1	0	0	0	0
I6	0	0	4	1	1	0	1	0	0	3
I7	3	3	1	2	0	1	0	0	4	1
I8	0	0	0	10	0	0	0	0	1	0
I9	2	2	0	6	0	0	4	1	0	1
I10	0	4	0	0	0	3	1	0	1	0

Given the pre-defined sorting of economic activities, it has been used as a reference to identify sectors that are proximal to each other, either in terms of the processes involved, the products or services produced, and the resources used. Hence, the classification has been translated with the use of the neural machine translation service DeepL. Subsequently, keywords pertaining to each sector have been identified within the NAF rev. 2 classification. The activities that seemed to belong to the industries identified previously were grouped in terms of their hierarchical level in the classification. They were then related to each other through cumulative point scoring. The relations were coded such that each occurrence of a divisions of different sector in the within the same section gave a score of 1, a relation of different groups within the same division a score of 2 and different classes within the same group a score of 3. This differentiation allows to advantage sectors that are closer in a lower hierarchical level, as they share more commonalities. The repartition of activities has been plotted and analysed with the code in Appendix C and is represented by Figure 17. Appendix C presents the This division gives the score matrix presented in Table 4. This matrix is then used with the code written by Pierre-Alexandre Balland in his work with Boschma et al. (2014, 2015) reported in Appendix C. The runs of the codes reported for the experimental set-up are after their respective codes in Appendix C. The resulting relatedness matrix for the sectors in Ile-de-France is shown in Table 19.

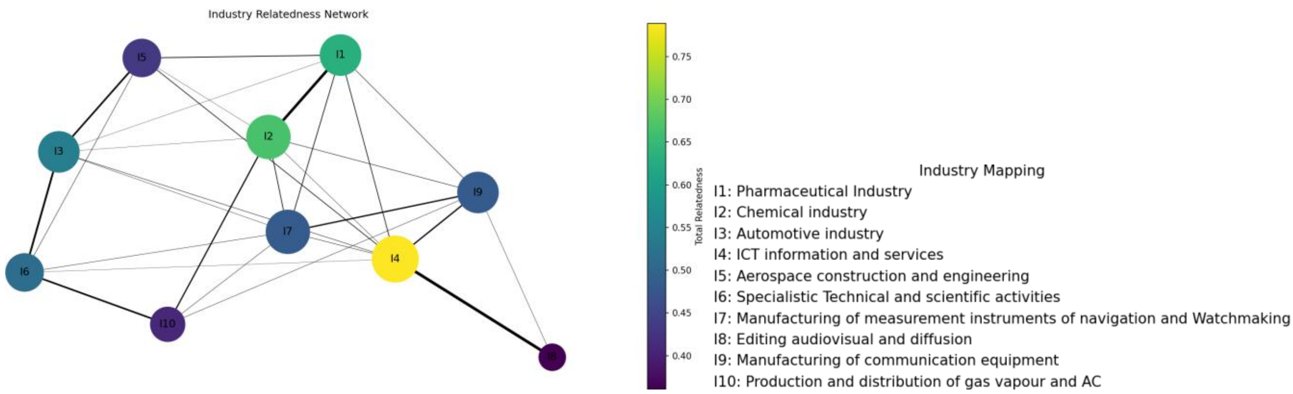

Figure 18: Network graph of the relatedness of the sectors in Ile-de-France. The node size is representative of the number of edges while the node colour represents the value of the total relatedness. The width of the edges represents the value of the pairwise relatedness.

The result of the relatedness matrix code can be plotted as a network graph. The code for the network graph plot if reported in the GitHub repository of my thesis as “Relatedness Matrix Network” (Mell, 2025). Figure 18 is a network graph between the sectors in Ile-de-France where each node represents a sector. The total relatedness is represented by the node colour while the node size is representative of the number of edges for that node. The width of the edge represents the pairwise relatedness value between sectors. From Figure 18, the node I4 representing the ICT sector appears as a central point of linkage. It represents the sector with the highest number of edges and the highest relatedness score, represented by the bright warmer colours. It can be seen as acting as strong brokerage for node I8, the editing, audiovisual and diffusion sector, for which it represents the strongest point of linkage (Yong, 2018). The node I8 on the other hand represents the sector with the lowest overall relatedness score and overall lower linkages. Nonetheless, when looking at his score per linkage, it has the strongest pairwise relatedness with I4, shortly followed by the pharmaceutical and chemical engineering sector.

For the MAR region described, given the presence of only two sectors, the relatedness matrix only has one structure possible.

$$Relatedness\ MAR = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$$

While these relatedness metrics are a simplification of reality, they are closely similar to the results shown by economic geography studies in European regions (Otto et al. 2025, Xiao et al. 2018, Straulino et al. 2021, Casadei et al. 2022, European Commission, 2025, Balland & Boschma, 2021). Even though relatedness values in these studies are different, they show the same pairwise connection between sectors.

To link graduate supply to sector-specific R&D demand, the (APEC, 2025) occupational profiles have been analysed for each discipline and are reflected in
Table 17. The relevant degrees identified for all the sectors of interest are:

- Arts,
- Foreign Languages,
- French Literature,
- Pharmaceutical Studies,
- Life Sciences,
- Multidisciplinary Fundamental Sciences,
- Electronics,
- Electrical Engineering,

- Computer Science,
- Mathematics,
- Technology and Industrial Sciences,
- Mechanics,
- Physics,
- Chemistry,
- Process Engineering,
- and Information and Communication.

Each degree program may qualify graduates for multiple R&D roles across sectors. Degrees are therefore grouped into orientation clusters to reduce model complexity while preserving key distinctions. “Arts,” “Foreign Languages,” and “French Literature” constitute the Audiovisual cluster since these fields appear exclusively in the Publishing and Audiovisual industry’s R&D roles. Similarly, “Pharmaceutical Studies,” “Life Sciences,” and related programs form the Health cluster. “Multidisciplinary Fundamental Sciences” aligns with the Specialised Technical and Scientific Services sector. “Digital” aggregates “Electronics,” “Electrical Engineering,” and “Computer Science,” and “Industry” comprises “Mathematics,” “Technology and Industrial Sciences.” The remaining programs from the analysis in
Table 17 are treated individually as they do not align with the previous grouping and amongst each other. The results of this distribution are given by the bipartite graph in Figure 19.

Graduates are allocated to sectors in proportion to each sector’s attractiveness, defined as the share of innovation expenditure per innovator in sector relative to the sum over all sectors. Figure 19 illustrates this distribution. For the MAR region, both prominent sectors involved students from the same studies. Since this is the case, no mapping is needed, and students were divided across the industries based on the sector attractiveness.

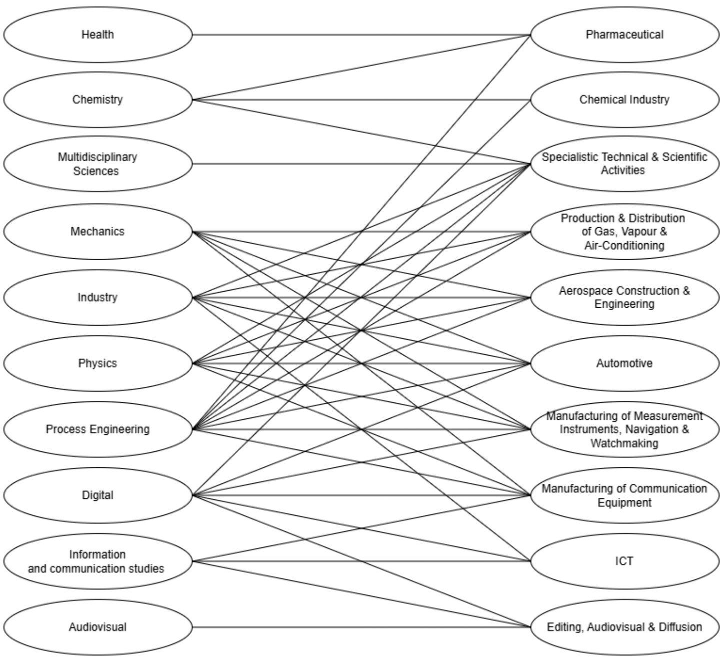

Figure 19: Bipartite graphic of the distribution of studies to sectors of work opportunities.

The base parameters are set from the previously described methodology for the year 2021. Finally, to execute simulations for Île-de-France and Bretagne in 2021, each sectoral subscript and educational cluster subscript is populated with the corresponding parameters detailed in Table 21 and Table 22. This setup ensures that the test reflect the region’s actual sectoral structure and graduate pipelines, allowing to connect the regional innovation system to the clusters populating it and the sectors between each other. Finally, both models for the Bretagne and the Ile-de-France regions are reported in the GitHub repository in the “Base Models” folder.

3.9 Replicative Validation Test

3.9.1 Replicative Validation

Replicative validation evaluates whether the model can reproduce observed historical patterns or align with outputs from other validated models. This replicative testing used real-world data to validate model outcomes over a timeline. This allows to some extent to further align "model-land" and reality (Thompson & Smith, 2019).
In this study, simulated trajectories from 2001 to 2022 were compared against recorded data; however, some base-year values in the model could not be matched precisely to 2001 observations due to data limitations at the required level of detail. Consequently, I applied a combination of validation approaches.
The Ile-de-France model outputs for the years 2001–2022 and the Bretagne model outputs for 2001-2011 are compared against the following variables, for the assessment of innovation development:

- Regional Population,
- Children,
- Young Adults,
- Adults in the workforce,
- Adults after retirement,
- Workforce employment in knowledge intensive activities in sector,
- Internal knowledge generation or size,
- R&D expenditure in Sector,
- Student enrolment stock in pharmaceutical studies,
- Knowledge workforce in public R&D.

The sectorial and academic values were measured in timeseries only for the Pharmaceutical sector in Ile-de-France and for the Telecommunication sector in Bretagne. I chose these sectors as they are the sectors with the most important knowledge base in the region, therefore the most influential in knowledge exchange in the rest of the region. Additionally, the pharmaceutical sector was selected for replicative validation because it possesses the most complete data available, hosts France's principal public health research institute with the largest concentration of domain-specific researchers and receives the largest share of government R&D funding.

While the pharmaceutical Industry in conjunction with cohorts of Chemical Engineering and Pharmaceutical students is chosen to be statistically analysed from 2001 to 2022 in Ile-de-France, the MAR model analysis focused on the results of the telecommunication sector, which was selected given its database quality, from 2001 until 2012. Consequently, the telecommunication sector and pharmaceutical case study enable both precise calibration of the public-sector R&D workforce dynamics and rigorous assessment of the public–private collaboration mechanism described in Section 2.3.5. The parametrisation necessary for the region in that period is given in Table 23 for Ile-de-France and Table 25 for Bretagne. The model's qualitative behaviour was cross-checked against past trends, acknowledging that historical alignment does not guarantee accurate future projections (Pruyt, 2013), particularly in the context of systemic transitions such as the ones in innovation development. Model outputs were also compared with findings from the literature.

Owing to data gaps, two parameters required imputation for Ile-de-France. Firstly, I estimated students in pharmaceutical studies for 2001–2015 by applying a constant enrolment ratio (1.675 % of the "Young Adults" cohort) to the population of Young Adults; and knowledge workforce in public R&D for 2014–2022 was interpolated by fitting a trendline in Excel to pre-2014 data and extrapolating forward.

Model accuracy is evaluated by plotting simulated and historical time series side by side from the data points in Table 24 and Table 26. For each historical series, the real-world value is contrasted with the modelled output. During the historical data collection, two exogenous inputs, government funding in the public sector and R&D expenditure per researcher for both public and private research, exhibit significant temporal variability. To capture the declining fertility trend from 2001 to 2022, the average female fertility was implemented as an exogenous lookup table rather than a constant parameter. Similarly, the year-to-year oscillations in the variable for R&D expenditure per researcher in the public and private domain are treated as an exogenous series, ensuring that the model reproduces observed fluctuations in hiring capacity and knowledge creation.

This dual approach, precise calibration for the pharmaceutical sector in Ile-de-France and Telecommunication in Bretagne, against extended longitudinal data, and qualitative behavioural checks for other sectors using base-year anchoring, enables me to verify that the model's structural logic and dynamics remain valid across a broader industrial landscape, even where multi-year parameterisation is not feasible.

3.9.2 Replicative Validation Results

The runs with the statistical data for the telecommunication sector in the MAR region presented in Table 25 in the Appendix are analysed with the results given in Table 26 in the Appendix. They are plotted in against the contextual data to allow for direct comparison in Figure 20 and Figure 21. The runs with the statistical data for the pharmaceutical sector from the Jacobs region presented in Table 23 are analysed with the results given in Table 24. They are plotted in Figure 22 and Figure 23 against the contextual data to allow for direct comparison. The code for the plotting and the dataset are uploaded in my GitHub repository under "Replicative Validation Test" folder (Melli, 2025).

The analysis precisely examined variable-to-variable observations, which are reported in the Appendix under Table 26. The analysis aimed to compare the overall evolution, the potential underestimation or overestimation bias and divergence trends between the model and historical data over the 2001 to 2022 period for Ile-de-France and over the 2001 to 2012 period for Bretagne. The replicative analysis revealed several main findings about the model's performance compared to historical data.

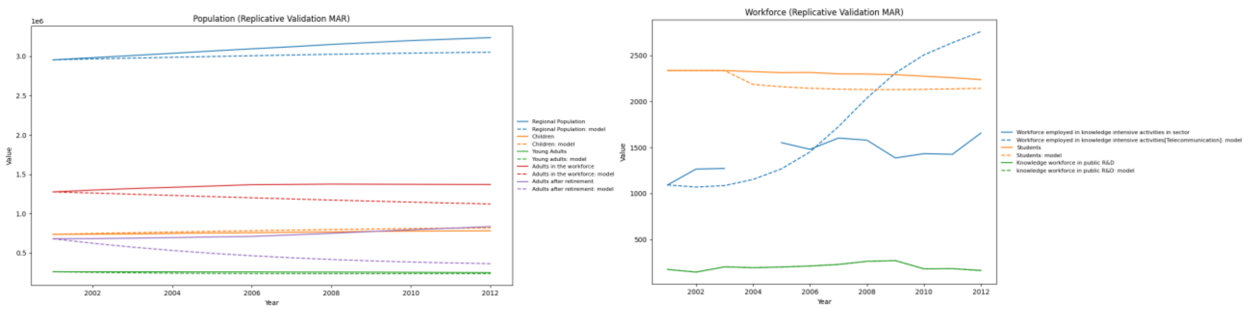

Figure 20: Graphical representations of population comparative data points between the Vensim model and collected data for MAR region. The data plotted correspond to the indicators Regional Population, Children, Young Adults, Adults in the workforce, adults after retirement, Students, Knowledge Workforce in Public R&D.

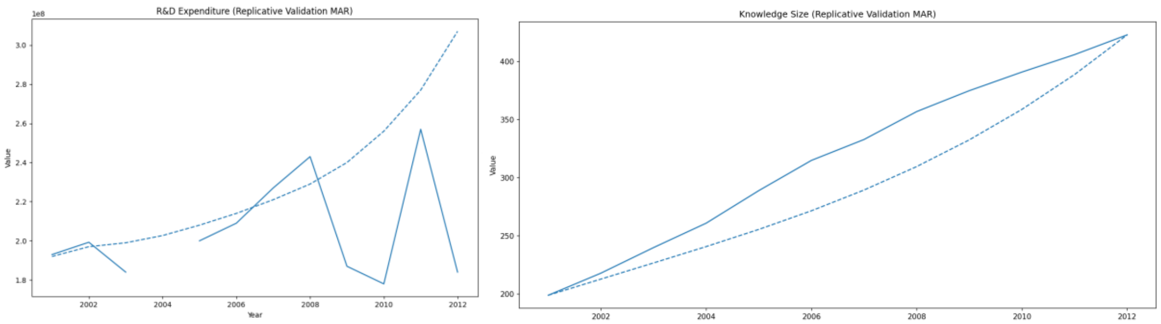

Figure 21: Graphical representations of R&D expenditure and knowledge size data points between the Vensim model and collected data for MAR region. The dashed lined (- -) represents the model output while the full line (–) represents the collected data.

The most consistent finding is that the model successfully replicated the qualitative behaviour and long-term trends of the real-world system, but it often struggled with quantitative accuracy. It correctly captured the general shape of the curves in growth, decline, or stabilization for most variables, but the exact numbers are often overestimated or underestimated. This confirmed the model's value as a tool for understanding systemic behaviour rather than as a precise forecasting instrument.

The analysis identified differences in the some of the population variables. The possible explanation for the difference in population growth between the model and measured data is that it treats the population growth uniquely endogenous to the population initially present in the model. Treating population as a closed system means that is disregards migratory flows that occur in the region, and the birth rate for that part of the population that moves to the region. Ile-de-France is the region where this difference is most pronounced. As it is a very dynamic region, it is expected to attract talent from all over France, Europe and the world. The national statistics institute censed indeed that 37% of the population in Ile-de-France in 2020 was from migratory flows (Insee, 2023). It is also therefore expected that this difference is substantial in the detailed levels of the population. This could be the primary reason why the model systematically underestimated the total population in both regions. Given that the Insee (2023) explicitly noted that 37% of Île-de-France's population comes from migration, excluding it could have created a significant and widening gap between the model and reality. The analysis therefore highlighted one of the model's structural limitations.

In the historical data, timeseries showed spikes or dips in their values which were not replicated in the model. This is for instance the case for the population towards 2022 and students in 2016. This might be due to some statistical difference in understanding the impact of Covid in the population until the population census post-Covid. During the Covid crisis, the national statistical institute in France did indeed publish that it was facing difficulties collecting the data during the health crisis, which would be postponed to 2022 that could partially explain sudden transitions in data (Insee, 2020). The model is not designed to handle sudden, external shocks, such as policy changes or crises like the COVID-19 pandemic. Where historical data showed abrupt jumps or dips, such as in student numbers in 2016 or population in 2022, the model instead produced a smooth curve that averages out the volatility. This highlights its nature as a representation of endogenous dynamics, not external events.

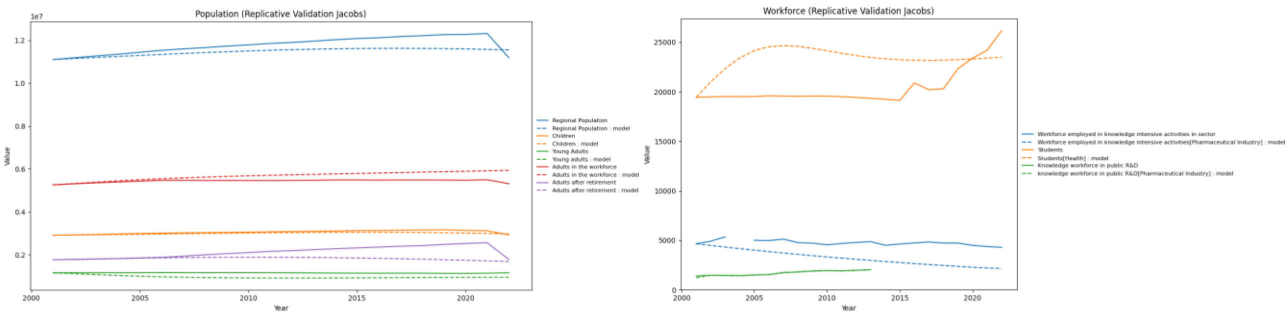

Figure 22: Graphical representations of population comparative data points between the Vensim model and collected data for Jacobs region. The data plotted correspond to the indicators Regional Population, Children, Young Adults, Adults in the workforce, adults after retirement, Students, Knowledge Workforce in Public R&D.

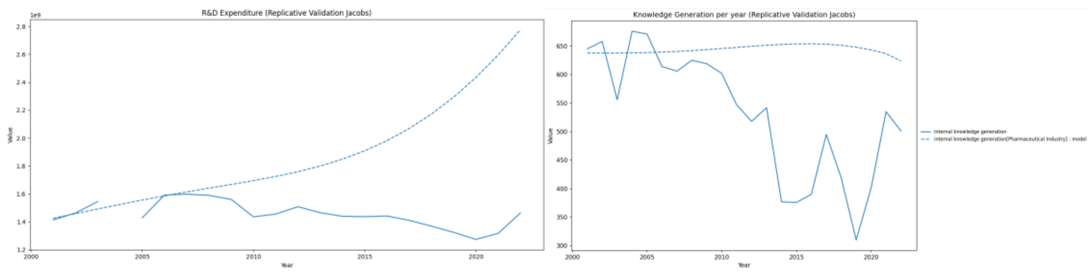

Figure 23: Graphical representations of R&D expenditure and knowledge size data points between the Vensim model and collected data for the Pharmaceutical sector in Jacobs region Ile-de-France. The dashed lined (- -) represents the model output while the full line (–) represents the collected data.

Overall, this analysis showed a dynamic that is relatively similar to the system data other than for unexplained perturbations or fluctuations in the data, which have not been reproduced by the model. Given the model's ignorance of local perturbations, it could not replicate the dips or peaks from shock events in the data that have not been encoded in the model. The model was parametrised for average values when specific values were not available which led to a behaviour that either anticipates or catches up to the final output with a smoother transition. This is because these shocks have not been modelled but have been significant enough during recent events to influence the final system output. Oscillations in real-life data are averaged over the period, leading to a model behaviour that tends to be more oriented towards the set of values showing more density and underestimating the impact that initial shocks have on the system (Savage, 2009, Ford, 2012). Simulating important shocks could help render model accuracy but remains beyond the scope of my thesis. The focus of my work is not centred on obtaining the exact results as what is observed but rather as having an overall behaviour that replicates the real system. This is overall the case for most of the variables presented as for the most important variables represented.

Nonetheless, the results of Figure 20, Figure 21, Figure 22 and Figure 23 suggested that it might be interesting to define a few additional flows that could improve the regional demographic dynamics, respectively, migratory flows in and outside of the region. However, despite the differences, the dynamics of student enrolment, R&D expenditure and knowledge generation are proximal of the real-world behaviour. Despite the inaccuracies for the population stock and expenditure fluctuation, the R&D employees and internal knowledge did not show variations to the same extent. The analysis demonstrated how inaccuracies in one part of the model have a small cascading effect towards other variables. For instance, the underestimation of the young adult population had a small effect over the student population although the stocks are linked. This highlighted the interconnected nature of the system's structure but also the model's robustness for variations in data. The latter can be attributed to the fine-tuned parametrisation of the remaining variables accounting for those inaccuracies.

Another improvement could be to assess whether there are variations in the proportion of R&D expenditure to total profit in a sector that could explain the variation of the historical data and be implemented as a function in the model. However, such data granularity is not available in public datasets from the regions. The results of this replicative validation test might suggest that certain variables have a higher uncertainty level than measured, such as the percentage of profit and percentage of R&D budget from the total budget leading to the R&D expenditure, the attrition rate and hiring time, and the population values. In order to inform further model validity and further possible modifications, these results have been shown to an innovation studies expert. The findings of the expert validation are presented followingly.

3.10 Expert Validation of model results and behaviour

3.10.1 Methodology for the Expert Validation

In a further attempt to align "model-land" and reality, I undertook a validation, analysing expert judgment of the model. This test is particularly useful in cases where out-of-sample or replicative testing isn't feasible given that the model validation would still rely on informed expert assessments of model limitations and relevance (Thompson & Smith, 2019). I conducted an expert review on the system dynamics model designed to simulate MAR and Jacobs agglomeration externalities in European regions. The goal of this expert validation is to bring added value to understand whether the model, in its context, structure and behaviour, is suitable for the purpose of answering the research question (Kannan & Swamindurai, 2019). This being said, the expert validation followed the methodology set out by Schwaningerand Groesser (2009), according to which the expert validation should take different degrees of resolution, micro, meso and macro, within different domains of validation, the structural, behavioural and contextual ones. These domains were originally reported for validation by Forrester and Senge (1980), but were used in a wide variety of system dynamics validation reviews given their completeness is assessing the model design (Schwaninger & Groesser, 2009, Kannan & Swamindurai, 2019, Arthur & Winch, 1999, Lemke & Małgorzata, 2013). This expert validation therefore aimed to ask micro, meso and macro questions for each of the three validation domains, structural, behavioural and contextual. I firstly shortly presented to the expert the model and its unified structure for both MAR and Jacobs mechanisms, with variations in sectoral definitions and parameterisation. The questions are reported in Table 27 in the Appendix. The methodology for the expert's feedback aligns with established validation practices in the field of system dynamics outlined in academic literature. The review process itself constitutes a form of validation. The expert's examination of the causal loops, parameters, and assumptions is a direct test of the model's structural validity.

3.10.2 Expert Validation Results

Starting with the structure, the expert found the model's structure to be generally consistent with economic reality and appropriate for its intended goal. The assessment touched upon the model's overall framework, inter-sectoral relationships, and variable definitions.

At the highest level, the causal loop diagram's structure is considered economically sensible. The sub-models are logically consistent, and the variables chosen as inputs are appropriate. The expert suggested that for clarity and adherence to standard practice in system dynamics, these external inputs should be explicitly represented in the causal loop diagram, which was considered for the final version of the Causal Loop Diagram.

A critical component of modelling agglomeration is the definition of "relatedness" between economic sectors. The expert noted that the model's computation of relatedness, while functional for the model's purpose, is a simplification of complex economic activities. This simplification stems from reliance on the NACE classification system, which may not fully capture the rapid evolution of modern industries. To validate and strengthen this core component, the expert recommended a comparative analysis, aligning the model's sectoral classifications with established classifications from the field of economic geography. These recommendations were implemented in the assessment of relatedness.

The expert identified opportunities for refinement at the variable level of the Causal Loop Diagram. To streamline the model, it was suggested that certain closely related variables could be consolidated, such as sales and revenues, hiring and workforce, and innovation and knowledge, as their distinction adds little value within the model's current scope. The two distinct attractiveness variables are a key feature, but they need to be made more distinct from one another. The underlying assumptions used to define them are logical but should be made more explicit in the model's documentation.

Secondly, the expert validation aimed to assess whether the model's behaviour is aligned with real-world dynamics. The model's ability to replicate real-world behaviour is crucial for its validity. The expert's feedback indicates that the model behaves realistically, though certain assumptions could be refined to better capture the complexities of regional economic systems.

The model successfully generates system characteristics endogenously, which is a primary goal of system dynamics modelling. However, the review highlighted a key assumption that deviates from reality: the constraint on the labour pool. The model assumes that if there is no local workforce, sectoral expansion halts. The expert pointed out that this is not true in an integrated economy due to migration. Fully modelling migration is complex and data-intensive. The expert brought up a pragmatic proposal to simplify the assumption to reflect the reality of the EU single market, where a theoretical availability of workers exists beyond the immediate region. This could be represented as a "foreign attractiveness" factor influencing hiring and should be reflected in the CLD. Another suggested mechanism is to model the retraining of the local unemployed workforce, reintroducing them into the available labour pool. While he concluded that it would potentially fall outside the project's immediate scope, he suggested to highlight it as a note for further steps if it appears as a significant variable hindering the development of a region.

While the core assumptions were deemed "good" and appropriately focused on economic factors, the expert recommended increasing the model's dynamism. Over a 20-year simulation period, several parameters assumed to be constant will, in reality, change. It was suggested to convert some parameters from constants to dynamic lookup variables based on historical data. These are the fertility and mortality rates and innovation expenditure per R&D employee. This suggestion was implemented in the case set-up.

The scenarios tested were considered "very interesting". For greater impact and intuitive understanding, the expert suggested reorganising the presentation of scenarios, such as restructuring high and low values scenarios for easy comparison by placing them adjacent to each other. This recommendation was implemented in the Extreme Value Test.

Finally, the expert has analysed the model's suitability for policymaking within its context. For a system dynamics model to be useful in a policy context, it must be validated against the system it represents. The previous feedback that the model's output behaviour appears realistic and the discussion around making its behaviour more robust through dynamic variables and migration assumptions are key components of behavioural validation. The ultimate goal is to create a tool for robust decision-making. Introducing negative scenarios or shocks to the system is a crucial recommendation given that testing the model's resilience to adverse conditions is vital for evaluating the robustness of potential policies. The expert's recommendation to test the model's resilience with negative scenarios directly addresses its utility for policymaking. I implemented this recommendation in the model testing section followingly. By understanding how the system behaves under stress, policymakers can formulate more robust innovation policies. The model provides a platform to test "what-if" scenarios related to government funding, R&D investment, and workforce development, making it a potentially powerful tool for regional innovation strategy.

The expert concluded that the model is fundamentally sound and well-conceived for its purpose. Overall, the key recommendations focus on refining specific assumptions, enhancing the representation of key variables to improve realism, and expanding the scope of scenario testing to increase its robustness for policy analysis.

3.11 The EMA Method for a Parameter Sweep

3.11.1 Overview of the General Application of the EMA Method

EMA posits that there is no singular 'correct' model of the world and that all models are inherently biased. Consequently, it advocates for the utilisation of multiple models to investigate the future of a system. To achieve this, EMA employs the XLRM framework: X represents uncertain inputs, L denotes levers, R signifies relationships within the system, and M refers to performance metrics, which are the results, as illustrated in Figure 24.

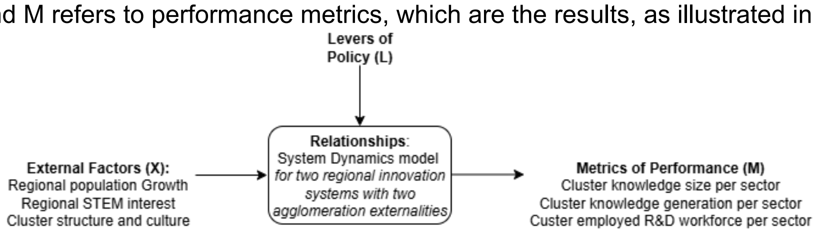

Figure 24: XLRM framework applied to regional innovation system: The aggregation of each variable is very high

By manipulating the uncertain inputs for different variations of the model, an ensemble of outputs is generated. Each model run reflects the dynamics of the model, parametrised singularly for each of the runs. Each execution of the model yields data regarding the performance metrics throughout the model's runtime, and collectively, all models generate an extensive output space of performance metrics. This process enables the EMA method to explicitly integrate profound uncertainties into the model (Auping, 2018).

One application of EMA is dedicated to multi-objective robust decision-making, which aims to discern the impact of various combinations of uncertainties on the behavioural landscape of model outcomes (Kwakkel et al., 2013, Kwakkel, 2017). Traditionally, exploratory modelling has concentrated on how combinations of uncertainties affect the terminal values of outcomes of interest. To advance this approach, one could also examine how these combinations influence the dynamics of outcomes of interest across individual model runs. To facilitate this, a range of machine learning techniques can be utilised. The selection of technique is contingent upon whether the focus is on the terminal value or the temporal dynamics of the interesting variables. In this research, the temporal dynamics are deemed most significant for validation purposes, considering that the quantitative final output of the mode is also subject to deep uncertainty. However, once the model validated, in order to suggest policy-level improvements for each regional innovation system based on their agglomeration externality, the final system performance was targeted for optimisation. Initially, rather than employing static clustering techniques that emphasise the terminal value of outcomes, a time series clustering technique is implemented to categorise the output data into groups that encompass runs exhibiting similar behaviour over time (Kwakkel et al., 2013).

3.11.2 Parameter Sweep Test by Merging EMA with SD

To effectively address the multifaceted deep uncertainty present in the modelling of agglomeration effects in regional innovation system, I needed to integrate various methodologies. Deep uncertainty complicates the comprehensive understanding of system behaviour within a model since the designed model must account for both structural and parametric uncertainties. Additionally, this methodology allowed the research to recognise that while making precise predictions for a system defined by deep uncertainty is unfeasible, it was still viable to explore the system through multiple models informed by the available data (Kwakkel & Pruyt, 2015). The integration of System Dynamics (SD) with Exploratory Modelling and Analysis (EMA) into what is termed Exploratory System Dynamics Modelling and Analysis (ESDMA) facilitates this exploration (Auping, 2018; Bankes, 1993; Kwakkel et al., 2013).

System Dynamics is particularly suited for investigating structural uncertainty, therefore testing hypotheses on model relations and causality links. However, it falls short in providing the necessary tools to capture all forms of uncertainty (Kwakkel & Pruyt, 2015). The synergy with Exploratory Modelling and Analysis (EMA) enables the development of multiple models that reflect parametric uncertainty, and the diverse decisions embedded within the model. Such complementarity thereby offers a comprehensive approach to encompass further dimensions of deep uncertainty. This uncertainty is therefore firstly identified per exogenous parameter thanks to the results of the expert validation, then implemented in the EMA workbench to test how deeply the uncertainty affects the model behaviour and outcomes.

3.11.3 Application of EMA for a Parameter Sweep

The parameter sweep is a method employed to ascertain model behaviour through a multivariate variation of parameters (Wibisono, 2008). The model setup involves simultaneously exploring uncertainties by sampling across them. In this configuration, 2000 distinct scenarios are generated to examine their combined impact on model outcomes. Within this context, a scenario represents a specific point within the uncertainty domain, while a policy denotes a particular configuration within the decision-making domain playing on the defined levers. Each unique pairing of a scenario and a policy forms an experiment (Kwakkel, 2017). Both uncertainties and levers are expressed using one of the RealParameter types, which indicates a continuous value range.
The sampling process for both scenarios and policies is executed using Latin Hypercube Sampling (LHS), ensuring stratified coverage of the input space (El Garroussi et al. 2019). Each policy is assessed across the entire suite of scenarios, resulting in a comprehensive factorial exploration of scenario combinations.
I parametrised the analysis on the set of uncertain parameters described in Table 5, which were sorted according to their behaviour. This resulted in one group for the MAR region and four groupings for Jacobs region.

3.12 System Uncertainties

3.12.1 System Boundary Uncertainties

The main system boundary uncertainty that transpires from the conceptual definition of the system arises from the dual definition of agglomeration externalities as either diversification or specialisation oriented (Antonelli et al. 2017). Specialisation dynamics (MAR) arise from a high degree of local specialisation in a single industry (Marshall, 1890). Drawing on Marshall's notions of labour-market pooling, supplier–customer linkages and intra-industry knowledge spillovers, Arrow's emphasis on learning-by-doing, and Romer's concept of knowledge spillovers with increasing returns, Glaeser et al. (1992) formalised the Marshall-Arrow-Romer model. In this view, a concentrated industry in a region benefits from a deep pool of specialised workers, a dense network of input–output relationships, and frequent face-to-face exchanges that accelerate innovation among firms in the same sector.

Diversification externalities stem from the diversity of industries co-located in an urban area rather than from specialisation (Jacobs, 1969, 1984). Jacobs (1969) argued that innovation thrives when firms draw on unrelated sectors. It allows ideas and skills spillover across industry boundaries, sparking novel combinations and applications. Empirical work on related and unrelated variety shows that industrial diversity fosters regional knowledge spillovers by providing a rich mix of competencies and broadening the local labour market's skill set (Aghion & Griffith, 2005).

This uncertainty is reflected in the level of granularity of the modelling. All prominent technological sectors in a region had their dynamics modelled individually to ensure knowledge generation and knowledge exchange are both represented. The two different regional models were tested separately for the parameter sweep.

3.12.2 System Parameter Uncertainties

The parametric uncertainties in the model are summarised in Table 5, which outlines their uncertainty levels and applied ranges for EMA experiments following Kwakkel et al. (2010). Expert interviews and the data collection process during model development informed both these parameters. I supplemented both of the previous with academic literature to strengthen my analysis. These parametric uncertainties represent variations in individual model parameters, calibrated through experimental observations and expert judgment as suggested by Smith (2013). Where these methods proved insufficient, I quantified academic findings by aligning uncertainty boundaries with other parameters, ensuring no single parameter disproportionately influenced outcomes simply due to larger interval assignments. This approach allows the calibrated model to reflect uncertainty in responses, enabling potential future recalibration as needed (Feng et al., 2023).

Kwakkel et al. (2010) established the four levels of uncertainty based on the research conducted by Walker et al. (2003). They defined shallow uncertainty as the ability to list several alternatives and assign probabilities to them. Medium uncertainty is characterised by the ability to list multiple alternatives and rank them according to their perceived likelihood. However, it remains unspecified how much more likely or unlikely one alternative is in comparison to another. Deep uncertainty is defined as the ability to enumerate several alternatives without the capacity to rank them based on their likelihood or plausibility. Lastly, recognised ignorance pertains to the inability to enumerate multiple alternatives while acknowledging the potential for unexpected outcomes. Building on Kwakkel et al.'s (2010) framework, I classified parametric uncertainty into these four tiers; shallow, medium, deep, and recognized ignorance. While I linked parametric uncertainties to parameter values, structural uncertainties emerged from ambiguities in system boundary definitions, conceptual frameworks, or model translation into computational forms (Kwakkel, 2017). Initial model runs incorporating these variables generated the behavioural graphs shown in Figure 25, Figure 26, Figure 28, Figure 27, Figure 29, Figure 30.

1. Shallow-Level Parameter Uncertainties

On a shallow level, the relative share of women in fertile age, the percentage of adults enrolling in studies, external investments, hiring and training time of employees and the attrition rate in sector are all factors that showed slower change over time in datasets and of which the uncertainty is supported by literature (Bentil et al. 2003, Tajaddini & Gholipour, 2020, Jaillet et al. 2022). Despite the change in these factors per region or sector, they are often in line with national standards or the parameters are easily obtainable from timeseries or easily measured, therefore presenting a shallow degree of uncertainty.

The uncertainty in the relative share of women in the population follows the uncertainty of demographic trends and varies of 20% around its baseline value. The sex ratio at birth is naturally male-biased, with slightly more males than females, but skewed ratios appear based on the geographic area reflecting gender preference and sex-selective practices (Chao et al. 2021). Additionally, mortality differences usually imply that female ratio is bigger towards the older age groups, which gets averaged across all age groups. Finally, labour migrations which used to be male-dominated, has shifted to a female domination in recent years, which might skew local ratio (Lee et al. 2022). The latter with the combination of economic uncertainties can delay fertility, altering future population structures and making the ratio of female sex appear smaller in the local population than it is (Barker & Buber-Ennser, 2024, Matera et al. 2022, Badolato et al. 2025).

The percentage of adults enrolling in studies has a fluctuation in data points of an average of 17.6 percentage points, which I rounded up to 20%. The fluctuation might be representative of financial constraints, perceived returns and job market conditions to which higher education enrolment is sensitive (Aker et al. 2024). Additionally, economic policies and financial aid can be particularly impactful, specifically towards fragile categories of the population, further influencing uncertainty in higher education enrolment (Wang et al. 2023, Bernal et al. 2024).

External investments follow economic uncertainty in their dynamics (Muslim et al. 2023, Bloom et al. 2007). Investment flows are volatile, influenced by geopolitical risks, tariffs, and country-specific policies. Historical data shows that external investments can swing by more than 20% during crises such as trade wars (Vortherms & Zhang, 2024). In alignment with the previous parameters, the external investment variable has been given a 20% uncertainty range.

The hiring and training time experiences uncertainty ranges based on the skill match and the training efficacy. Companies increasingly delay hiring when faced with uncertainty, with a reduction in job postings and hiring (Li et al. 2024). However, training can also become more efficient derived from organizational dynamics, environmental circumstances, motivational influences, skill levels, aptitudes, and perceptions of roles (Arulsamy et al. 2023). Finally, these changes are very sector-specific, as sector gaps introduce variability in the attrition and hiring time. Once more, this variable appears dependant on the economic uncertainty of the context (Martínez-Matute & Urtasun, 2022). Due to the lack of specific experimental data and expertise in this domain, an uncertainty range equivalent to the one from the previous parameters is assigned to this variable, ensuring that it has an equal chance of varying of the results. Hence, the hiring and training time has a 20% uncertainty range.
Finally, the attrition rate shows time-bound fluctuations based on the economic context, with high attrition rate following the Covid crisis (Linzer et al. 2022). Not only is training and development, work environment, and job satisfaction influencing employee retention (Xuecheng et al. 2022) but norms and culture also changed within the workforce, affecting these trends. Increased trust and self-reliance led to a higher employee turnover during what is known as "the great resignation" (Shukla et al. 2022). However, Eurostat shows a progressive decrease in employee resignation since 2023, supporting upper and lower variations from the baseline value (Eurostat, 2025). Given the lack of historical data specific to each sector and each region, the uncertainty in attrition rate has been quantified with 20% boundaries around its initial value.

The initial parameters of the added value in sectors, employed R&D workforce in sectors, knowledge specialisation in sectors and population have also been considered as shallow levels of uncertainty.

The initial added value in sector has been extrapolated from national measures by using a fixed ratio that might not be representative of the real sectorial values. Macroeconomic and policy shocks could alter its value across regions. In fact, economic policy uncertainty negatively impacts sectoral gross value-added. For instance, currency and debt policy uncertainties are particularly disruptive, reducing gross value-added in trade and construction sectors by up to 20% (Kafka, 2023). Additionally, geopolitical risks such as trade wars can reduce industrial value-added by 5–10%, especially in export-dependent sectors (Shams, 2024). Finally, different sectors show different sensitivity to economic uncertainty. Resilient sectors show lower sensitivity by 5% to 10%, while volatile sectors face more than 20% swings due to demand shocks (Kafka, 2023). Hence, I attributed a 20% uncertainty interval to the baseline of the initial added value.

The employed R&D workforce can experience uncertainty due to funding volatility and labour mobility. A 1% rise in economic policy uncertainty is shown to correlate with a 0.8% drop in R&D employment, as firms delay hiring for long-term projects (Jackson et al. 2018). Additionally, R&D employment in policy-sensitive sectors fluctuates by more than 20% during regulatory changes (Nguyen & Kim, 2023). Given the sectorial difference and policy-based uncertainty, I gave this parameter a 20% uncertainty range around its computed value.

The initial knowledge specialisation in sector has been manually computed, and despite the completeness of the patent identification, it might not consider patents in very specific categories or patents which have been registered in a different region than the one in which the research was done. Hence, these variables can be seen as uncertain in this experiment. Furthermore, variations in knowledge obsolescence and average time to market spill over to knowledge size, influencing its uncertainty. Sectors with rapid innovation cycles face higher uncertainty in specialization value due to patent cliffs (Ma, 2021). Economic policy uncertainty also played a role for this variable, creating uncertainty in the applicability of knowledge (Tajaddini & Gholipour, 2021). The empirical data fluctuations from the replicative validation supported a range of 20% uncertainty around the base value.

Finally, the initial population showed possible uncertainty by not taking into account migratory flows (*Insee*, 2023). As shown by the replicative data analysis, there is a persistent difference between the model outcomes and the empirical measurements. While migration flows might inflate the numbers, shocks cause sudden dips which are not simulated by the model. On top of this, changing fertility rates and aging population impact the growth of the population forecasted by the model (Bentil et al. 2003). Given the variation observed in the replication test, I gave the initial population a factor of 20% uncertainty around its baseline.

2. **Medium-Level Parameter Uncertainties**

I then analysed medium uncertainty levels. The percentage of profit from revenue in different sectors usually fluctuates and is dependent on parameters beyond the scope of the current model (Manos et al. 2023). However, from its observed value in different sectors, the fluctuations remained relatively stable when the external conditions of the system's environment did not experience significant change. This is therefore classified as a medium uncertainty level and was attributed a 20% uncertainty range.

Knowledge obsolescence time seemed to progressively change with the evolution of technology (Edquist, 1998). Studies half a century apart showed a two-year difference in knowledge obsolescence time (Rosen, 1975, Boitier et al. 2022), giving an uncertainty range of 20%. This change is not necessarily unidirectional. The change in knowledge obsolescence is often attributed to an existing technology, which becomes obsolete with the addition of an improved version of the previous (Mellal, 2020). What is not considered by this definition is that the newly improved version might also make use of complex knowledge which would increase the knowledge obsolescence of the sector as a whole (Ma, 2021). This is industry dependent. As noted by Ma (2021), the phenomenon of technological obsolescence is distinct from the emergence of new innovations, suggesting that these are two separate concepts. Accordingly, larger corporations experience a greater degree of knowledge obsolescence, potentially attributable to the inherent rigidity of such organizations. There are instances where large corporations constituted merely a minor fraction of the overall business landscape, while this model assessed knowledge obsolescence across various industries for the whole sector. Certain industries seemed to adopt a counter-cyclical strategy, enhancing the relevance of their innovations for other industries in the sectorial landscape as time progresses. Given that this is linked to the diffusion of an innovation is society and not simply the emergence of new technologies, the knowledge obsolescence across sectors can potentially show increased or decreased variations, to which I attributed a 20% range.

Average time-to-market often fluctuate between firms and time (Belay, 2011, Bloom, 2007). In fact, a set of studies show that the evolution of the average time-to-market in a sector is more complex than simple time-bound decrease (Cohen et al. 1996, Belay, 2011, de Barros et al. 2015, Moleka, 2024). As technology becomes more complex with time, sectors envision a longer time to market. A quicker product development does not necessarily lead to a decrease in the time to market for the sector (de Barros et al. 2015). Belay (2011) compares time-to-market specifically linked to the automotive sector, finding a 20% difference between different firms in the same domain.

Given the lack of more generalised studies regarding the uncertainty for the average time-to-market, I applied the 20% difference from Belay (2011) as uncertainty range for all the sectors parametrised in the model.

Finally, the public funding for private R&D in the sector and the government funding for public R&D showed different values on a sector-to-sector basis, and even firm to firm basis (Redon-Sarrazy & Paoli-Gagin, 2022). The OPEN DATA MENESR (MESR, 2025) show stable values over the years, with a general variation of 18% depending on the sector, which I then used to define a 20% uncertainty range for this parameter.

3. Deep-Level Parameter Uncertainties

Finally, on the level of deep uncertainty, the percentage of SMEs collaborating with each other, the public-private collaboration per million population, the percentage of workforce wanting to go to R&D and the percentage of R&D budget on total budget per sector are not directly obtainable from database sources, have been described in more parse literature in which the measurement method remains subjective or esoteric (European Commission, 2023, Manos et al. 2023).

The percentage of SMEs collaborating with each other might have an uncertainty around 20% due to sectoral and regional variability. This parameter experiences sectoral dependence given that collaboration rates vary by industry. For instance, technology-centred SMEs were found to collaborate more than traditional manufacturing with a 20% difference (Audretsch et al. 2023). Beyond sectors, collaboration is also skewed between firms. The OECD (2025) highlights that only 15–25% of SMEs engage in formal partnerships, with lower rates in developing economies while programs like EU's Horizon Europe aimed at boosting collaboration witness uneven uptake between firms (European Parliament, 2025).
Public-private co-publication rates experience uncertainty due to sectoral variability, data reporting inconsistencies, and policy volatility. Co-publication rates may vary significantly by sector and country due to the different environment and policies. For instance, public-private partnership projects in health and infrastructure often involve more co-publications due to long-term R&D commitments, whereas short-term collaborations yield fewer publications (Cruz & Marquez, 2013). Additionally, some regions might show more informal collaborations which may go underreported, skewing per-capita metrics. Shifts in societal needs, demographics, fluctuations in interest rates, inflation, or funding availability, amendments in laws, political changes, organisational changes, project boundaries, negotiations, environmental shifts impacting infrastructure resilience or sustainability goals, emergence of new technologies or obsolescence of existing ones and engineering challenges are all factors contributing to public-private co-publication uncertainties (Demirel, 2022, Koppenjan & Klijn, 2004). These uncertainties are not easily quantifiable, which distinguishes them from traditional risks. Thus, I set the uncertainty range to 20% around its baseline, in line with the other parameters.

Like for the sector attrition rate, the percentage of workforce wanting to move to R&D shows uncertainty due to labour market volatility and macroeconomic conditions (Cotofan et al. 2023). Economic downturns lead to groups of employees who prioritize earnings more highly, while periods of economic growth result in these groups valuing the significance of their work throughout their careers. This factor is therefore also varied within a 20% change of its base value.

Finally, the percentage of R&D budget on total budget per sector experienced changes across industries due to policy shocks' reduction of R&D intensity in policy-sensitive sectors (Nguyen & Kim, 2023). Additionally, firms sometimes underinvest due to appropriation risks. On the other hand, the rise of global competition is pressuring other nations to fluctuate budgets based on the global trends, inducing differences in the percentage of R&D budget not captured by the model (Andes & Correa, 2017). These fluctuations are embodied by a 20% change around the baseline value. No parameter has been identified as recognised ignorance. This can be considered a strong point of the model as all parameters present in the model are somewhat anchored to reality and measurable or being reported in literature and proxied.

Table 5: Uncertain parameters in the system model.

Variable	Uncertainty Level	Ranges
Initial Added Value in Sector	Shallow	+/- 20%
Initial Employed R&D Workforce in Sector	Shallow	+/- 20%
Initial knowledge specialisation in Sector	Shallow	+/- 20%
Initial Population	Shallow	+/- 20%
Percentage of profit from revenue in Sector	Medium	+/- 20%
Relative share women in fertile age	Shallow	+/- 20%
Percentage of innovative SMEs collaborating with others	Deep	+/- 20%
Percentage of adults enrolling in studies	Shallow	+/- 20%
Knowledge obsolescence time	Medium	+/- 20%
External investments	Shallow	+/- 20%
Average Time to Market in Sector	Medium	+/- 20%
Hiring and training time of employees	Shallow	+/- 20%
Attrition rate in sector	Shallow	+/- 20%
Public-private collaboration per million population	Deep	+/- 20%
Public Funding for Private R&D in Sector	Medium	+/- 20%
Percentage of workforce wanting to go to R&D	Deep	+/- 20%
Percentage of R&D budget on total budget in Sector	Deep	+/- 20%
Government funding for public R&D in sector	Medium	+/- 20%

3.13 Parameter Sweep Results

The parameter sweep results have been plotted over a time span of 20 years and have been grouped according to their final knowledge size. The python codes for the parameter sweep has been uploaded in the GitHub repository under the "Parameter Sweep" folder (Melli, 2025). Each coloured curves in Figure 25 and Figure 26 represent behaviours that are the Specifically associated with one sector. Figure 25 showcases the results for all the sectors in MAR region Bretagne and Figure 26 the results for all sectors present in Jacobs region Ile-de-France.

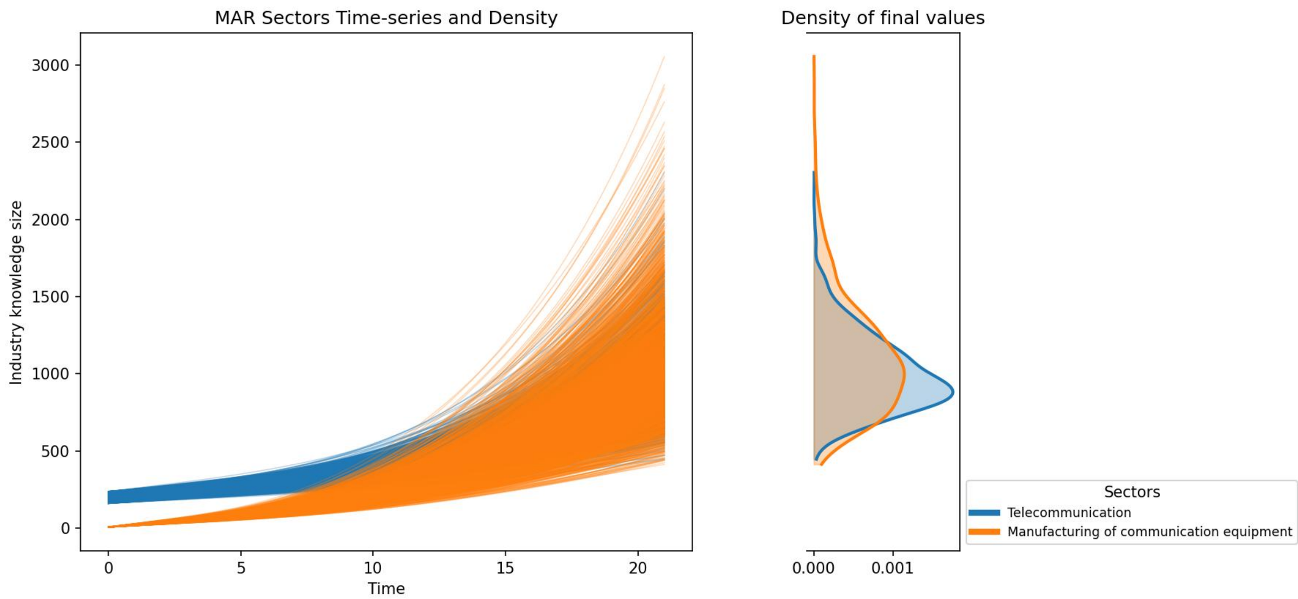

Figure 25: Parameter Sweep run results per sector in MAR region varying uncertainty parameters.

Comparing Figure 25 to Figure 26, uncertainties in the MAR region seem to have a lower variation in the dynamics of the runs than in Jacobs region. This being said, the number of uncertainties varied is also overall lower, even though the same parameters are explored. This is due to the number of sectors in a Jacobs region that experience uncertainty on the same parameter. For instance, while a MAR region only has one inflow of students that can go to both sectors, a Jacobs region has multiple inflows of students able to go to a variety of sectors in the region. As such, the uncertainty levels tested for student enrolment in a study has to be applied to all different studies that can lead to employed in the prominent technological sectors in the region.

In addition, the density plot in Figure 25 shows a bell-shaped curve over a similar y-axis interval for both blue and orange curves. Thus, the distribution of output densities is aligned over both sectors. This resonates with the results from the extreme value test, that showed the same behavioural distribution. The model shows the same dependency and interconnection of both sectors as influential over the results of the parameter sweep. That connection is not entirely similar and not immediate as the percentage of collaboration between both industries remains between 42% and 64%. The average time to market between 4 and 6 years also phases out both distributions as the telecommunication sector is not benefitting from the similar knowledge generated by the manufacturing of communication equipment sector from time 15 as much as the manufacturing of communication equipment sector is benefiting from the higher knowledge size of the telecommunication sector from time 0. However, the wide range of outcome distributions on the upper side of the density plot for both graphs shows potential for increased performance if more alignment was possible between both sectors. The model once again puts forward the reliance of both sector on each other for growth.

Comparing Figure 26 of the Jacobs model outcomes to Figure 25 of the MAR model outcomes, the interesting notice is that uncertainty of the system's parameters in a Jacobs region can lead to a more distributed density of results and a wider possibility of positive results than in a MAR region. The distribution of runs that lead to a higher knowledge size in Jacobs sectors is larger than runs that lead to a lower knowledge size, represented by the width of the density graph for the green, brown and red curves. This difference is minor in a MAR region. This would mean that while MAR regions are less sensitive to the uncertainty in parameters in the region, Jacobs regions have more possibility of growth from those uncertainties than MAR regions, still showing robustness towards growth decline. The difference is less marked than for a MAR region, supporting the idea mentioned previously that MAR regions show overall less variability in knowledge size from uncertainty while Jacobs regions can leverage those uncertainties to build a higher knowledge growth. The density of the low knowledge generation sectors in Jacobs regional model remains the highest between all sectors, showing less possibility for growth therefore reinforcing the previous statement.

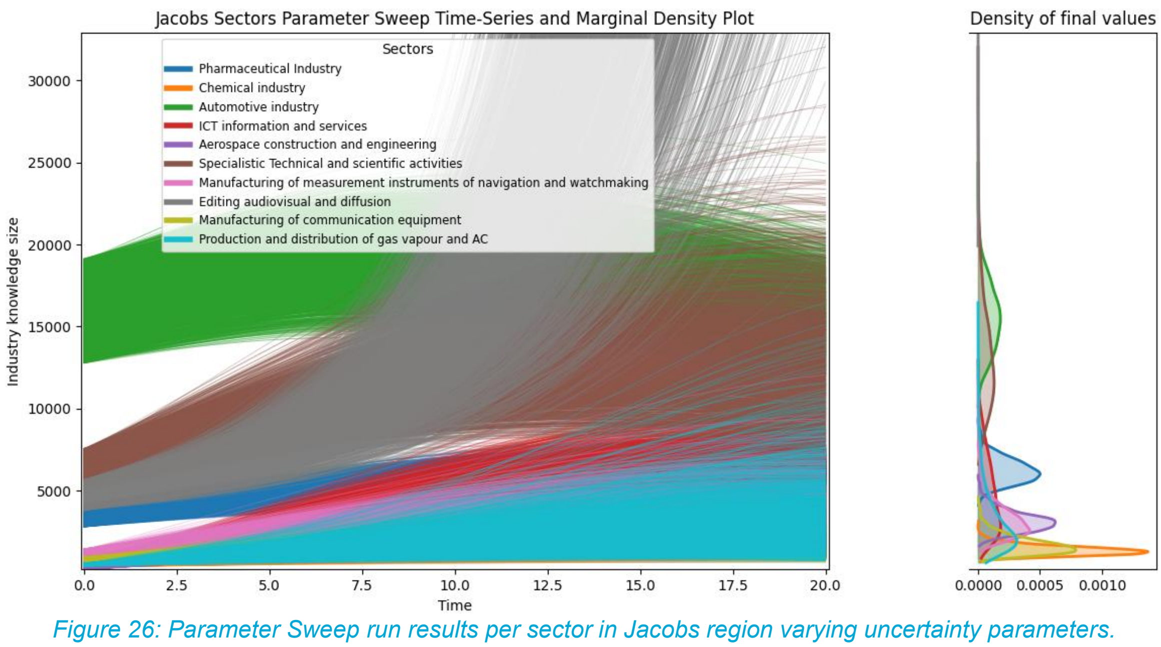

Figure 26: Parameter Sweep run results per sector in Jacobs region varying uncertainty parameters.

Within the Jacobs model itself, I clustered sectors based on their final outcome distribution to allow for a better comparison of their behaviour. Figure 26 shows sectors having very low and wide density distribution, represented by the brown, red and green marginal densities. These correspond to the Automotive industry, ICT information and services and the Specialistic Technical and scientific activities sectors. These sectors show a similar behaviour in their model outcome and have therefore been grouped together as subset 1 in Figure 28.

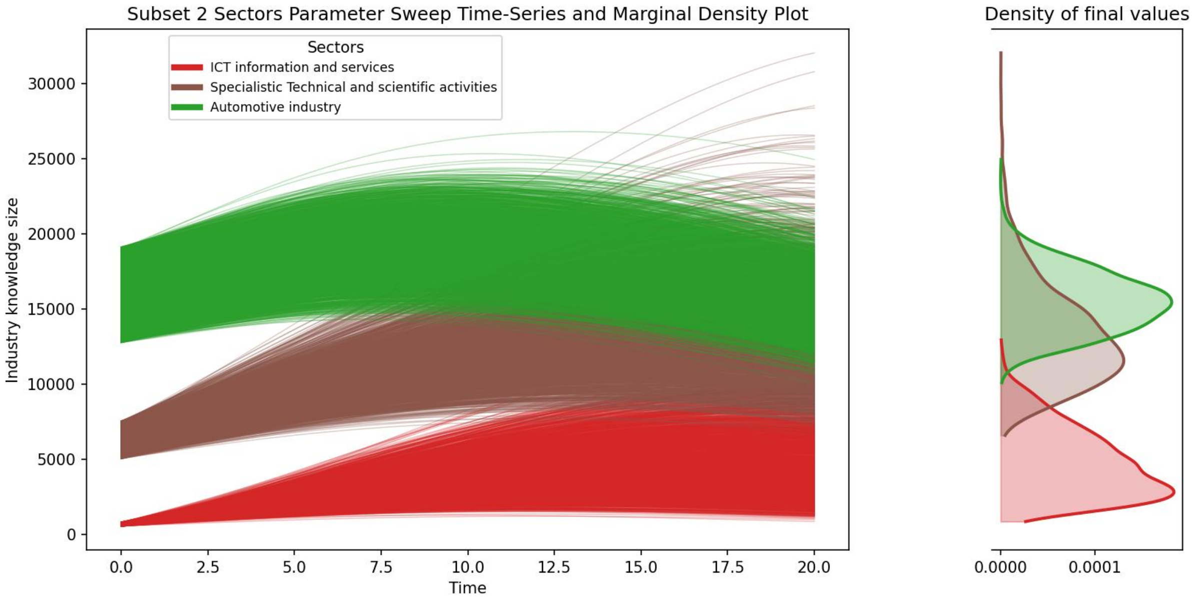

Figure 27: Parameter Sweep run results for subset 1 in Jacobs region varying uncertainty parameters.

The blue, purple and pink curves show peaks that are either around the same y-axis value or have the same density and have therefore been grouped together in Figure 28. These correspond to the Pharmaceutical Industry, Aerospace construction and engineering and Manufacturing of measurement instruments of navigation and watchmaking.

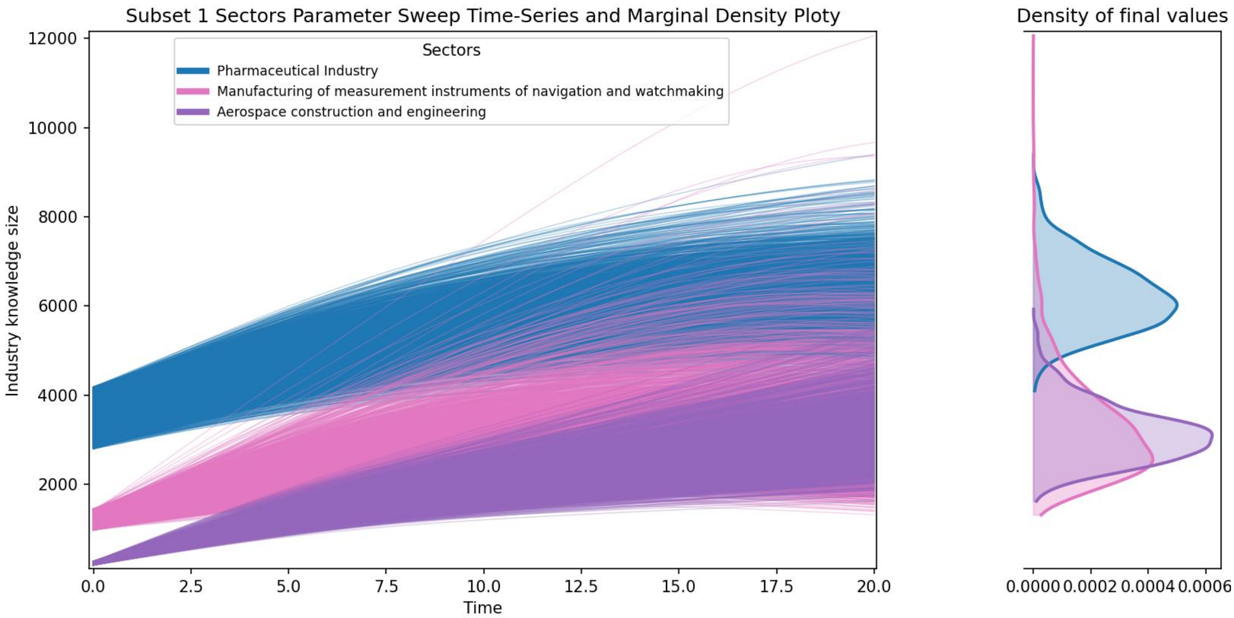

Figure 28: Parameter Sweep run results for subset 2 in Jacobs region varying uncertainty parameters. Subset 2: Pharmaceutical Industry, Aerospace construction and engineering and Manufacturing of measurement instruments of navigation and watchmaking.

The orange, yellow and cyan curves show a density peak around the same y-axis value and have therefore been grouped together in subset 3 Figure 29. Nonetheless, the cyan curve also has a wider distribution of outcomes that the blue, purple, yellow and orange curve, meaning that it could be placed with the sectors in subset 1 if we consider its breadth instead of its peak. The sectors in subset 3 are Manufacturing of communication equipment sectors, Chemical industry and Production and distribution of gas vapour and AC sector.

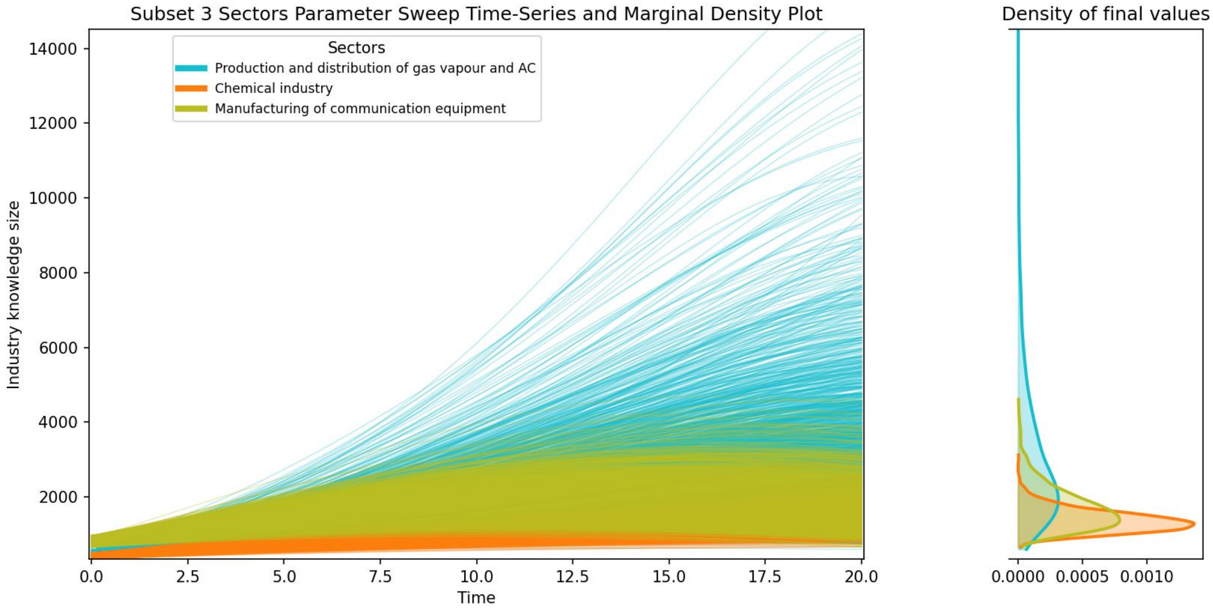

Figure 29: Parameter Sweep run results for subset 3 in Jacobs region varying uncertainty parameters. Subset 3: Manufacturing of communication equipment sectors, Chemical industry and Production and distribution of gas vapour and AC sector.

Finally, the grey curve has the lowest density peak but the widest density outcomes and is separately plotted in Figure 30. It represents the Editing audiovisual and diffusion sector, market as subset 4.

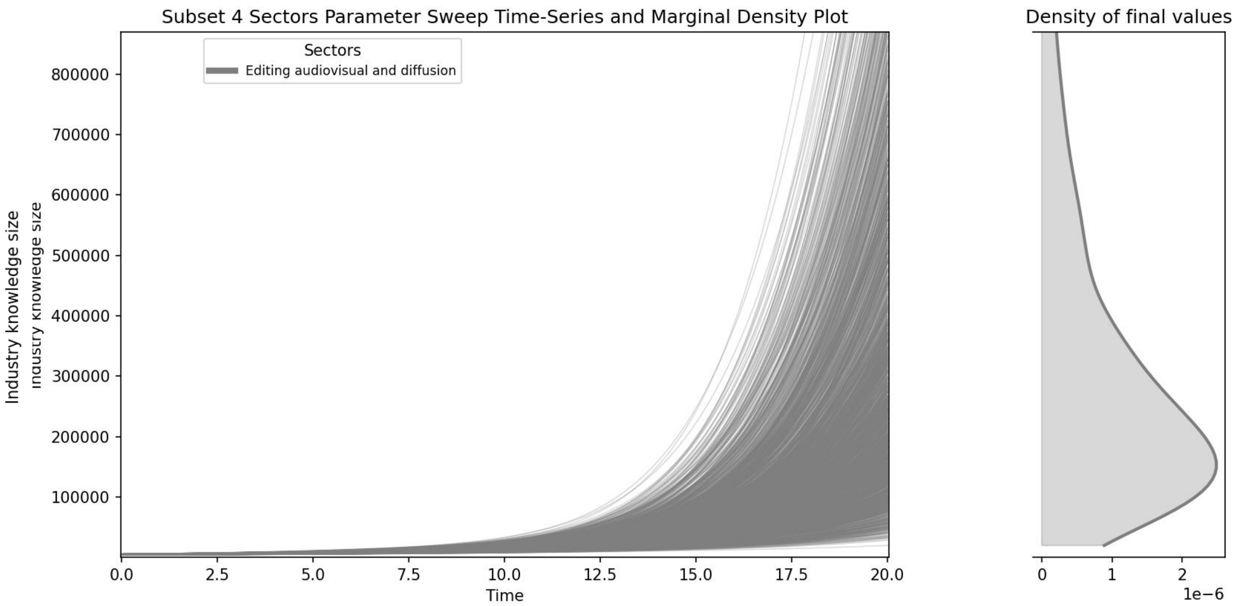

Figure 30: Parameter Sweep run results for subset 4 in Jacobs region varying uncertainty parameters. Subset 4: Editing audiovisual and diffusion.

The grey curves in Figure 30 show possibilities of very high growth but equally chances of low staggering outcomes. The prominence of the sector in subset 4 over the rest of the sectors follows from the results first noted in the extreme value test. This sector has the lowest average time to market, between 1.6 and 2.4 years. It also has the highest attrition rate, varying between 0.19 to 0.29. This results in a workforce with a high turnover rate that is still able to produce a lot of knowledge in a short amount of time. Given the model parametrisation, this sector is able to benefit from knowledge spillover that boosts its initial knowledge size. With short average time to market compared to knowledge obsolescence and high employee turnover rate, it increases the knowledge generation per researcher function $g(t) = \frac{p(t-1)}{w(t)}$, leading a very high knowledge size if the knowledge spillover is high. The fact that the outcomes of the industry knowledge size do not necessarily increase exponentially indicate that there are scenarios for this sector in which its growth is staggering. This indicates that the sector benefits from uncertainty parameters influencing the outcome of other sectors. Hence, while dependant from its own initial parametrisation, the sector in subset 4 would benefit from performance in other sectors due to the value of their knowledge spillover to provide an initial boost.

The second widest density distributions pertain to subset 1 observed in Figure 27. The sectors in this subset have the highest initial R&D workforce and amongst the highest initial added values between the sector in the Jacobs model as shown by Table 6 and Table 7. This implies that the capacity for knowledge generation in those sectors is the highest given that there are a lot of workers able to produce knowledge that can then be sold for high return. Hence, the knowledge the workforce generates has a high commercial value.

Table 6: Initial Employed R&D Workforce per Sector sorted by most important to least important

Sector	**Initial R&D Workforce**
ICT information and services	11580.59961
Automotive industry	10162
Specialistic Technical and scientific activities	6352.72998
Manufacturing of measurement instruments of navigation and watchmaking	5728
Editing audiovisual and diffusion	5250
Manufacturing of communication equipment	4973
Pharmaceutical Industry	4880.52002
Aerospace construction and engineering	4646
Chemical industry	2143.429932
Production and distribution of gas vapour and AC	2005

Another remark is that the curves from the automotive sector are the only ones showing a distinct inverted-U shape. This means that even though there is an initial increase in the knowledge size of the sector, starting from around year 10, the knowledge starts decreasing, implying that its generation is lower than its expiry. Conceptually, because of the long time to market before the knowledge generated can conceptualise itself into a product, the returns from the R&D expenditure in that sector take longer than in the remaining two, meaning that less revenue is generated with respect to the high workforce employed. Given this lack of returns in the simulation run, the sector is unable to hire new workforce. As R&D workforce constantly leaves and no new recruits are incorporated and knowledge is generated more slowly that the attrition rate in the sector, the knowledge generation function decreases. Finally, this amplifies the effect of an already decreasing workforce, leading to continuously less knowledge in the sector. What can be understood from this example is the presence of a saturation mechanism. If a sector has a large workforce and a lot of knowledge that takes time to produce, its capacity for increased innovation decreases.

Table 7: Initial Added Value per Sector sorted by most important to least important

Sector	**Initial Added Value**
ICT information and services	21080000512
Automotive industry	10880000000
Production and distribution of gas vapour and AC	5500000256
Editing audiovisual and diffusion	4300000256
Chemical industry	3400000000
Pharmaceutical Industry	2600000000
Specialistic Technical and scientific activities	2600000000

Manufacturing of measurement instruments of navigation and watchmaking	2000000000
Manufacturing of communication equipment	1400000000
Aerospace construction and engineering	1400000000

Additionally, the sectors in Figure 27 are distributed over the graph according to their initial knowledge size. As shown by Table 8, the automotive industry has the highest initial knowledge size amongst the parameters, followed by the specialistic technical and scientific activities. While ICT information services sector is in the lower half of the classification, it still has a high likelihood of increasing the knowledge over the span of 20 years of simulation given the high workforce and high added value. What the model then represents if that even though the knowledge generation per researcher is initially low, given the high number of researchers but the low number of patents, the patents they produce are very valuable and allow the sector to offset the cost of all those researchers and hire more R&D personnel as the returns from very valuable knowledge in that sector increases.

The previous statements can be reinforced when looking at the Production and distribution of gas vapour and AC sector represented by the cyan curve in Figure 29. The wide density distribution shows that this sector has potential for increased performance if these outputs were to be changed, but its low-density peak shows that most of the simulation outcomes do not diverge significantly from a value of around 2000. This sector has one of the highest initial added values but a very low initial R&D workforce and initial knowledge size in comparison. On top of that, it also has one of the lowest percentages of R&D budget on total budget (7.6%) along with the ICT sector and the highest percentage of profit from revenues, 79%, while other sectors have it from 27 to 47%. When comparing it to the ICT sector, the biggest differences of the production and distribution of gas vapour and AC is the higher percentage of profit from revenues, the lower initial R&D workforce, and lower relatedness scores. High percentage of profit from revenues implies less R&D expenditure, which then leads to less workers being hired. Since both workers leave and knowledge expires, the knowledge generated in the sector decreases.

Table 8: Initial Knowledge Size per Sector sorted by most important to least important

Sector	**Initial Knowledge Size**
Automotive industry	15951
Specialistic Technical and scientific activities	6310
Editing audiovisual and diffusion	4730
Pharmaceutical Industry	3490
Manufacturing of measurement instruments of navigation and watchmaking	1210
Manufacturing of communication equipment	811
ICT information and services	710
Production and distribution of gas vapour and AC	491
Chemical industry	430
Aerospace construction and engineering	230

Additionally, with the low relatedness score, the sector is not likely to have significant knowledge spillovers from other sectors, leading to the low spike in knowledge outcome density. However, production and distribution of gas vapour and AC is strongly related to a sector which has a high knowledge size, the specialistic technical and scientific activities. Hence, if a significant knowledge spillover was to occur, the knowledge size of the sector would increase for low workers, which would lead to a higher knowledge generation per worker, therefore an increasing knowledge size. In addition, with the high initial added value and low initial knowledge size, the commercial value of knowledge is very high, leading to a higher profit, therefore a higher R&D expenditure despite the low ration of R&D expenditure to profit. This would explain the possibility for high knowledge generation, and the increasing cyan curves seen in Figure 29.

Finally, considering the lower curves of Figure 27 and Figure 29, I can make a similar statement. The lower yellow and orange curves represent the chemical industry and manufacturing of communication equipment sector. From Table 6, Table 7 and Table 8, these sectors have a lower initial R&D workforce, lower initial added values and low initial knowledge size than most sectors, complemented by weak connections with strong regional sectors in the model. Their knowledge generation function is therefore lower than other sectors and so are the returns from their knowledge generation. Given their weak connections, they are not able to gain considerable knowledge from knowledge spillover to be able to experience a growth such as the one in the production and distribution of gas vapour and AC.

The variations shown by model outputs subject to uncertainty levels affirms that MAR model outcomes are more dependent on the neighbouring sectors for performance while Jacobs outcomes are more dependent on their initial values, with the collaboration with the other sectors being of added value for their own innovation generation. Trade-offs between cluster crowdedness and innovation performance varied based on sector characteristics.

3.13.1 Key Analytical Insights

Based on the results from the parameter sweep analysis, there are several main findings that explain how uncertainty affects MAR and Jacobs regional models differently.

The core comparative finding between both regions laid in their sector's interdependence. The two regional models show fundamentally different responses to uncertainty. MAR Regions are highly interdependent and stable. The sectors show very similar output distributions, indicating that they rise and fall together. They are less sensitive to uncertainty, resulting in a smaller range of possible outcomes.
Jacobs Regions are composed of more independent sectors that have a much wider range of possible outcomes. They are more sensitive to uncertainty, which can be leveraged for higher growth potential but also carries the risk of stagnation. Their performance depends more on their own initial conditions, with the potential for a "boost" from neighbours.

The analysis of the automotive sector revealed a critical dynamic corresponding to a saturation mechanism. The combination of a large initial workforce and a long average time to market creates an inverted-U shaped growth curve where growth is quickly followed by decline. The key finding is that if R&D returns are too slow to materialise, the sector cannot afford to replace its leaving workforce, leading to an eventual decline in knowledge generation. This highlights the risk that large, slow-moving sectors can innovate themselves into a decline.

A recurring theme, especially in the Jacobs model, is the powerful role of knowledge spillovers in triggering explosive growth. The results show that sectors with weak internal conditions such as low R&D workforce or low capital can still achieve very high performance if they meet two criteria. They have a strong connection to a high-knowledge sector or a "broker" sector or if they have a high initial added value, making any new knowledge commercially potent. This shows that strategic network position can be more important than initial internal capacity for certain sectors.

Finally, the analysis revealed that there is no single path to success. Instead, different sectors follow distinct behavioural archetypes based on their unique combination of parameters. Sectors is subset 1 such as the Automotive or ICT start with high workforce and high added value, giving them strong internal capacity for growth. Sectors is subset 2 and some sectors in subset 3 such as the chemical have a combination of low internal capacity and weak external connections, resulting in consistently low growth. Sectors in subset 4 such as the editing have a very short time-to-market, allowing them to rapidly capitalize on knowledge spillovers and achieve explosive growth. Lastly, sectors such as the gas production and distribution in subset 3 have low internal capacity but high potential if they receive the right knowledge spillover from a key neighbour.

4 Model Tests for Robust Decision-Making

4.1 Global Sensitivity Analysis

Once the verification and validation of the model are completed, to gain a deeper insight into the dynamics and emergent patterns present in real-world systems represented by System Dynamics I first identified which input most strongly drives the system's knowledge generation and innovation dynamics. I conducted a sensitivity analysis on the Île-de-France and Bretagne base parametrisation. Hence, the experimental set-up took the parameters collected for the replicative validation test in their final year 2021 and used those for the experimental set-up. I did this given that 2021 data assured more completeness than 2001 datasets. I completed this analysis with the Salib library in Python (Herman & Usher, 2017). Due to the intricate nature of many SD models, grasping the model dynamics is often a complex endeavour. Sensitivity analysis can assist in this regard, as the impact of parameter modifications on model outcomes provides insights into the underlying model dynamics associated with these results (Ligmann-Zielinska et al. 2014). For instance, determining whether these impacts are linear, non-linear, or induce a significant shift in the system by reaching a tipping point offers critical information regarding how a parameter influences the system's dynamics.

Another reason for conducting sensitivity analysis is to assess the robustness of model outcomes in relation to variations in parameter values (Leamer, 1985, 2010; Axtell, 1999). A spectrum of model parameter values corresponds to a variety of assumptions that lead to specific inferences (i.e., model outcomes). For these inferences to be deemed credible, they must not rely on a limited and uncertain set of assumptions. Thus, it is vital to demonstrate that the inferences remain robust despite changes in parameters. This is especially pertinent when the model seeks to elucidate a phenomenon that manifests across a broad range of real-world circumstances. For example, the renowned Schelling model (Schelling, 1971) investigates the emergence of patterns of ethnic segregation. The model illustrates that segregation patterns arise from a few fundamental assumptions regarding the movement of agents within a spatial context. Moreover, this emergence is resilient to alterations in the parameter values and the movement rules governing the agents (Gilbert, 2002). This robustness enhances the model's credibility, particularly given the observation that segregation occurs in diverse locations and under varying conditions in reality. The results from this test would therefore allow me to form a parallel with the results from the previous validation and verification steps and assess whether they are cohesive.

Even though I did not pursue this, a third and more conventional application of sensitivity analysis involves quantifying the uncertainty in model outcomes that arises from parameter uncertainties (Hamby, 1994; Saltelli et al., 2004). Numerous sources contribute to the uncertainty of model outcomes. One such source is the uncertainty inherent in the parameter set. For instance, in this research, I assigned values to model parameters based on measurements or expert judgments; however, these values are not without uncertainty. The uncertainty present in the parameter set leads to uncertainty in the model outcomes. Sensitivity analysis serves to quantify this variability in output and breaks it down into components attributed to various parameters. This process enables the user to prioritize input uncertainties according to their impact on output uncertainty.

Numerous methodologies have been established to conduct sensitivity analysis. Saltelli et al. (2004, 2008) and Cariboni et al. (2007) give a comprehensive overview of these methodologies. Among these, one-at-a-time (OAT) is particularly prevalent due to its availability in statistical software packages (Thiele et al. 2014). Even though it is straightforward and simple, researchers view it as inherently flawed for a global sensitivity analysis given the univariate modification of parameters (ten Broeke et al. 2016). The Sobol sensitivity analysis bridges this gap but is very computationally intensive. Given the small model size, I used Sobol testing to assess the functional forms, structural choices, and boundary definitions most strongly influenced model behaviour. Once these were identified, I varied a combination of inputs in different runs with an exploratory scenario analysis to analyse model response to changes in highly sensitive elements. Hence, I treated these as experimental factors, with parameter ranges and pulse functions included in the design of simulation experiments.

I complemented the results of the sensitivity analysis with a scenario test exploring a set of negative and positive scenarios as recommended during the expert validation. I built scenarios based on the European economic outlook presented by the JRC and Mario Draghi's report on competitiveness to the European Commission (European Commission, 2024, Vesnic-Alujevic et al. 2024). I then elaborated on a set of parameters to modify for the scenario test based on the results of the sensitivity analysis. I observed the model runs' behaviour to the parameter changes from the scenarios. For both the scenario testing and the sensitivity analysis, I used the base model with values from 2021 as this is the year with the most complete data. I complemented this base run by varying the value of variables in the scenarios according based on the scenario development. The sensitivity analysis examined each exogenous variable in the model that is not an initial parameter by applying a 20% range of variation to the parameter's value. Although model validation employs data back to 2001 to capture long-run dynamics, many 2001 parameters are unavailable and must be extrapolated from later observations; hence I considered 2001 data unsuitable for sensitivity testing.

4.2 The EMA method for Global Sensitivity Analysis

Subsequent to the parameter sweep, I used the EMA workbench to conduct a dynamic sensitivity analysis to evaluate multi-variate impact of a set of input parameters on the targeted metrics of performance.
Despite the many methodologies for sensitivity analysis, two appeared as conventional possibilities; Sensitivity2All or Sobol. Nonetheless these conventional sensitivity analysis methods showcase a set of drawbacks.

Sensitivity2All is tool provided by Ventana in their Vensim software. It uses a one-at-a-time (OAT) structure which is particularly prevalent due to its availability in statistical software packages (Thiele et al. 2014). Its popularity stems from its straightforward application, requiring minimal statistical and computational resources. However, it oversimplifies the complexity of the system in its analysis (Saltelli, et al: 2019).

On the opposite hand, Sobol offers a better global design but necessitate numerous model executions to conduct a comprehensive global sensitivity analysis. Given the small model size, I selected Sobol as the method to use for the sensitivity analysis. Selecting this more advanced sensitivity analysis technique ensured model appropriateness and robustness in results (Saltelli et al. 2019). I plotted the results in bar graphs with confidence intervals, to visually depict the individual influences of input variables on the interest outcome variables.

4.2.1 Sobol Sensitivity Analysis with the EMA Workbench

Variance-based global sensitivity analysis, as formulated by Sobol (2001) and Saltelli (2002), is widely recognised as a leading method in the field. It can be applied in both factor-prioritisation and factor-fixing frameworks to quantify how much each uncertain input contributes to the overall variance of the model's outputs. In a typical Sobol implementation, first-order indices that measure each factor's individual share of output variance, alongside total-order indices that capture both that individual effect and all higher-order interactions involving the factor are computed.

These Sobol metrics fulfil nearly all desirable GSA properties except moment independence. Since they use variance to represent uncertainty; this reliance can lead to misleading results when outputs have multimodal or highly skewed distributions (Pianosi and Wagener, 2015). Because Sobol indices are mathematically rigorous and relatively straightforward to calculate, they have seen growing adoption in disciplines such as hydrology and integrated assessment modelling (Tang et al., 2007; Pappenberger et al., 2008; Nossent et al., 2011; Herman et al., 2013; Butler et al., 2014).

A key drawback is that the required number of model evaluations, N, increases linearly with the number of uncertain parameters, p, following N = n (p + 2) for calculating both first-order, second-order and total-order indices, where n is the baseline sample size. As a result, variance-based GSA can become impractical for models with long runtimes, or a large parameter set.

This analysis has been performed over a set of levers. While the uncertainty domain is structured around the defined uncertainties, the decision domain is shaped by the applied levers. These have been defined to be all the exogenous variables of the model. The output ascertained the highest scoring indices for the levers. The analysis was done to try to optimise the internal knowledge size. The reasoning behind this choice is that knowledge size links to a region's innovation performance. Therefore, the goal of the sensitivity was to understand which are the most significant factor for the increase internal knowledge generation.

Table 9: Sobol Sensitivity Analysis Levers

Variable	Maximum Theoretical Lower Boundary	Maximum Theoretical Upper Boundary
Attrition rate in sector	0	1
Average mortality per age	0	1
External investments	0	Infinite
Government funding for public R&D in sector	0	Infinite
Hiring and training time of employees	0	Infinite
Percentage of innovative SMEs collaborating with others	0	1
Percentage of profit from revenue in Sector	0	1
Percentage of R&D budget on total budget in Sector	0	1
Percentage of workforce wanting to go the private sector	0	1
Percentage of workforce wanting to go to R&D	0	1
Public Funding for Private R&D in Sector	0	1
Public R&D expenditure per personnel	0	Infinite
Public-private collaboration per academic	0	Infinite
Relatedness	0	1
Relative share women in fertile age	0	1
Percentage of adults enrolling in studies	0	1

The Sobol Sensitivity Analysis aimed to test the model's sensitivity to a set of levers defined in the system. The sensitivity results can then support robust research-informed decision-making (Kwakkel, 2017). The levers are set to be the exogenous auxiliary variables of the system varied with a 20% range within the boundaries of their realistic values then ranked by their total Sobol score in a descending way. For instance, this means that a relatedness of 1 would not be increased to 1.2 given the realistic upper limit being kept at 1. This is represented by Table 9. This lever specification has been done for every sector, ensuring that subscripted variables where considered. It resulted in 215 different levers. The levers have been numbered from 1 until the total number of levers according to the mapping shown in Table 29 for the indices in the MAR region model and Table 28 for the indices in the Jacobs regional model. This mapping was done to improve the graphical readability of outputs.

The methodology from Miu, Jaxa-Rozen and Kwakkel (2018) and Liu & Liu (2023) has been adopted to create a Boltzmann machine-type of network graph given in Figure 31. The size of the circles represents the number of normalised total Sobol indices (ST), and the colour of the circle represents the number of normalise first-order Sobol indices (S1). The connecting lines' width is representative of second-order Sobol indices (S2). The codes of the Sobol analysis and the plotting of the results have been uploaded in my thesis' GitHub repository under the folder named "Sobol Analysis" (Melli, 2025).

4.3 Sensitivity Analysis Results

4.3.1 MAR Region Sensitivity Results

The Sobol sensitivity analysis of the MAR regional model reveals a very accentuated total influence for the same 10 levers for both sectors, ranked in Figure 32. Both the manufacturing of communication equipment sector and the telecommunication sector experience the largest total effect from a variation of the percentage of innovative SMEs collaborating with others (Lever 25, ST= 0.5 and ST= 0.51). Subsequently, the manufacturing of communication equipment sector in the MAR region undergoes a higher influence for a reduced time to market in its sector (Lever 11, ST= 0.19), followed by knowledge obsolescence time (Lever 23, ST=0.11).

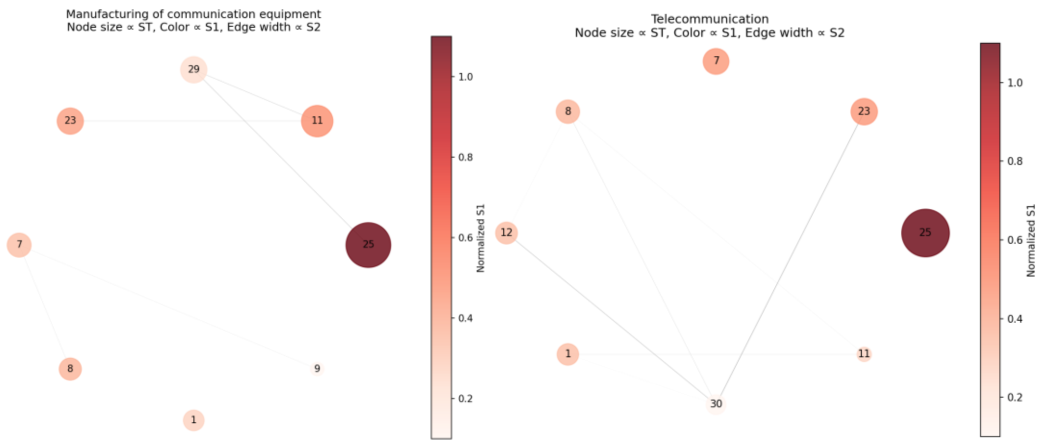

Figure 31: Network graph of top eight Sobol scores for Bretagne MAR region sectors.

The opposite result appears for the telecommunication sector, for which the second highest influence is exerted by the knowledge obsolescence time (Lever 23, ST=0.11), then the public-private collaboration per academic (Lever 8, ST=0.074). In the telecommunication sector, levers 25 and 7 do not have strong pairwise interactions, indicating that most of their influence comes from a 1st order interaction with the model output. This is represented differently for the manufacturing of communication equipment sector for which every lever has a significant S2 value but lever 1, which mainly influences the model through a first order interaction. Hence, for the manufacturing of communication equipment sector, the effect of lever 25 also comes from its pairwise interactions.

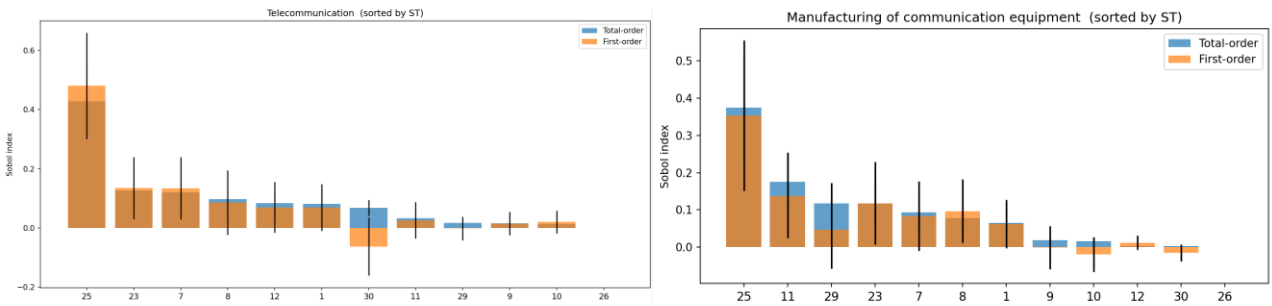

Figure 32: Total Sobol scores per sector in MAR region ranked from highest to lowest. The blue bar represents ST scores and the orange bar represents S1 scores.

The model's behaviour seems driven by Lever 25 (percentage of innovative SMEs collaborating), which accounts for roughly half of output variability in both sectors (ST ≈ 0.50). This tells us that collaborative innovation among SMEs is the single most critical driver in the MAR regional model. Additionally, the manufacturing of communication equipment sector and telecommunication follow divergent second-rank drivers. In the manufacturing of communication equipment sector, shortening time-to-market (Lever 11) has nearly a fifth of total influence (ST = 0.19). In telecommunications, knowledge obsolescence time (Lever 23) takes the runner-up spot (ST = 0.11).

For the manufacturing of communication equipment sector, every top lever shows significant second-order indices (S_2), except Lever 1. Lever 25's impact arises both from its main effect and from pairwise synergies, highlighting a

web of non-linear dependencies among drivers.This pattern signals a highly interconnected response surface where changes in one input often amplify or dampen the effects of another.
However, for the telecommunication sector, Lever 25 and Lever 7 display negligible pairwise interactions. As mentioned earlier, most of their variation is purely of first-order nature. The remaining levers exhibit small S_2 contributions, indicating limited two-way coupling. This sector behaves more linearly, making it easier to interpret and approximate.

Table 10: Mapping of the top 10 levers for each sector from lever to code by ST score

Lever	ST for Manufacturing of communication equipment	ST for Telecommunication	Lever number
Percentage of innovative SMEs collaborating with others	0.5075	0.5159	25
Average Time to Market in Sector[Manufacturing of communication equipment]	0.1927	0.0378	11
Knowledge obsolescence time	0.1134	0.1108	23
Public R&D expenditure per personnel	0.0694	0.0772	7
Public-private collaboration per academic	0.0654	0.074	8
Government funding for public R&D in sector	0.0608	0.0678	1
Attrition rate in sector[Manufacturing of communication equipment]	0.0193	0.0136	9
Attrition rate in sector[Telecommunication]	0.0181	0.0703	10
Average Time to Market in Sector[Telecommunication]	0.0045	0.002334	12
Relative share of women	0.0865	0.00002436	29
Relatedness[Telecommunication,Manufacturing of communication equipment]	0.0023	0.0546	30

These results are reflected in the heatmap in the MAR region in Figure 33, which shows mild gradients for every lever but lever 25. Parameters with the least influence are reflected by Levers 2 to 6, 13 to 22, 24, 26 to 28 and 31. The remaining parameters are present in the network graph in Figure 31. Not a lot of divergence is observed between the sensitivity result of both sectors, other than for Lever 12 (Average Time to Market in Sector) and 30 (Relatedness between Telecommunication and Manufacturing of communication equipment) for the telecommunication sector.

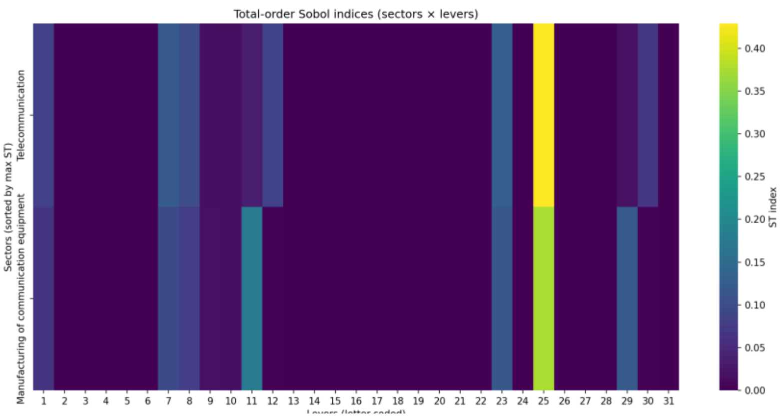

Figure 33: Heatmap of the total Sobol scores per lever per sector in MAR region.

These results would suggest that the manufacturing of communication equipment sector sub-model is richly non-linear, with multiple interacting levers influencing the model. This complexity emphasises the previously mentioned requirement for careful calibration, as small errors in one input can cascade when paired with another. On the other hand, the telecommunications sub-model is more mathematically simplistic, meaning that it could perhaps be simplified without sacrificing much fidelity. These results also urge us to prioritize accurate estimation and uncertainty quantification for Lever 25 across both sectors, since it is a significant driver of at least half the outcome's variance. For the manufacturing of communication equipment sector, paying additional attention to the time-to-market dynamics could also support higher accuracy. On the other hand, in the telecommunication sector, focusing on knowledge decay rates and public-private collaboration metrics could pay-off with the main effect calibration of Lever 25.

4.3.2 Jacobs Region Sensitivity Results

Similarly to Figure 31, a Boltzmann machine-type of network graph has been plotted for each sector in the Jacobs regional model.. Figure 34 shows the results for Manufacturing of measurement instruments of navigation and watchmaking, Editing audiovisual and diffusion, Manufacturing of communication equipment, Production and distribution of gas vapour and AC. The remaining results are added to the Appendix in Figure 48.

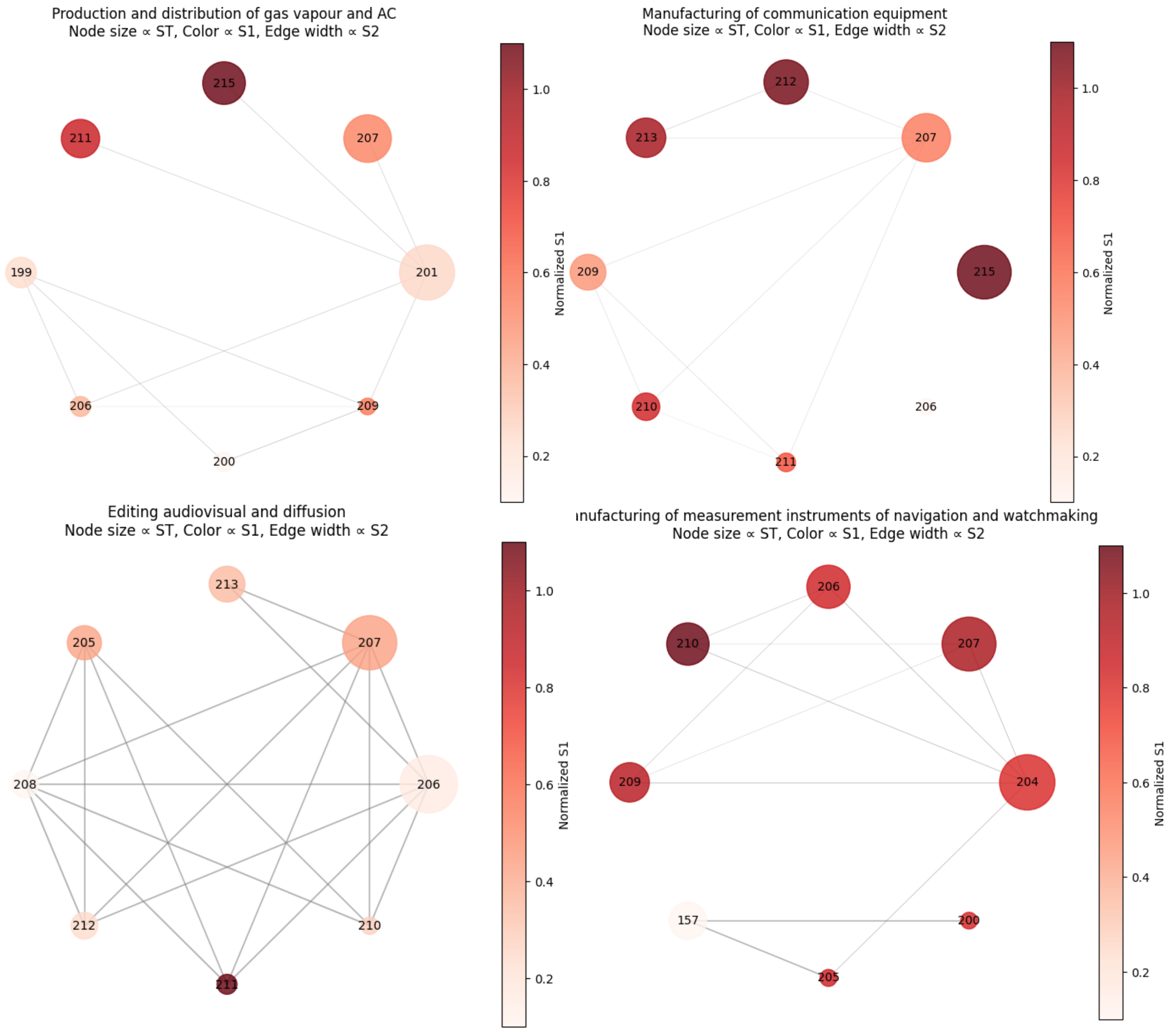

Figure 34: Network graph of top eight Sobol scores for Ile-de-France Jacobs region sectors.

The first point of interest from Figure 34 is the nature of the top scores. All top 8 lever except Lever 215 are relatedness levers, as shown by Table 11. They vary mostly in relatedness variables from the specialistic technical and scientific activities and the production and distribution of gas and vapour AC. The score varies from ST= 1.441 to ST=1.02 depending on the sector and relatedness. These levers have significant S1 scores indicated by the warm node colour, or significant S2 scores, shown by the width of their edges. All the nodes have at least a significant S2 score except Lever 206 in the manufacturing and communication equipment sector, which has a node with no edge. This indicates that no single input acts in isolation. Each lever's impact on the output is inseparable from its pairing with at least one other factor. These pervasive pairwise effects mean the model's response surface is richly non-linear, with synergies or trade-offs emerging whenever two levers move in tandem.

Table 11: Mapping of the top 8 scores from lever to code in Jacobs region. I7: Manufacturing of measurement instruments of navigation and Watchmaking, I8: Editing audiovisual and diffusion, I9: Manufacturing of communication equipment, I10: Production and distribution of gas vapour and AC

Lever	**Lever code**	**ST score I7**	**ST score I8**	**ST score I9**	**ST score I10**
Relative share women in fertile age	215	1.068	1.14	1.422	1.334
Relatedness[Specialistic Technical and scientific activities,Production and distribution of gas vapour and AC]	213	1.060	1.215	1.408	1.322
Relatedness[Specialistic Technical and scientific activities,Pharmaceutical Industry]	212	1.062	1.211	1.412	1.301
Relatedness[Specialistic Technical and scientific activities,Manufacturing of measurement instruments of navigation and watchmaking]	211	1.074	1.208	1.396	1.332
Relatedness[Specialistic Technical and scientific activities,Manufacturing of communication equipment]	210	1.086	1.208	1.400	1.320
Relatedness[Specialistic Technical and scientific activities,ICT information and services]	209	1.084	1.19	1.405	1.325
Relatedness[Specialistic Technical and scientific activities,Editing audiovisual and diffusion]	208	1.076	1.21	1.392	1.303
Relatedness[Specialistic Technical and scientific activities,Chemical industry]	207	1.092	1.22	1.416	1.337
Relatedness[Specialistic Technical and scientific activities,Automotive industry]	206	1.086	1.23	1.395	1.326
Relatedness[Specialistic Technical and scientific activities,Aerospace construction and engineering]	205	1.076	1.21	1.387	1.313
Relatedness[Production and distribution of gas vapour and AC,Specialistic Technical and scientific activities]	204	1.093	1.19	1.395	1.301
Relatedness[Production and distribution of gas vapour and AC,Pharmaceutical Industry]	202	1.065	1.19	1.388	1.317
Relatedness[Production and distribution of gas vapour and AC,Manufacturing of measurement instruments of navigation and watchmaking]	201	1.071	1.205	1.362	1.308
Relatedness[Production and distribution of gas vapour and AC,Manufacturing of communication equipment]	200	1.075	1.206	1.378	1.342
Relatedness[Production and distribution of gas vapour and AC,ICT information and services]	199	1.076	1.114	1.389	1.325
Relatedness[ICT information and services,Chemical industry]	157	1.083	1.02	1.209	1.210

Overall, the sensitivity analysis for Jacobs region follows different patterns based on the sector of interest and per indicator. However, in line with Figure 34, Figure 35 shows a warmer tone for levers 124-215. These levers correspond to the 90 single sector-to-sector relatedness factors in the relatedness matrix after the redundant relatedness between the same sectors has been removed. For all the sectors, these levers are the most decisive, with ST scores varying from 1.61 to 0.9 depending on the sector. For instance, the aerospace sector would majorly benefit from an increase in the relatedness between the production and distribution of gas vapour and AC and specialistic technical and scientific activities (ST= 1.26), while the automotive sector would mainly benefit from an increase in relatedness between aerospace construction and engineering and specialistic technical and scientific activities (ST=1.44).

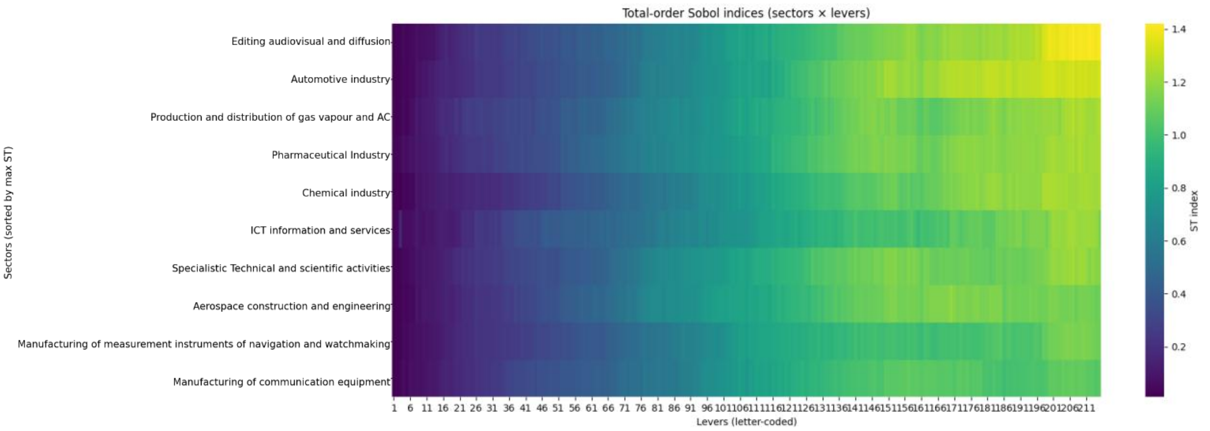

Figure 35: Heatmap of the total Sobol scores per lever per sector in Jacobs region.

Interestingly for the automotive sector, it would benefit from an increase in relatedness within levels 90 to 110 while the other sectors perceive a higher score from increased relatedness in levers 150-170. The chemical industry and specialistic technical and scientific activities have a rather uniform distribution of Sobol scores across all levers, meaning that they would equally benefit from an increase in relatedness in any of the fields.

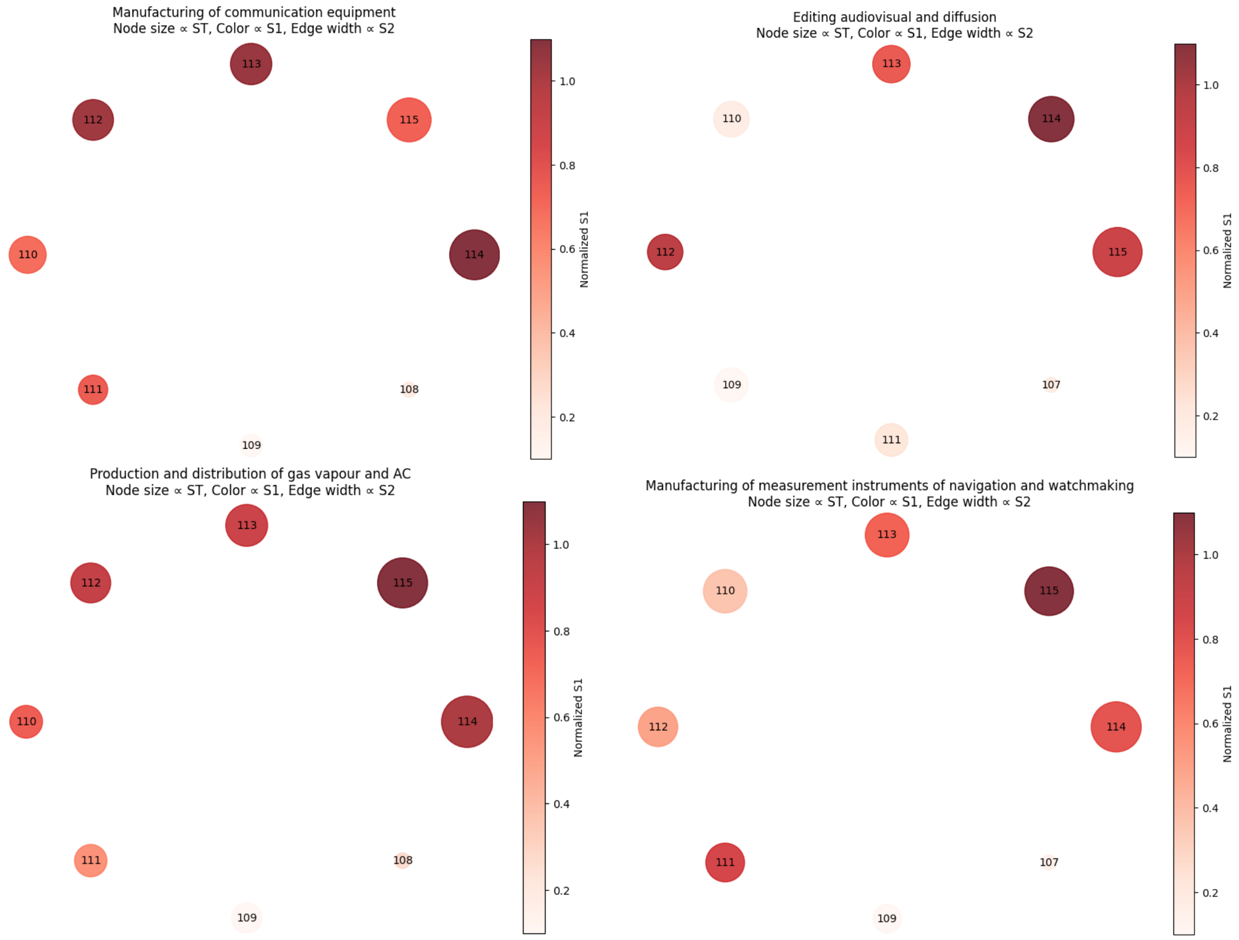

Figure 36: Network graph of top eight Sobol scores for Ile-de-France Jacobs region sectors without relatedness.

The S2 scores being present for most of the influential parameters in every sector of the Jacobs model imply that it is not possible to explain output variance simply by summing each lever's standalone first-order contribution. While the presence of S2 scores rules out a purely additive decomposition, it requires further modelling expertise to ensure that its reflection of model outputs is in line with reality and that the increase in its values is pragmatic. Finally, this result implies that model tuning or policy experiments will always be influenced by the relatedness values and their cross-effects, not just by adjusting one lever at a time.

The relatedness scores are implemented in the model as exogenous variables where an increase in 20% might theoretically not be realistic. They are used as proxies for cognitive proximity between sectors. Given the ignorance of relatedness evolution mechanisms from the model, it is possible to perceive relatedness as a constant parameter which does not evolve over time, therefore which cannot be subject to changes. Given this assumption I evaluated the role of the remaining parameters in the regional innovation system when removing the relatedness levers. The top 8 scores for the same sectors of Figure 34 are given in Figure 36. The remaining sectors are presented in Figure 37.

Table 12: Mapping of the top 8 scores from lever to code in Jacobs region without relatedness. I7: Manufacturing of measurement instruments of navigation and Watchmaking, I8: Editing audiovisual and diffusion, I9: Manufacturing of communication equipment, I10: Production and distribution of gas vapour and AC

Lever	Lever Code	ST Score I7	ST Score I8	ST Score I9	ST Score I10
Relative share women in fertile age	115	0.778	0.841	0.795	0.822
Percentage of workforce wanting to go the private sector	114	0.782	0.834	0.817	0.824
Percentage of profit from revenue in Sector[Specialistic Technical and scientific activities]	113	0.766	0.820	0.786	0.806
Percentage of profit from revenue in Sector[Manufacturing of measurement instruments of navigation and watchmaking]	110	0.765	0.818	0.773	0.792
Percentage of profit from revenue in Sector[Production and distribution of gas vapour and AC]	112	0.756	0.818	0.784	0.803
Percentage of profit from revenue in Sector[Manufacturing of communication equipment]	109	0.737	0.815	0.738	0.789
Percentage of profit from revenue in Sector[Pharmaceutical Industry]	111	0.755	0.814	0.753	0.792
Percentage of profit from revenue in Sector[Editing audiovisual and diffusion]	107	0.722	0.796	0.716	0.747
Percentage of profit from revenue in Sector[ICT information and services]	108	0.721	0.793	0.728	0.775

The highest explainability in the system variation shows similar levers as relevant for each sector. Relative share women in fertile age (Lever 115) is the most significant for the Editing audiovisual and diffusion sector (ST=0.841) while the remaining three sectors show the percentage of workforce wanting to go the private sector as the most relevant (ST= 0.782 for *Manufacturing of measurement instruments of navigation and Watchmaking,* ST= 0.817 for *Manufacturing of communication equipment* and ST= 0.824 for production and distribution of gas vapour and AC). This might indicate a ceiling in the available population that hinders knowledge from increasingly growing. Increasing the share of women in fertile age in society would lead to a bigger population, not only at the working level, but also at the academic level. The more the students and workers available in the system, the larger the capacity to satisfy the human capital need in the sector. The average fertility per woman was not tested in the sensitivity analysis given that it is set as a LOOKUP table which already represents exogenous variations.

The remaining levers of interest represent the percentage of profit from revenue in different sectors, which has a score between 0.721 and 0.820.

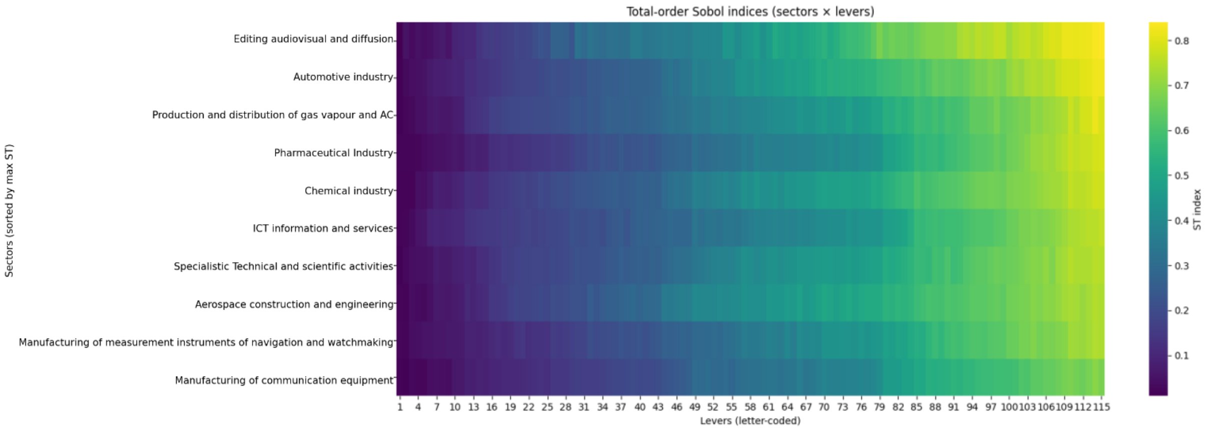

Figure 37: Heatmap of the total Sobol scores per lever per sector in Jacobs region without relatedness.

These results are represented by the heatmap in Figure 37. The warmer colours are from lever 103 to 115 for every sector, while the colder one are from lever 1 to 20. This alignment between sectors allows me to conclude that the most important levers are the same across all sectors even though the order might slightly change from one sector to the next.

A final key point of analysis is the absence of S2 values in the connections. In none of the nodes in Figure 36 is an edge attached, meaning that no node experiences a significant pairwise dynamic. Each lever's total effect on sectoral output variance is driven almost entirely by its first-order, standalone contribution. Output variance is simply dependent of each lever's main effect as there are no hidden two-way trade-offs or amplifications. This finding could result in a simplified calibration and scenario testing with the model. By varying one lever at a time in policy scenarios, its impact will not change when another lever shifts. While cross-effects are negligible, improving the accuracy of each lever's main-effect estimate and its input uncertainty distribution can help render decision-making more robust.

4.3.3 Key Analytical Insights

Based on the Sobol sensitivity analysis, the results revealed distinct sets of key drivers and systemic behaviours for the MAR and Jacobs regional models.

For the MAR regional model, collaboration is paramount. The single most critical driver for both sectors in the MAR model is the "percentage of innovative SMEs collaborating with others." This one lever accounts for approximately 50% of the output variability, making inter-firm collaboration the undeniable core of the MAR system's performance.
While collaboration is the top driver for both sectors, their next most important levers differ, indicating distinct priorities. For the manufacturing sector, the second most important driver is "time to market," emphasizing the need for speed and efficiency in commercialization. For the telecommunication sector, the next most important drivers are "knowledge obsolescence time" and "public-private collaboration," highlighting the importance of knowledge longevity and institutional ties.
Finally, both sectors showcase asymmetric complexity. The two sectors within the MAR model exhibit different internal dynamics. The manufacturing sector is highly non-linear, with its key drivers having significant S2 interaction effects. In contrast, the telecommunication sector behaves much more linearly, with its main drivers acting independently through important first-order scores.

For Jacobs' regional model, relatedness is key. When all factors are considered, the most influential levers by a large margin are the sector-to-sector relatedness scores. These proxies for cognitive proximity create a complex, non-linear web of interactions where no single input acts in isolation. This means the system's performance is fundamentally governed by the synergistic relationships between sectors.
When the complex "relatedness" factors are held constant to see the next layer of influence, a new set of universal drivers emerges. The most important levers across all sectors become demographic and human capital levers such as the "relative share of women in fertile age" or the "percentage of workforce wanting to go to the private sector", or financial levers, mainly the "percentage of profit from revenue". This reveals that once the inter-sector network is set, the fundamental constraint on growth is the talent pipeline and its financial viability.
The Jacobs model shows two distinct faces. It is highly complex and non-linear when considering the interactions between sectors. However, once those inter-sector relationships are fixed, the model becomes simple and linear, with each lever acting independently. This implies the system's complexity arises almost entirely from the inter-sectoral network itself, not from the internal dynamics within each sector.

4.4 Scenario Testing

With the global sensitivity analysis completed, the model behaviour was assessed with a scenario test with key variables. The utility of the latter resides in the possibility to study model response respective to certain parameters

(Wibisono, 2008). For this evaluation, a series of simulations were executed with varying parameters based on their expected impact on the model for each scenario. In the scenario testing, it is interesting to examine whether both MAR and Jacobs models behave in the expected manner based on a set of scenarios. For each scenario, variables of interest were selected and their value described based on the implications of the scenario. These variables were used as testing parameters meaning that during these runs, values from the selected parameters were drawn. Besides the testing parameters, it is necessary to select the variables which would hold an interesting result for the analysis, which is the innovation size of the region, proxied by the number of patents in the industry knowledge size. The variables of interest were then plotted as individual traces comparatively with each other.

To construct the scenarios, I relied on two key documents, Mario Draghi's T*he future of European competitiveness* (2024) and the JRC's *Reference foresight scenarios on the global standing of the European Union in 2040* (2024). The scenarios constructed by the JRC originated from applying the Oxford Scenario Planning Approach (Ramírez & Wilkinson, 2016) and consulting more than 100 experts. Both documents present uncertainties and complement each other for the creation of industrial scenarios. The JRC's document formally introduces 4 scenarios likely affecting Europe in the proximal future, while Draghi's report makes it specifically applicable to the EU industry.

In the "Storms" scenario, the EU faces a fragmented global economy marked by protectionism, disrupted supply chains, and declining investment, leading to stagnation and rising costs due to climate-related disruptions and resource scarcity. Innovation slows as trust and cooperation erode. This has implications for the regional economy such that the aging population is maintaining a position in the workforce with lower attrition rates, the youth is excluded from the job market, not being able to secure a job, the birth rate decrease. Due to the increase in taxes from an aging population, this leads to an economic inflation where the price of knowledge goes up.
Conversely, the "Endgame" scenario envisions rapid technological advancement and digital growth, driven by powerful multinational corporations. While this brings short-term prosperity, it exacerbates social inequality and environmental degradation, threatening long-term stability. Universities are excluded from technological advancement, the funding for public research drastically decreases. This scenario emphasises self-interests as the main drivers of the economy. Uncoordinated firms seek maximum growth, depleting environmental resources and creating a deep mistrust in each other. Collaboration becomes non-existent and the firms thrive solely on their own knowledge.

The "Struggle Synergy" scenario presents a more balanced but fragile path, where moderate growth is achieved through policy-led innovation and a green transition. However, the EU risks falling behind more aggressive global competitors due to slower consensus-driven decision-making. Due to the uncertain and slow decision making, institutional and private funding is sporadic and irregular. Private firm participation in the social economy fluctuates along with their ratio of R&D spendings.

Finally, the "Opposing Views" scenario emphasizes resilience and sustainability over growth, as the EU forms a regenerative economic bloc with like-minded partners. Although innovation continues, it is constrained by ideological divides, and economic stagnation persists due to limited global market access. The EU increases the collaboration and coordination of regions through the institutional players. Universities and public institutes' funding increases as well as the number of qualified personnel wanting to work in the region.

Together, these scenarios highlight the trade-offs between growth, sustainability, and resilience in shaping the EU's economic future. By applying the JRC's scenarios to the industry along competition and coordination axes, I obtain a set of four industry-specific scenarios to be implemented in the modelling for MAR and Jacobs regions. These are presented in Figure with each scenario detailing the shock induced in the model's parameters. Vensim's base model parametrisation was changed based on the scenarios in Figure 38. The parameters listed for each scenario were used for the scenario testing.

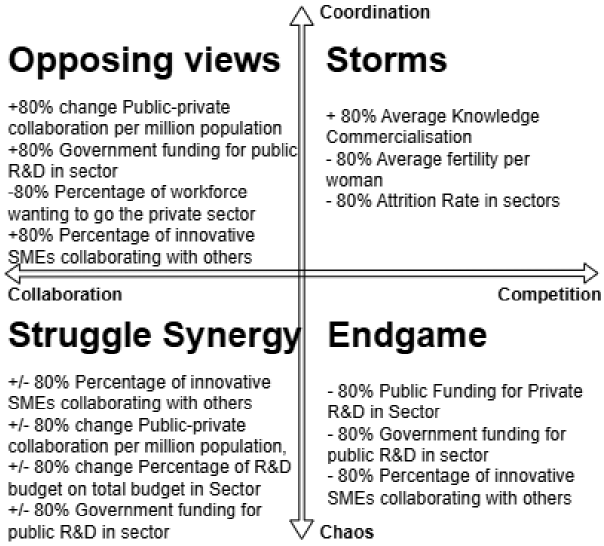

Figure 38: Scenario-based variation of parameters for regional agglomeration model

The Storms scenario represents a 80% increase in the price of knowledge as a result of inflation, an 80% decrease in average fertility and attrition rate in sectors given the protectionist climate of Europe blocking youth integration into society. Based on the results of the sensitivity analysis, the relative ratio of women in society could bring important variance in the model output. Since I did not test the average fertility per woman, this scenario allows to visualise whether it would strongly impact the system when varied and add an additional layer to the results of the sensitivity analysis.

Endgame sees a decrease in collaboration represented by an 80% decrease in public funding for private and public R&D as well as 80% less collaboration amongst industries. This represents a decrease in collaboration both between the private and public sector and withing the private sector. The percentage of innovative SMEs collaborating with others appears as a significant variable from the sensitivity analysis of the MAR region. Hence, this setting represents a negative scenario meant to test whether a decrease a decrease in this variable would impact MAR and Jacobs regions similarly.

The Struggle Synergy scenario enacted constant fluctuations 80% around the base value in the percentage of innovative SMEs collaborating with others, in public-private collaboration per million population, percentage of R&D budget on total budget in sectors and government funding for public R&D in sector to reflect the coordination uncertainty afflicting Europe. This allows to assess whether constant variation in the input parameters of significant and less significant variables affects the model outcome.

Finally, the Opposing Views scenario reflects an internal alignment along complementary axes, enhancing coordination and collaboration of regions. This is reflected by a 80% increase in the public-private collaboration per million population, in government funding for public R&D in sector and in percentage of workforce wanting to go the private sector. These are variables that appeared significant from the sensitivity analysis for both MAR and Jacobs regions.

These parametric changes were implemented at time 10 of the model until time 15 and were added on top of the already existing parameter uncertainties. This allows to understand model endurance to a shock for a time of 5 years and model recovery from the shock for a time of 5 years. The model runs in were done with the EMA workbench as it enables the change in a set of variables to happen contemporarily and facilitates the identification of the assumptions made on the values of the model and the interpretation of the output result. The models capturing each scenario as well as the Python code analysing the results and plotting them have been uploaded in the GitHub repository under the folder “Scenario Tests” (Melli, 2025).

4.5 Scenario Results

The scenario evaluation assists in assessing the model’s behaviour with respect to specific simulation parameters. These parameters have been identified and implemented in each model as shock at time step 10 for the duration of

5 time steps. This has been implemented with the Pulse function in Vensim. In the following sections, the behaviour of the agglomeration externalities models were examined based on the set of scenarios defined in Figure 38.

4.5.1 MAR Region Analysis

In this section, I analysed the response of the MAR model of Bretagne to the scenarios. Figure 39 represents the scenario response of the model for the knowledge size variable in Bretagne.

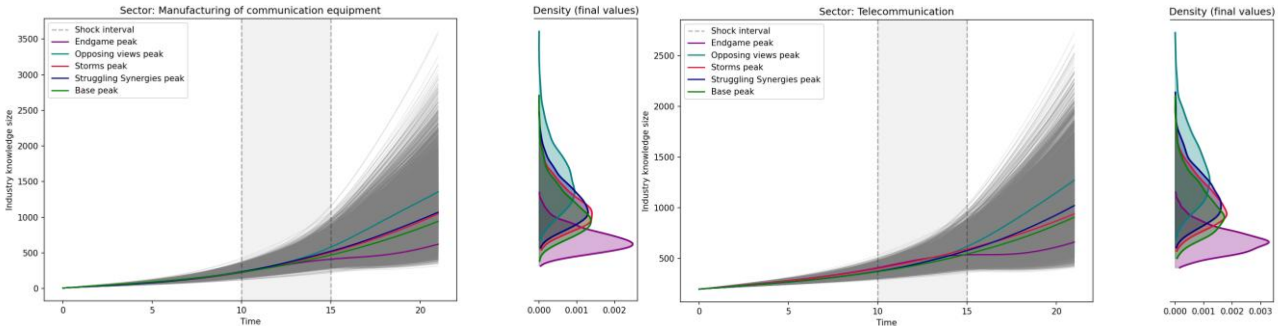

Figure 39: Scenario response plotting for the knowledge size from sectors in MAR region.

The runs from the scenario simulation in the MAR regional model show a similar output for both sectors in the region. The runs in both sectors showcase a convex curve shape. The blue and cyan curves representing the Opposing Views scenario and Struggle Synergy scenario have a higher final output that the base run, with a more significant increase for the Opposing Views cyan curve. This scenario stimulates parameters that are linked to inter-regional collaboration. Despite no major changes during the period of implementation, after the shock the outcomes keep significantly growing. This is in line with the results of the sensitivity analysis, for which an increase in percentage of innovative SMEs collaborating with each other would lead to a significant variance in the system output. The upper boundary of the density plot for the Manufacturing of communication equipment sector is higher than the one for the telecommunication sector, which is aligned with the results from the extreme value test and the parameter sweep.

The Endgame scenario on the other hand is the one with the biggest negative divergence from the base run, with both outputs differing by around 500 patents. This sustains the finding that the percentage of innovative SMEs collaborating with each other, the government funding for public R&D are significant factors of performance of the sectors in the MAR regional model. Despite the negative influence of the shocks on the performance of the model, it is possible to notice a partial increase towards the end of the simulation run, indicating a recovery of the system.

Given these two scenarios showing opposing trends, the Struggle Synergy scenario shows the results of constant fluctuations of the parameters presented in both scenarios. The Struggle Synergy scenario presents an overall increasing curve and its final outcome is higher than the base run. Therefore, the system does not perceive the oscillations induced by the shock. It might also indicate that the positive variances of parameters are perceived more strongly than the negative variances. Since the Opposing Views scenario and Struggle Synergy scenario both out-perform the base run, with Opposing Views yielding the highest final patent counts, the results would confirm that inter-regional and public-private collaboration are the essential drivers of innovation output.
Even when collaboration parameters fluctuate wildly such as in the Struggle Synergy, the model amplifies positive deviations more than negative ones, suggesting strong positive feedback loops.

Finally, the Storms scenario varies some parameters that are not considered significant by the sensitivity analysis but that directly impact a significant parameter and a parameter that is amongst the most influential for the MAR regional model which is the attrition rate per sector. The red curve of the Storms scenario does not largely differ from the based run. The alignment between the base run and the Storms scenario is less marked for the manufacturing of communication equipment than it is for the telecommunication sector. Given that from the output of the sensitivity analysis the attrition rate should overall exerts a higher influence on the telecommunication sector, it is possible that inducing a decreasing shock on that variable hinders the beneficial output that the other two variable changes can bring. As mentioned previously, the Endgame scenario produces the largest negative variance with the base run but still shows partial recovery by the end of the run. In addition to this, the Storms scenario scarcely diverges from the base run, especially in the telecommunication sector, indicating the model filters out or dampens effects from parameters deemed “less significant” in the sensitivity analysis. The model thus confirms the asymmetric sensitivity found in the Sobol test. It reacts strongly to negative shocks on critical collaboration variables but is resilient or buffered against shocks on other inputs.

Overall, the results of the scenario test show non-linear dynamics and asymmetric shock responses and underscores the model’s sensitivity to collaboration-related variables with relatively important sector-specific effects. Every scenario yields a convex curve, implying accelerating returns once positive collaboration effects kick in. Despite large parameter swings, the model never collapses as shown by the patent output remaining positive and convex. Constant oscillations fail to act as a type of “reset” on the system as the positive spikes compound over time, suggesting the presence of thresholds beyond which the system locks into higher growth trajectories. The recovery after the negative shock induced by the Endgame scenario indicates built-in self-reinforcing mechanisms. This shock timing and recovery might highlight hysteresis. In this case, the system retains memory of shocks, and positive changes propagate long after the intervention period. Storms’ minimal impact suggests the model is robust to volatility in socio-demographic inputs but highly responsive to R&D and collaboration pathways.

4.5.2 Jacobs Region Analysis

This section aimed to describe the model behaviour based on the set of scenarios for Jacobs region Ile-de-France. The graphed output was clustered according to the same subsets created for the parameter sweep presented in Figure 40, Figure 41, Figure 42 and Figure 43.

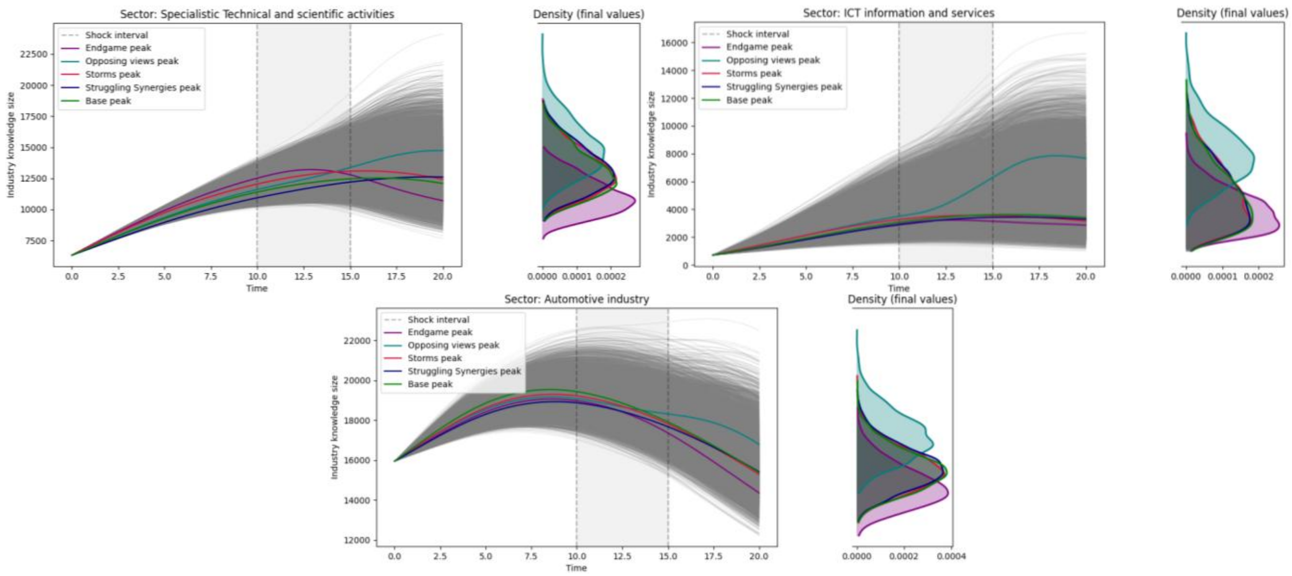

Figure 40: Scenario response plotting for the knowledge size for sectors in subset 1 in Jacobs region.

Contrary to the MAR regional model outputs, most curves in the Jacobs model follow a concave shape. This would indicate a decrease in knowledge growth as time progresses. Some of the results from the MAR model analysis of the response to shocks can be expanded to Jacobs scenario analysis test. A concave trajectory means the marginal gain in knowledge declines as time progresses. Even though early shocks produce a visible change, their impact tapers off even if the input drivers remain elevated. This contrasts with the convex curves in the MAR model, where positive feedback loops accelerated growth after shocks.

In alignment with the results from the MAR model, the Struggle Synergy scenario represents a higher performance than the base case, although lower than the Opposing Views scenario. As such, the sectors lock in on the positive peaks more than the lower ones. Fluctuations in the sectors are too transient for concave sectors to develop oscillations. This implies that the Jacobs model is resistant to volatility but less prone to sustained acceleration from oscillatory inputs.

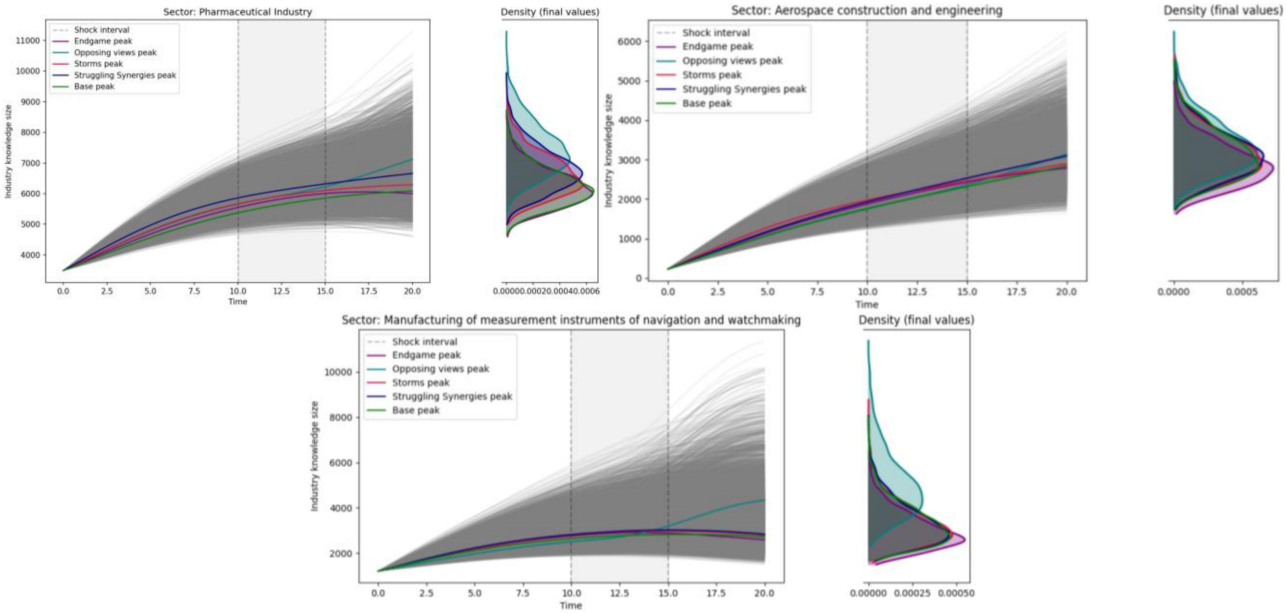

Figure 41: Scenario response plotting for the knowledge size for sectors in subset 2 in Jacobs region.

Each sector has a more preforming knowledge output for the Opposing Views scenario, with most sectors amplifying the positive effects after the shock induction. This does not appear as marked for the ICT sector and Aerospace sector. This could be due to their average time to market significantly deviating from the rest of the sectors. The aerospace sector shows little to no variance to the Opposing Views scenario. Aerospace has the longest time to market of 15 years meaning that at time 10 when the shock happens, it would take 15 additional years before the effect can be fully perceived on the sector. This reasoning is applicable to the other scenarios as well for which the sector shows little response. The ICT would present the opposite case. The cyan curve for the ICT sector increases shortly after the shock has begun, peaking and decreasing shortly after the shock has ended. Along with the editing and diffusion sector, it has the lowest average time to market. This implies that the shock is perceived very soon by the sector, leading to a recovery time that happens sooner when the shock is lifted.

When looking at the Endgame scenario, every sector perceives this scenario as the more negative one except the pharmaceutical sector, for which the Endgame scenario aligns with the base run. This scenario is the only one introducing only negative inputs for its shocks, which might imply that the pharmaceutical sector is less sensitive to negative funding or collaboration cuts. While the Aerospace sector shows little variance to any of the other scenarios, the outcomes from the Endgame shock are lower than the rest. This might indicate that, opposite of the pharmaceutical sector, the aerospace sector is more sensitive to negative shocks. For the Endgame scenario, the ICT sector is also the one showing the quickest recovery out of every sector, indicating the beginning of an increase at the end of the simulation run. This aligns with the previous statement on the importance of the average time to market.

Finally, the Storms outcomes are aligned to the base run for most sectors except the pharmaceutical and the editing and diffusion sectors. The Storms scenario shows higher output than the base run for the pharmaceutical sector, which is aligned with the idea that the pharmaceutical sector is more sensitive to positive input than negative one. For the editing and diffusion sector, the Storms distribution is aligned to the Endgame scenario. This indicates how a variation in the parameters of the Storms scenario impact the editing sector. From the sensitivity analysis results, the attrition rate per sector does not appear as a critically influential parameter. Hence it is possible that the sector is very sensitive the other two parameters not captured in the sensitivity analysis.
However, for most sectors the alignment between the base run and the Storms scenario indicates that the varied parameters have little influence on the model outcome.

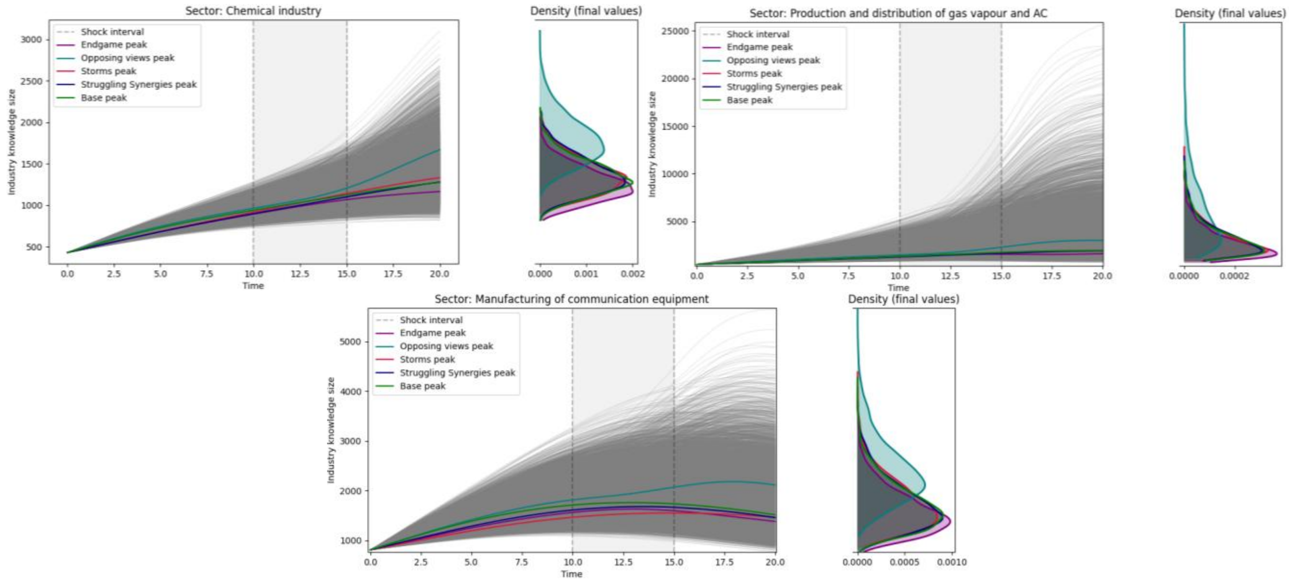

Figure 42: Scenario response plotting for the knowledge size for sectors in subset 3 in Jacobs region.

Overall, both regional models show the same relationship between the scenario responses and their base run. Some exceptions are observed in the curve shape and the sector specific results. By revealing concavity over convexity and time-lag effects, the Jacobs and MAR models stressed to consider shock timing and sector-specific inertia as they can dampen or delay policy impacts.

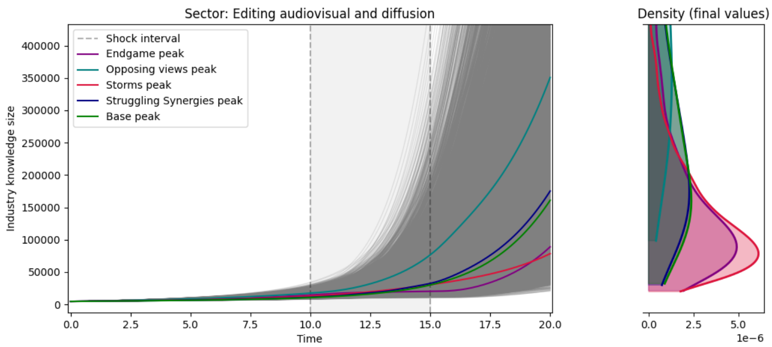

Figure 43: Scenario response plotting for the knowledge size for sectors in subset 4 in Jacobs region

4.5.3 Key Analytical Insights

Based on the scenario analysis for both the MAR and Jacobs regional models, several main findings emerge about their dynamic behaviour and response to shocks.
The structure is the most fundamental difference revealed by the scenarios is contrasting growth paths. The MAR model consistently displays convex growth curves. This indicates that once positive feedback loops are activated, particularly through collaboration, growth becomes self-reinforcing and accelerates over time. Jacobs model mostly displays concave growth curves. This suggests that while shocks have an initial impact, their effect tapers off, and the system is less prone to the kind of sustained acceleration seen in the MAR model.

Across both regional models, the scenarios confirm that collaboration is the most powerful driver of innovation. The positive scenarios were the ones boosting inter-regional and public-private collaboration. They consistently produced the best outcomes, outperforming the base run. The negative scenarios were the ones that cut collaboration and funding, producing the worst outcomes, causing the largest negative divergence from the base run.

Both models demonstrate a sophisticated, non-linear response to interventions. They amplified positives scenarios. In the Struggle Synergy scenario with fluctuating parameters, the models amplified the positive spikes more than the negative dips, resulting in a net positive outcome. This suggests the systems are inherently biased towards growth and can "lock in" gains. They showed hysteresis. The effects of interventions persisted long after the shock period was over, indicating that the systems have a "memory" and do not immediately revert to the baseline. Lastly, they filter "noise". Both models are highly responsive to shocks on critical levers but are resilient and largely unaffected by shocks to less significant parameters, confirming the asymmetric sensitivity found in previous tests.

A key finding specific to the Jacobs model is that a sector's "average time to market" is the primary factor determining its response time to shocks. Fast sectors are considered the ones having a short time-to-market, such as the ICT sector. They react to and recover from shocks very quickly within the simulation. On the other hand, slow sectors, such as the aerospace, have a very long time-to-market, making them appear unresponsive to scenarios because the effects of the shock have not had enough time to materialize. This explains the high degree of performance variation between sectors in the Jacobs model.

5 Discussion

In this research, I set out to model the complex agglomeration dynamics within Regional Innovation Systems (RIS) to derive actionable insights for improvement of innovation performance with research informed decision-making. By constructing, verifying, and validating a System Dynamics (SD) model for both specialised MAR and diversified Jacobs regional archetypes, my study offers a nuanced understanding of the drivers of innovation. In this chapter, I analysed and interpreted the core findings, compared them against established academic literature, and addressed the guiding research questions.

5.1 Key Actors, Relations, and Institutions in Regional Innovation Agglomerations

The first research sub-question sought to identify the crucial actors, their relationships, and the institutional frameworks that drive innovation in MAR and Jacobs regional agglomerations, and how these can be simulated using an SD model. The contribution of this research question to the academic field moves beyond reviewing different theories. I synthesised and integrated the latter by adopting an institutional tool to create a new lens that revealed fundamental structural differences between regional innovation models and provided a deeper explanation for their observed behaviours.

5.1.1 Methodological Contribution

A significant contribution is the application of Williamson's (2000) four-layer institutional model to structure the analysis. This framework provided a robust methodology for dissecting how deep-seated cultural norms in Layer 1, formal rules in Layer 2, governance mechanisms in Layer 3, and resource allocation decisions in Layer 4 collectively enabled or constrained innovations. This multi-layered institutional perspective allowed the model to account for abstract concepts like "cultural norms" or "governance" into stocks and flows that can be tested, demonstrating a pragmatic way to bridge the gap between economic theory and empirical modelling. Equally, the "stickiness" and path-dependent nature of regional development are a critical aspect often highlighted in modern regional policy discourse and appeared relevant through Williamson’s institutional analysis (McCann & Ortega-Argilés, 2013). Williamson’s model created a novel bridge between institutional economics represented through Williamson's layers, economic geography embodied by MAR and Jacobs agglomerations and System Dynamics modelling of quantitative flows. This interdisciplinary integration appeared as a significant contribution. By identifying transactions from evolutionary economic theoretical concepts with Williamson’s institutional layer framework and translating these institutional layers into quantifiable flows and stocks, the model also provided a quantification of “soft” variables. The SD model provided a pragmatic and formal representation of established field theories.

5.1.2 Conceptual Contribution

The application of the institutional layer model to theories in economic geography provided a significant contribution to clarity. With the many overlapping concepts of economic geography, such as RIS, clusters, and externalities, I integrated theories by creating a clear, nested framework that visually organised these ideas and their origins. It synthesised the work of scholars like Moulaert, Sekia (2003), Trippl, and Tödtling (2007) into a coherent scheme that clarified the relationships for future researchers. This structured visualisation served as a robust foundation for the rest of the thesis.

The framework highlighted the crucial distinction in the structure of MAR and Jacobs knowledge flows. In MAR systems, knowledge generation and exchange are both located within the same subsystem (Marshall, 1890). In Jacobs systems, knowledge generation is internal to individual sectors, but knowledge exchange happens between different subsystems (Jacobs, 1969). This finding reflects the conceptual difference between both MAR and Jacobs agglomeration externalities (Antonelli & Colombelli, 2015). Beyond shedding light on the structural difference between the two types of Jacobs externalities, it provided a structural view of the coordination needs between both agglomerations. This structural difference offered a powerful explanation for why Jacobs regions require more coordination to succeed. Since their transactions are inherently more diverse and cross more subsystem boundaries, the need for formal and informal coordination mechanisms is structurally greater than in MAR regions, where cognitive alignment is already high. This moves the argument from a simple observation to a conceptually grounded explanation.

5.2 Model-Reality Alignment and Validation of Model Behaviour

The second research sub-question assesses the fidelity of the model in representing real-world dynamics, thereby verifying and validating the conceptualised causal relationships. During the research, I undertook a multi-faceted verification and validation process, combining replicative data comparison with expert review, to establish the model's credibility. Additionally, with the second research sub-question, I aimed to assess whether the model can offer further insights into existing theories.

5.2.1 Methodological Contribution

The validation of the model represented a successful quantification of institutional and social factors within MAR and Jacobs agglomerations. A major methodological contribution was translating the qualitative framework from Williamson's institutional layers into a formal, quantifiable model. It turned abstract concepts like "cultural norms" or "governance" into stocks and flows that can be tested, demonstrating a pragmatic way to bridge the gap between theory and empirical modelling.

The modelling structure is reinforced by its behavioural realism. For instance, with the extreme value test, I showed how lower fertility leads to slower population growth despite mortality being very low. This aligns with findings from demographic projection sensitivity studies, where population outcomes show greater sensitivity to fertility than mortality (Caswell & Sánchez Gassen, 2015, Caswell, 2000). Additionally, the model’s behaviour showcased historical accuracy. The model successfully reproduced long-term historical trends of real-world examples of the Jacobs-type Île-de-France and the MAR-type Bretagne. This confirmed its qualitative accuracy as a "what-if" laboratory, even if it doesn't predict short-term shocks (Auping et al. 2024). Finally, expert endorsement validated the model’s structure and behaviour. The expert validation provided crucial external confidence in the model's structural integrity and behavioural realism. The expert confirmed that the causal loops were economically sensible, and the variable definitions were appropriate. The suggestions for refinement, such as incorporating a "foreign attractiveness" factor to proxy for labour migration and converting static parameters like fertility rates into dynamic variables, were valuable and correctly partially implemented, strengthening the model's robustness. The results from this multi-faceted validation process together point to the finding that model structure is credible and aligns with real-world dynamics.

Collectively, the verification and validation tests confirm that the model's behaviour aligns with reality sufficiently to posit its use and expansion for future studies. The model successfully demonstrates that innovation in regional agglomerations is a function of multi-actor interactions, institutional layering, and feedback dynamics, providing a credible basis for the subsequent sensitivity and policy analysis. Despite the current advancements in using SD to model innovation systems, I examined the lack of a model considering agglomeration externalities as a noticeable gap in the field. This model offers a flexible structure to simulate agglomeration externalities within the broader context of a RIS, filling this gap. Given the general CLD and adaptable parametrisation, the model appeared as a validated SD structure that can be further refined for specific regions and clusters, as was done with Bretagne and Ile-de-France. Hence, the model’s flexibility and validity represent a significant methodological contribution for the further study of innovation creation in multi-actor systems.

5.2.2 Conceptual Contribution

The validated model revealed several important dynamic behaviours that refine the understanding of agglomeration externalities and offer further depth to existing concepts.

1. Firm-Government-University as foundational actors in Systems

The first conceptual contribution is in validating the firms-government-universities link in the system and at emphasising its importance for agglomeration externalities (Edquist, 2011, Boschma, 2005). In Chapter 2, I successfully modelled a multi-actor system, identifying firms, government entities, and public research and university centres as the core innovation drivers. This aligns with the widely shared view of innovation systems which posit that the locus of innovation is found in the dynamic, non-linear interactions between university, industry, and government (Etzkowitz & Leydesdorff, 2000, Capello & Lenzi, 2018). The creation of a simulation of these relationships through feedback loops representing knowledge flows, R&D investment, and institutional support captured this systemic complexity. It viewed innovation as an emergent property of a complex adaptive system rather than a simple linear output (McKelvey, 2004). The model confirms that innovation is driven by the dynamic, non-linear interactions between the three core actors. This finding provides further depth to the MAR and Jacobs agglomeration externalities debate, by emphasising the role of government and universities in the transactions of firms. Finally, the dynamic interplay across these layers, as highlighted by studies on industry life cycles (Neffke et al., 2011) and the evolving nature of knowledge (Antonelli et al., 2017), suggests that the optimal balance between MAR and Jacobs externalities is not static.

2. MAR and Jacobs Dichotomy

The distinction between MAR and Jacobs externalities is foundational to my analysis. In line with classic economic geography, the model represented MAR regions as benefiting from deep specialisation and robust connections with similar sectors above or below in the supply chain (Duranton & Puga, 2004, Storper & Venables, 2004). This concept is rooted in the work of Marshall (1890), Arrow (1962), and Romer (1986). Conversely, Jacobs regions thrive on diversity and inter-sectoral knowledge spillovers, a dynamic first articulated by Jacobs (1969).
Through the results of my analysis, I successfully identified MAR regions as highly interdependent systems where success or failure in one sector tightly affects others. I differentiated MAR regions with Jacobs regions as loosely coupled networks where sectors largely stand on their own yet benefit from spillovers. However, for both Jacobs and MAR regional models, having knowledge spillovers is not simply sufficient for increased performance. The quantity of that knowledge spillover in relation to the quantity of internal knowledge is important. Hence, to benefit from sector connections, the sectors connected to each other need to have a quick knowledge generation time or an important knowledge base.
This bifurcation deepens cluster theory by showing that the type of agglomeration matters structurally and initial conditions are of importance. Specialized systems seem to propagate internal shocks, whereas diverse systems harbour independent volatility and potential (Neffke et al., 2011). This clarifies real-world behaviours that cluster studies often overgeneralize.

3. Timing is Key

The analysis highlights the critical importance of the temporal dimension of innovation, specifically the interplay between "average time to market" and knowledge obsolescence. The automotive sector in the parameter sweep provided a compelling example of a Schumpeterian trade-off (Schumpeter, 1934). The results of the latter showed that a large initial workforce and knowledge base, combined with a long time-to-market, led to an inverted U-shaped growth curve. This demonstrated that if innovations took too long to commercialise, their value diminished as the technology became obsolete, and the initial R&D investment failed to generate reinforcing revenue streams. Theory suggests that once knowledge is generated, its value is realised through commercialisation, and delays in this process impose opportunity costs (Aghion & Griffith, 2005, Feldman & Audretsch, 1996). Hence, this result is consistent with literature on regional productivity and firm-driven innovation cycles.

Jacobs regions, sectors with a high number of patents and high number of workers can hinder innovation from system over-crowdedness, reflecting findings from Dangelico et al. (2010). High number of workers and long time-to-market of knowledge leads firms to experience slower returns than their costs, hampering their knowledge generation. Conversely, the editing sector, with its short time-to-market, exhibited the potential for explosive, Porter-like growth where rapid innovation cycles create compounding advantages (Porter, 1990). This dynamic revealed that pace might perhaps be a critical variable in regional innovation system dynamics needing more careful consideration (Uriona & Grobbelaar, 2018). The exploration of competing time delays offers a critical improvement to traditional agglomeration and cluster theories. Most existing models emphasise spatial proximity or cognitive diversity but seldom delve into temporal dynamics (Uriona & Grobbelaar, 2018).

By showing how temporal mismatches can amplify or dampen innovation outcomes, my results added a new layer of sophistication to existing theories. It aligns with and extends literature on dynamic cluster evolution, which increasingly acknowledges that the effectiveness of externalities depends not just on structure, but also on timing (MacGregor & Madsen, 2018).

4. Differentiating Sectors within Agglomerations

An additional conceptual emphasis from the results is that not all sectors benefit from being in an agglomeration in the same way. Neffke et al. (2011) firstly introduced the idea that industries benefit differently from MAR and Jacobs agglomeration externalities based on their lifecycle. He argued that firms in the early stages benefit more from Jacobs than from MAR agglomerations, which are more beneficial for the innovation in more advanced stages of the industry. I would complement this theory by not focusing uniquely on the industry lifecycle but on its position in the network. My findings emphasised that certain sectors can leap ahead through knowledge spillovers alone, even with low workforce input. This is especially valid for sectors with strong connections to key "broker" industries such as the ICT sector with the Editing sector. Both the Editing sector in Jacobs regional model and the Manufacturing of communication equipment sector in MAR regional model had very low starting conditions, but were able to leverage knowledge spillovers from their network connections to generate additional innovations and grow their innovation performance. This underscores the importance of network position in RIS theory and supports theory on knowledge spillover between firms, which argues that institutional and network context matters as much as internal R&D stock (Audretsch et al. 2025). The findings added nuance by identifying specific conditions that enable exponential spillover-driven growth. These conditions are short time-to-market and long obsolescence time

By identifying and differentiating sectorial characteristics, agglomeration externality theory can move beyond one-size-fits-all assumptions and consider specific sectorial needs based on their network position and resources. This aligns with evolutionary cluster literature, which suggests that cluster dynamics vary across sectors and stages of development (MacGregor & Madsen, 2018)

5. Non-Linearity between MAR and Jacobs regions

My thesis's greatest strength laid in its ability to simulate non-linear behaviour of agglomeration externalities in innovation systems. A key finding from the scenario tests was the distinction between the convex accelerating growth curves seen in the MAR model and the largely concave decelerating growth curves in the Jacobs model. The MAR system, with its tightly coupled reinforcing loops, created the potential for accelerating growth once a positive trajectory is established. The Jacobs system, with its greater complexity and diversity, appeared to encounter diminishing returns more quickly, perhaps due to competition in terms of attractiveness across sectors in a region or due to sector over crowdedness in terms of patents and workers. The most dramatic increases occurred with variables influencing knowledge generation per researcher, reflecting the convexity in knowledge production functions argued by Pakes and Griliches (1980). On one hand, long knowledge obsolescence time with short average time to market led to an exponential increase in knowledge size. On the opposite hand, short knowledge obsolescence time produced a flattening outcome, highlighting the importance of knowledge decay parameters. This is supported in studies that consider obsolescence in techno-economic cycles, such as the NEMESIS model (Boitier et al. 2022).

5.3 Influential Variables and Implications for Decision-Making

The final and most critical research sub-question identifies the model's high-leverage variables and their implications for policies aimed at improving innovation in EU NUTS 2 regions. The Sobol sensitivity analysis and scenario testing provided clear data-driven answers.

5.3.1 Implications for Regional-Level decision-making

1. Government Role as a Coordinator

A striking finding from the results is that direct government funding was not a primary driver of knowledge development in either model archetype. This supported a modern view of innovation policy, which argued that simply increasing R&D funding is insufficient (Edquist, 2011), the institutional framework and the quality of the network that absorb and utilise that funding are more powerful determinants of success (Cooke, 2004). Instead, the most impactful role of the public sector is to foster public-private collaboration. The quality of the interaction and alignment between public research and private firms matters more than the amount of funding provided.

This was first evident in the extreme value and parameter sweep tests. In the MAR model, the knowledge growth trajectories of the two sectors were highly aligned, showing similar output distributions regardless of the initial parameter variations. This systemic co-dependence suggests that the fate of one sector is inextricably linked to the other. The same observation was not present in Jacobs regions due to the lack of aligned coordination. However, the model operationalises this through a "relatedness" matrix, which proved to be a highly sensitive parameter in the Jacobs region simulation.

Hence, according to the model results, there needs to be a focus on prioritising network building over direct funding. The primary role of policy should be to act as a "network weaver" or "innovation broker" (Howells, 2006). For both MAR and Jacobs regions, interventions that foster collaboration between firms, and between industry and academia are the highest-leverage investments. This involves supporting cluster organisations, creating shared R&D platforms, and facilitating inter-sectoral dialogue.

Overall, the role of the public sector was shown to be more nuanced than simply that of a funder. While direct government funding was not the most significant driver, parameters like public-private collaboration and public R&D expenditure per person proved moderately influential in the MAR model. This implies that it is not the funding itself, but the alignment between public research institutions and private firms and the interaction between private firms that matters most (Cooke, 2004, Etzkowitz & Leydesdorff, 2000). This finding provides a dynamic validation of classic localisation economies, where co-located firms in the same industry benefit from a shared ecosystem of suppliers, labour, and knowledge, creating a powerful set of reinforcing feedback loops (Feldman, 2000; Ghemawat, 2001, McKelvey et al., 2003).

2. Shock Hysteresis and Asymmetric Responses

The models also powerfully illustrated path dependence and hysteresis. The scenario tests showed that the systems retained a "memory of shocks," with the effects of a temporary intervention propagating long after it has ceased, its influence modulated by the sector's time-to-market. This aligns with the work of Brian Arthur (1989), who argued that early events and small perturbations can lock an economy into a specific, and not necessarily optimal, long-term path. Furthermore, the asymmetric response to shocks, where both models reacted more strongly to negative a shocks in collaboration variables than to other inputs, highlights the fragility of the trust and social capital that underpins the model’s innovation ecosystem. This is in line with Edquist (2011) and Boschma (2005) who stress how mutual cultural and institutional trust and proximity have a key role in innovation performance of regions.

3. Beyond a “One-size-fits-all” Perspective

The impact of agglomeration dynamics has been shown to vary significantly across different sectors both through this model’s results and literature (Nielsen et al., 2021, Yangjun et al., 2019), emphasising that a "one-size-fits-all" policy approach is ineffective. This multi-layered perspective underscores the need for adaptive and context-sensitive policy interventions that consider the deep institutional, formal, and governance structures influencing a region's innovation dynamics. While investing in network weaving is deemed necessary for knowledge growth across all sectors independently of the region, adopting a differentiated policy can also bring big advantages. The divergent sensitivities of the MAR and Jacobs models provide strong evidence against "one-size-fits-all" innovation policies (Tödtling & Trippl, 2005). Specialised regions require a focus on deepening internal cluster collaboration and efficiency, while diversified regions must prioritize human capital and cross-sectoral knowledge exchange. Policymakers should use a systemic lens to diagnose and address the specific bottlenecks within their unique regional context.

A central, recurring finding throughout my research is the fundamental difference in the systemic structure of MAR and Jacobs regions. The model consistently demonstrates that MAR regions behave as tightly coupled, interdependent systems, while Jacobs regions act as more robust, loosely coupled networks with higher adaptive potential. This leads to different findings for both agglomerations to support decision-making. This multi-layered perspective underscores the need for adaptive and context-sensitive policy interventions that consider the deep institutional, formal, and governance structures influencing each region's innovation dynamics.

5.3.2 Implications for MAR Regional Agglomeration Decision-Making

To begin with, the model's behaviour confirmed foundational theories. The model showed that increasing the share of innovative SMEs engaged in collaboration is the most impactful parameter for knowledge size increase. MAR results highlight the importance of close proximity and local networks for interactive learning (Breschi & Lissoni, 2003). This is supported by Boschma & Iammarino (2009), who linked dense local interaction networks with increased absorptive capacity and innovation efficiency and with Marshall (1890), Griliches (1992), Henderson et al. (1995) who showed that strong inter-sectoral interactions with a dense firm network and efficient internal processes enhance both workforce absorption and knowledge generation. The sensitivity analysis of the MAR regional model unequivocally identified inter-firm collaboration, proxied by "percentage of innovative SMEs collaborating with others" as the paramount driver of innovation, explaining over 50% of the variance in knowledge growth. It confirms that in specialised regions, it is the density and quality of intra-cluster linkages that overwhelmingly determine the system's innovative capacity (Marshall, 1890; Arrow, 1962; Romer, 1986). This empirically grounds the theoretical emphasis on localised knowledge spillovers within specialised clusters (Fritsch & Slavtchev, 2011). The subsequent sensitivity of the system to "time-to-market" and "knowledge obsolescence" further suggests that for these specialised regions, policy should focus on accelerating the translation of knowledge into commercial products and supporting continuous adaptation to prevent technological lock-in. Since MAR externalities are relevant across a specialised region, stronger local collaboration environments justify this result (Henderson et al., 1995).
MAR regions were shown to be resilient and driven by internal collaboration (Marshall, 1890). The recovery in outcomes for the MAR regional model observed throughout the scenario tests indicated better recovery to external changes for MAR regions than for Jacobs, in line with Zhang et al. 2021. Additionally, this sector also demonstrates a high variance with variables influencing public-private collaboration supporting theoretical models that indicate that public-sector funding enhances private innovation through network effects (Arcos-Guanga, 2024).

Cantwell and Piscitello (2005) emphasize that MAR agglomerations depend critically on the knowledge generation and workforce capacity within their cluster, while Jacobs agglomerations are emphasised by the absorption and inter-sectoral flow. Removal of these inputs is expected to degrade regional innovation capacity, as seen from the decreasing results induced by the Endgame scenario. MAR regions saw dramatic declines in knowledge stock and workforce, consistent with regional specialisation decline post-shock seen in regional resilience literature (Martin & Sunley, 2015).

5.3.3 Implications for Jacobs Regional Agglomerations Decision-Making

In contrast to the results of the Sobol analysis for the MAR model, the Jacobs model displayed distribution of outcomes more centred around relatedness and demographic flows and financial expenditure across its ten sectors. The tests revealed that sectors were more dependent on their own initial conditions, such as the R&D workforce or the added value but could receive a significant performance "boost" from knowledge spillovers from successful neighbours. This dynamic reflects Jacobs' (1969) foundational theory of urbanisation economies, where regional resilience and innovation potential stem not from specialisation, but from diversity.

The wide variety of outcomes demonstrated by variations in the Jacobs regional model align with Antonelli and Colombelli (2015). The latter documented increased innovation benefits through enhanced external knowledge in Jacobs regions, replicating empirical observations that Jacobs agglomerations benefit from both diversity and evolving inter-sector ties (Boschma, 2015, Balland et al., 2018). Frenken and Boschma (2007) emphasize that inter-sector spillovers primarily occur among related industries, defined as related variety, while unrelated diversity plays a risk-buffering role without significantly enhancing knowledge transfer. The results of the sensitivity analysis support this theoretical refinement by showing a higher knowledge size for sectors having connections with key industries, such as the ICT and audiovisual and diffusion sector. Furthermore, the sensitivity analysis confirmed that inter-sector "relatedness" was the most powerful driver of variance, validating the concept that it is the cognitive proximity between diverse industries that facilitates the novel recombination of ideas, a cornerstone of modern evolutionary economic geography (Frenken and Boschma, 2007). The scenario tests show that diversified Jacobs regions are more robust to uncertainties and recover better from shocks than their specialised MAR counterparts. The model demonstrated that a diversified base provides a buffer; the failure or stagnation of one sector does not necessarily drag down the entire system. This result also confirms core theories. The model’s findings support more recent scholarship which emphasizes that it is specifically "related variety" that most effectively fuels regional growth by facilitating knowledge recombination (Frenken and Boschma, 2007, Antonelli et al. 2017). Jacobs regions benefited most from external knowledge spillovers from "related" industries such as the ICT sector. The research findings can translate into a few clear and robust implications for regional innovation policy. This suggests that policies promoting "related variety" can enhance long-term economic resilience. Furthermore, the model's demonstration of hysteresis, where the effects of shocks persist long after the event, argues for proactive policies that build resilient systems capable of weathering future negative scenarios.

Once relatedness parameters were held constant in the Jacobs regional model, the most influential variables were related to demographic vitality and talent attraction, specifically the "relative share of women in fertile age" and the "percentage of workforce wanting to go to the private sector" and the “percentage of profit from sector”. This suggests that for large, complex regional economies, the ultimate ceiling on growth is not capital or technology, but the sustainable supply of skilled people. This aligns with endogenous growth theory, which posits knowledge and human capital as the core engines of long-run growth (Romer, 1990; Lucas, 1988). This finding has also been implemented in the CLD by Lin et al. (2006). The model’s acknowledged limitation in the replication validation which underestimates population due to the lack of migration flows further strengthens this conclusion, implying that the real system's reliance on attracting talent is greater than modelled. This is a crucial finding, suggesting that for diversified, knowledge-based economies, the long-term health of the human capital pipeline is a more fundamental driver than any single industrial policy.

The initial high sensitivity to inter-sector "relatedness" confirms the theoretical importance of cognitive proximity in Jacobs regions, while the highlight of the percentage of profit from sector emphasises the Schumpeterian competition factor between sectors for high skilled talent, aligned with research and labour-economic models replicating that higher R&D expenditure should attract more talent (Griliches, 1992) and that graduate allocation drives R&D capacity (Graddy-Reed, et al. 2021). This supports the idea that long term appeal has a fundamental role for knowledge generation and distribution (Arthur, 1989, Garnsey & Hefferson, 2005, Ibrahim & Fallah, 2005). Hence, there can be a focus on investing in “soft” and human infrastructure. The results emphasize the importance of factors beyond tangible assets. For Jacobs regions, policies must ensure long-term demographic health and the attractiveness of the region for skilled talent. For all regions, cultivating a collaborative culture and investing in the "soft infrastructure" of trust, shared norms, and social capital is essential for a thriving innovation ecosystem (Cooke & Morgan, 1998).

5.4 Limitations

5.4.1 Model Limitations

According to Thomspon & Smith (2019), models are powerful tools for understanding complex systems, but they often operate in a hypothetical realm called "model-land", where assumptions are idealised and simulations are internally consistent but may not reflect real-world complexities. This leads mathematical modelling and simulation in decision-making to exhibit a series of limitations. Hence, treating model-generated probabilities as real-world probabilities can be misleading. The authors argued for a hawkmoth effect, embodied in structural model error.
Unlike initial condition errors generating a “butterfly effect”, structural errors are harder to detect and correct. Even small structural errors in models can lead to large deviations in outcomes, undermining forecast reliability.
The primary structural limitations of the model include the model's lack of inter-regional flows influencing the regional innovation system, such as the migration flows pointed out by the expert validation. These inter-regional connections are applicable to knowledge flows, innovation as well as human and capital flows (Derudder & Liu, 2024). They represent the challenges in delineating system boundaries for innovation systems. The model does not cater to specific firms, aside from the aggregated sector-level stocks and flows. Nevertheless, resource and capital flows are often firm dependant (Arulsamy et al. 2023, Nguyen & Kim, 2023, Andes & Correa, 2017).

Additionally, its sensitivity to the formulas governing knowledge spillover place emphasis on knowledge spillover and knowledge collaboration flows over the others. The parametric uncertainty associated with the input parameters of these formulas affects the rate at which knowledge gets generated, sometimes leading to an exponential behaviour. Although these relations are derived from existing literature and historical data, their values may evolve over time or have a different order of magnitude than the ones used in the model. Even if desk research indicates that these connections were valid in the past, this does not ensure their continued validity in the future, particularly almost four decades after the creation of the theories used. Hence, further empirical research is needed to concretely understand how these flows occur and influence the system.

An important emphasis plays on the balance between knowledge obsolescence and average time-to-market, which could lead to exponential growth in the model. Empirical literature suggests that while Jacobs regions benefit from related variety, unbounded exponential innovation growth is unrealistic due to cognitive and absorptive constraints. Fine-tuning on saturation thresholds and nonlinear absorptive capacity may improve model fidelity (Scherngell & Barber, 2010).

Finally, knowledge is not represented qualitatively by the model, meaning that any patent acquired by the system can influence sector knowledge generation, even if that patent has already been used to generate knowledge. This stems from the assumption that any patent in the system further contributes to create new patents either through knowledge exchange or internal knowledge generation. However, this might not be in line with reality, as not every patent has a chance of influencing the creation of other patents in the same way. This reflects the difficulty in establishing system boundaries for a model of innovation generation. Consequently, it becomes challenging to determine whether a patent should still be accounted for in the further generation of knowledge. Modelling the attractiveness of sectors for other sectors partially addresses this issue. On one hand, it provides a competition factor between firms for which a relatively higher knowledge base influences future knowledge exchanges, diversifying knowledge exchange for firms with different patent sizes. On the other hand, it complicates the task of defining what should be included in the model. Each patent generated in the model has the potential to enhance knowledge generation. Even those that may appear to be of little value today could become significant in the future, contingent upon average time to market and knowledge obsolescence. Nevertheless, due to the structural limitations of the software itself, it is not feasible to incorporate every conceivable patent for each knowledge type. The model fails to account for scenarios in which, for instance, there is a complete transition from a sector to another by firms. It therefore is also unable to replicate the growth of unknown sectors. This makes it challenging to concretely assert when a sector is experiencing a detrimental effect of agglomeration externalities such as "lock-in" (Boschma, 2005). Finally, the MAR and Jacobs models should be evaluated for their adequacy for purpose, not just their internal consistency. This means that the models should be limited to an exploratory function rather than a predictive one.

5.4.2 EMA Limitations

Despite the fact that this study relies on exploratory modelling instead of predictive modelling, it is essential to exercise caution when interpreting the findings. The application of predictive models to systems characterised by profound uncertainty is a subject of debate, as it can be contended that modelling a structure whose functioning is largely unknown is futile (Kwakkel & Pruyt, 2015). While this research employs Exploratory Modelling and Analysis (EMA) rather than predictive modelling, it is crucial to remember that the outcomes of this study should not be regarded as forecasts of future events. As shown by the quantitative deviations of the replicative validation, the model does not predict dips or surges in the outcomes. In the words of Thompson & Smith (2019), these are coined as "Big Surprises". The authors define them as events that models fail to predict due to structural limitations.

These surprises challenge the reliability of model-based forecasts. Given the exploratory instead of predictive application of this model, big surprises remain unaccounted for in the EMA method.
Hence, the results derived from the model should be analysed with an emphasis on qualitative behavioural patterns rather than on precise numerical outcomes. The model's results are contingent upon the assumptions made, which may be erroneous. Although the integration of SD and EMA allows for the consideration of various uncertainties, there remains a possibility that the actual values of parameters or the true structure of the system have not been adequately represented in the model. This relates to the concept of unknown unknowns. The latter are uncertainties that were previously unrecognized as uncertain or that should have been factored into the system. This research primarily aims to explore factors increasing innovation potential in regional innovation systems through MAR and Jacobs agglomeration externalities. Nevertheless, the output space of the model, which encompasses the explored potential outcomes, may not accurately represent the true space of possible outcomes, as, despite the centrality of uncertainty in this research, it is still conceivable that certain elements fell outside the purview of this study that ought to have been included.

5.4.3 Data Limitations

The replicative validation for Île-de-France (Jacobs) and Bretagne (MAR) reveals a strong qualitative alignment with historical data, particularly in capturing long-term trends in population, R&D expenditure, and student enrolment. However, the analysis also pragmatically acknowledges its limitations, such as the underestimation of population growth due to the exclusion of migratory flows and its inability to reproduce short-term volatility caused by external shocks. This highlights the inherent and accepted trade-off in strategic SD modelling that the model is a "what-if" laboratory, not a "crystal ball" (Sterman, 2000). The goal is to correctly represent the underlying feedback structure and long-term behavioural tendencies of a system, not to achieve perfect point-predictive accuracy (Auping et al.2024). Restricted availability of data concerning knowledge collaboration leads to one of the main limitations of this research.
In terms of innovation sharing, data is scarcely accessible, often aggregated due to the sensitive nature of the data (European Central Bank, 2024). The available data is frequently biased towards the advantages of knowledge spillover and collaboration. In particular, data pertaining sector level, private education and firm level exchanges is scarce. The percentage of SMEs collaborating with each other, public-private co-publishing per researcher and relatedness values significantly impact the broader system; however, long-term historical data on the precise values of these is not readily accessible. Currently, the collaboration trends are derived from the limited data made available by European Commission on the Regional Innovation Scoreboard (2023), which could be enhanced by local

governments that possess access to long-term historical data providing their own metrics and metadata information. A set of assumptions were presented for the model creation, which entail limitations. Firstly, the collaboration factor between SMEs has been assumed to be the same across all sectors, following the simplification from the Regional Innovation Scoreboard (European Commission, 2023). The percentage of graduates wanting to go to different fields or positions is also assumed constant across sectors and across time, as well as the enrolment rates in higher education domains. However, the spatial and temporary simplification of these datapoints due to lack of more detailed measurements also entails a lack of specificity in the model outcomes. The outcome itself is quantified via patents. Considering patents as proxy for innovation has numerous limitations previously reported in state-of-the-art literature. Regions for which the diversification outcomes are mainly represented by other knowledge type and capabilities than patents, such as products, industries, scientific disciplines and jobs, were not reflected in through the patent measures in these runs (Cortinovis et al., 2017; Unterlass et al., 2015, Balland et al. 2018).
Furthermore, the replicative data validation involved more climate-like than weather-like tests (Thompson & Smith, 2019). Weather-like test are frequent, short-term forecasts allowing for out-of-sample testing. On the other hand, climate-like test are long-term predictions which often lack sufficient data for validation, making expert judgment crucial. The climate-like replicative validation should therefore be repeated on smaller scale with out-of-sample testing.

Hence, the unavailability of long-term series hampers the working of the model for its decision-making advising scope. Real-world decisions require models to be tested against actual outcomes, not just theoretical consistency, which becomes challenging when the data used and the data measured against is incomplete or biased.

5.5 Future Directions

The rigorous validation process confirms the model's credibility as a tool for strategic exploration. The structural alignment with theory, the behavioural alignment with historical trends, and the positive assessment from expert review all lend confidence to the findings. However, a robust discussion must also acknowledge the model's limitations, which themselves point toward avenues for future research.

The replication validation clearly showed that treating the region as a closed system is a major simplification. Future iterations should incorporate migration flows and exchanges with the neighbouring geographical environment beyond the neighbouring regional clusters, modelling the region's ability to attract and retain talent as an endogenous factor.

The current model measures the quantity of knowledge, proxied by the number of patents. It cannot distinguish between incremental and radical innovation, nor can it explicitly model the risk of "knowledge lock-in," where a region becomes so efficient at exploiting an existing knowledge base that it fails to explore new ones (Boschma, 2005). Integrating Agent-Based Modelling could allow for the simulation of individual agents and the quality of their ideas, providing a richer picture of the innovation landscape. Paasi et al. (2023) strongly emphasised the role of orchestration in innovation ecosystems. Future work could delve deeper into the co-evolving roles of active orchestration versus self-organisation in different innovation system contexts by deepening the granularity of the model’s causal loops.

The model smooths out the short-term cyclical fluctuations present in the real-world data. While appropriate for strategic analysis, future work could incorporate stochastic elements or model the business cycle explicitly to better understand the interaction between long-term innovation dynamics and short-term economic pressures.

Finally, this research successfully translated complex, abstract theories of regional innovation into a formal, dynamic model. Its findings provide strong, systems-level evidence for the differentiated nature of specialised and diversified economies and highlight the paramount importance of collaboration, human capital, and the temporal pace of innovation. By revealing the non-linear, path-dependent behaviour of these systems, the model offers a compelling argument for a more nuanced, systemic, and context-aware approach to innovation policy.

Future work should include targeted modelling of innovation in sectoral technology regimes, not only between regimes, and the incorporation of non-linear parameter estimation via variance-based sensitivity analysis (Saltelli et al., 2007). The implications for future research trajectories are substantial and multi-faceted. The demonstrated success of coupling SD with Network Analysis (NA) by Maruccia et al. (2020) suggests a promising avenue for quantitatively analysing SD models, allowing for more objective identification of leverage points and structural features. This research path would be recommended in the pursuit of this research trajectory.

An important drawback in the traditional use of System Dynamics as a standalone tool is the lack of dynamism, not in the results, but in the structure. The model is itself constructed with defined variables and parameters that remain present during the entire simulation period. However, is the case in real-life scenarios, industrial sectors change, disappear and get created over time. A next step would be to examine the parameters influencing that occurrence, linking agent flows in RIS to change in the structure of the RIS itself. Future research should explore other multi-methodological integrations to further enhance SD's analytical power.

6 Conclusion

The enduring quest to understand and foster regional innovation remains one of the most critical challenges for economic policy. For decades, a central debate has revolved around the competing advantages of industrial specialisation, as described by Marshall, Arrow, and Romer (MAR), and the creative power of industrial diversity, championed by Jane Jacobs. Yet, traditional static and linear analytical methods have consistently fallen short, unable to capture the intricate feedback loops, time delays, and non-linear dynamics that govern how regional economies truly evolve. This methodological gap has left policymakers with an incomplete toolkit, often resorting to "one-size-fits-all" strategies that fail to account for the unique systemic structure of a given region, thereby limiting their effectiveness and leaving the drivers of sustainable growth and resilience poorly understood.

My study embarked on an ambitious task: to move beyond static analysis and dynamically model the complex agglomeration externalities that drive regional innovation. In my study, I confronted this challenge directly by developing, verifying, and validating a System Dynamics (SD) model to materialize the mechanics of two distinct typed of agglomeration externalities. By simulating the behaviour of both specialised MAR and diversified Jacobs regional archetypes, I sought to uncover the high-leverage points for policy intervention. The findings confirm that specialisation and diversification are not merely different industrial structures. They are distinct dynamic systems, each with their own logic, leverage points, and growth trajectory. The study unequivocally refutes the efficacy of "one-size-fits-all" innovation policies.

The implications of this research can be considered both profound and pragmatic. Theoretically, the study provides a formal, dynamic representation of foundational concepts in economic geography, demonstrating that MAR and Jacobs externalities are not fixed regional attributes but developing properties of a complex adaptive system. It validates the use of SD as a powerful methodology for untangling the complexities of innovation systems, a field where such tools are still nascent.

The core finding of this study is that MAR and Jacobs agglomerations exhibit fundamentally different non-linear behaviours. Specialised MAR regions, driven by intra-cluster knowledge spillovers, function as tightly coupled, interdependent systems. Their dynamic is one of reinforcement, leading to convex, accelerating growth curves once a positive trajectory is established. The system's components are so intertwined that the fate of one sector is inextricably linked to the other, making the density and quality of internal collaboration the paramount driver of success. This systemic interdependence means that policies aimed at fostering innovation in MAR-type regions must prioritise the role of a "network weaver," focusing on strengthening the collaborative tissue that binds firms together.

Conversely, diversified Jacobs regions operate as loosely coupled networks where sectors are more independent, and innovation emerges from the recombination of knowledge across different but related industries. Their dynamic signature is largely concave, suggesting a tendency towards diminishing returns as complexity and coordination costs rise. The results demonstrated that the performance of this system is fundamentally constrained not by internal collaboration density, but by the health of the human capital pipeline and the "relatedness" between its diverse sectors. They showed that the diversified Jacobs region was more robust to external shocks and recovered more effectively than its specialised counterpart. For decision-makers, this shifts the policy focus towards becoming a "talent magnet" and an "innovation broker," ensuring a sustainable supply of skilled individuals and facilitating the cross-sectoral dialogues that spark breakthrough ideas. Hence, this finding lends strong support to policies that encourage the development of "related variety", a mix of cognitively adjacent industries as a core strategy for building long-term regional economic resilience.

For decision-makers, the implications are a clear call for a paradigm shift. The most striking finding is that the structure of the innovation system in the model, specifically the density and quality of collaborative networks designed in the model, is a far more potent driver of innovation than the volume of direct government funding. Additionally, the high sensitivity to parameters representing collaborative culture and the attractiveness of research careers underscores the critical importance of "soft" infrastructure. Lasting innovation ecosystems are built on a foundation of trust, shared norms, and social capital. Therefore, policy must extend beyond financial incentives to cultivate an economy where collaboration is the default. This supports a modern view of policy that emphasizes the role of government as a "network weaver" or "innovation broker", whose primary function is to foster the connections that allow knowledge to flow and recombine.

This research makes a significant academic contribution by providing dynamic, quantitative evidence for long-standing theories in economic geography and institutional economics. It moves beyond static validation to illustrate time-bound properties such as path dependence and hysteresis, showing how systems retain a "memory of shocks" and how the fragility of trust can lead to asymmetric responses to negative events. By translating Williamson's institutional layers into a formal model, this study demonstrates a pragmatic method for integrating deep institutional factors into quantitative analysis. The distinction between the convex growth of MAR systems and the concave growth of Jacobs systems is a novel insight, offering a new behavioural lens through which to understand regional development paths.

Ultimately, my research provides a robust, dynamic, and context-sensitive lens through which to view regional innovation. By moving beyond simplistic correlations and embracing systemic complexity, it offers a pathway toward more effective, evidence-based policies that can truly unlock the innovative potential of Europe's diverse regions and build a more prosperous and resilient economic future.

While this study provides a robust framework, its limitations, such as the exclusion of migratory flows and external shocks, highlight avenues for future research. Enhancing the model with endogenous migration dynamics and simulating specific policy interventions could yield even more granular insights. Nonetheless, the central conclusion remains valid. Understanding the systemic structure and behavioural signature of a region's innovation system is a prerequisite for effective policy. By embracing a dynamic, systemic perspective, decision-makers can move beyond simple interventions and begin to cultivate the unique conditions that allow innovation to flourish.

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Appendix A: Research Addendum

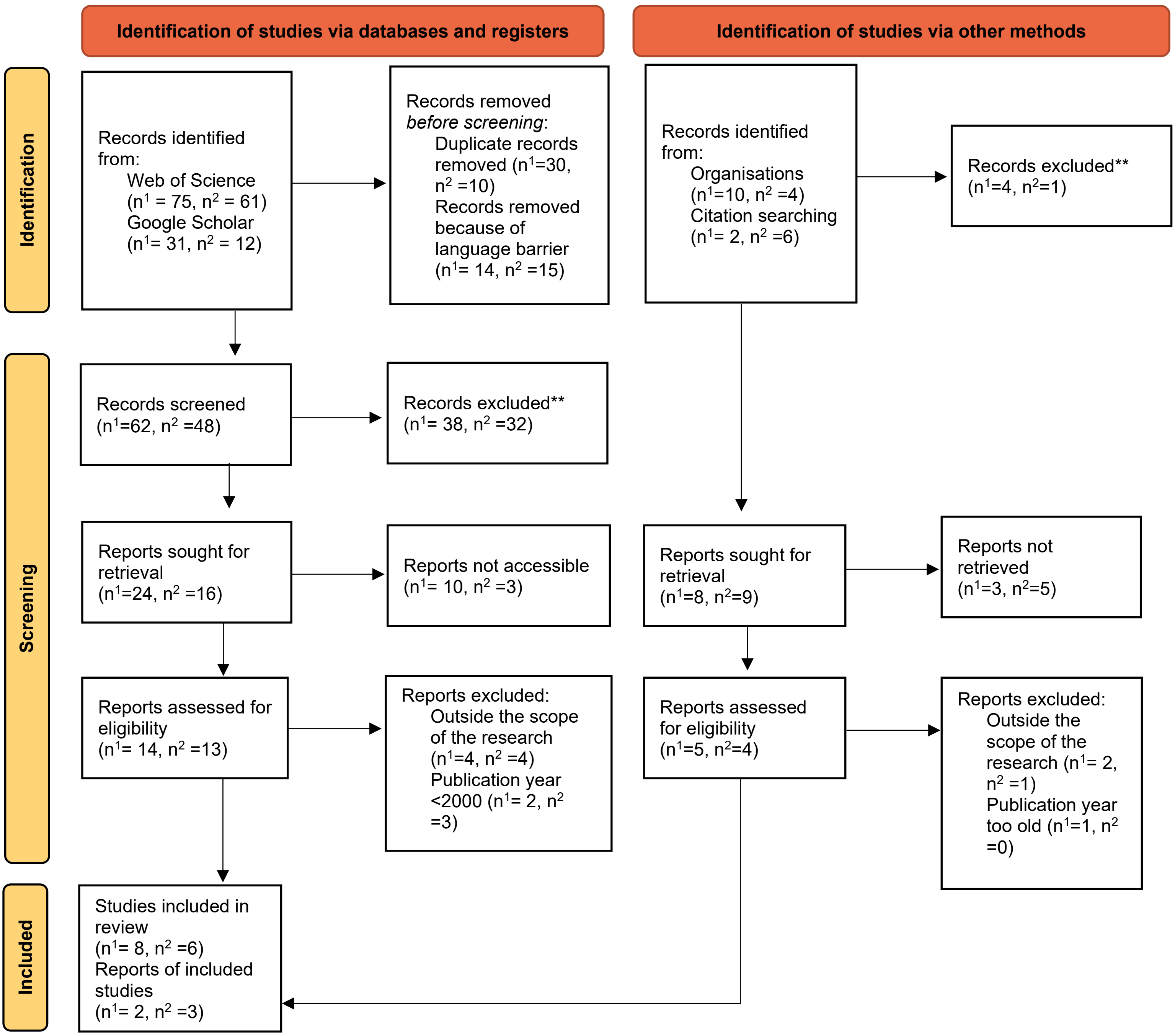

*Figure 44: PRISMA 2020 Flow Diagram for Systematic Literature Review (Page et al. 2021). [1]: Studies linked to agglomeration externalities in RIS, [2]: Studies linked to the application of SD in RIS, **: reports excluded from the analysis of the title or the abstract*

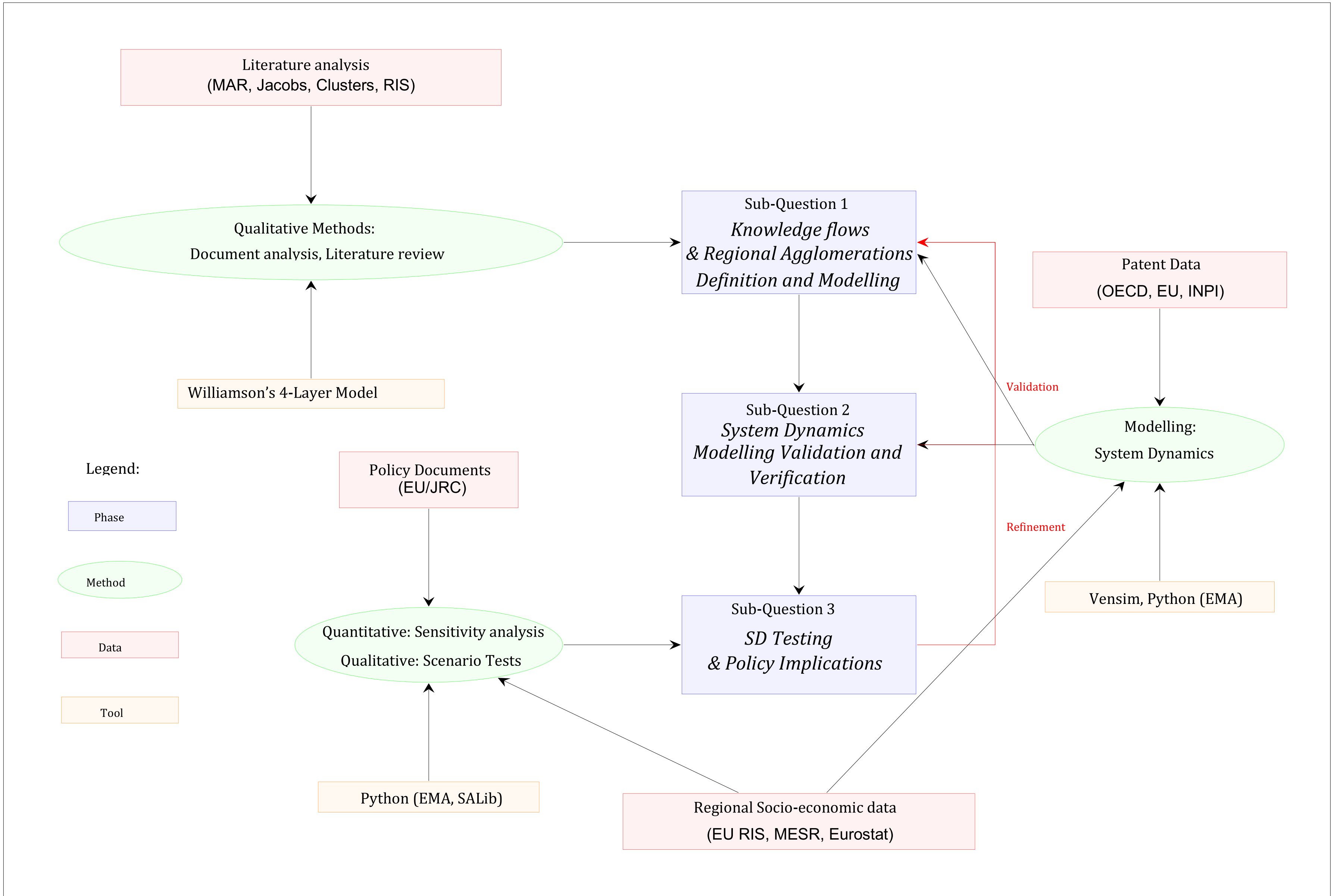

Figure 45: Research Flow Diagram of the Research Framework

Table 13: Overview of System Dynamics Studies in Regional Innovation Systems

Author(s)	Date	Localisation	Research Objective	Method for the SD model	Results
Kim & Choi	2009	South Korea	Examine firm's dynamic circulation R&D to innovation, optimize profit via policy variables, complement limitations of existing theories.	Causal Loop Diagram with firm-centric variables based on three theories of technology and innovation (the R&D and technological knowledge concept, product-process concept, technological interdependence concept).	SD is superior to static for long-term analysis. Product-focused investment is more effective for short-term profitability than process-focused. R&D time lag is negative in early stages but positive in the long-term. Product innovation reduces process innovation due to complexity; process innovation reduces product innovation due to fixed production process.
Lin et al.	2006	Taiwan	Explore factors affecting industrial cluster effect using SD, establish dynamic model.	Interpretative approach from literature review on competitive advantage, concept of industrial clusters and system dynamics leading to a multi-dimensional flows (manpower, technology, money, market).	All factors (manpower, technology, money, market) positively influence industrial cluster effect, but growth is restrained by "interference points" (e.g., limited government resources, economic recession, land use value, industrial complexity). SD is recognised as more effective for complex relationships.
Dangelico et al.	2010	Seattle	Develop SD model to investigate influence of knowledge/proximity on firms agglomeration in technology districts.	Modelling informed by literature analysis. Patent-based proxies. Knowledge-based perspective, ceteris paribus (institutional, economic, social).	As cognitive and organisational proximities increase, district actors fully exploit agglomeration benefits (knowledge sharing/creation), favouring growth. Inverted U-shaped relationship between proximity and number of actors (too low/too high proximity leads to lock-in/decay). Reinforcing and balancing loops govern agglomeration.
Walrave & Raven	2016	Netherlands	Develop SD model integrating 'motors of innovation' and 'transition pathways' (Multi-Level Perspective) to understand TIS (Technology Innovation System) emergence/decline.	Uses TIS literature detailing "Motors of Innovation" studies. Experiments with Monte-Carlo experiments. Integrates TIS functions and MLP concepts.	Model produces results similar to TIS/MLP literature. Hybrid resource conditions best for niche market size. Reconfiguration pathway (symbiotic, TIS developed) leads to larger niche market. Shorter, substantial funding better than longer, less intense. Strong influence of 'sailing ship effect' (regime resistance). TIS developed before landscape pressure leads to higher success. Model captures non-linear dynamics, uncertainties, tipping points.
Maruccia et al.	2020	Italy (using Global Innovation Index (GII) data)	Focus on relationships between Quintuple Helix and SD; discuss how Network Analysis (NA) advances understanding of	Modelling with Quintuple Helix variables informed by GII (government, industry, university, media/culture-based public, natural environment). Combination with Network Analysis metrics (centrality, modularity, graph theory, Gephi).	Coupling NA with SD is that it identifies structural features, central drivers, leverage points. Results confirm Quintuple Helix framework for NIS. ICT use, Regulatory Quality, Knowledge Creation, GDP, Entertainment/media market,

			innovation system mapped with Quintuple Helix model.		Employment in knowledge-intensive services are influential. Society and environment are essential supporting elements.
Zeng et al.	2021	China	Conduct systematic research on relationship between Foreign Direct Investment (FDI), Outward Foreign Direct Investment (OFDI), Intellectual Property Rights (IPR) for RTI using SD.	Models Regional Techonology Innovation as information feedback system with subsystems, then leading a sensitivity analysis and forecasting to validate the assumed mechanisms.	High fitting precision, good extrapolating performance. IPR policy has different effects at different stages (early stage no significant influence on efficiency, later positive; strong early IPR causes financial burden for domestic R&D). IPR royalties trade deficit can turn into surplus. ETD decreases, IPR royalties trade deficit turns into surplus by 2038. IPR policy has positive and negative effects simultaneously.
Paasi et al.	2023	Finland (based on 10 case Innovation Ecosystems (IEs))	Increase understanding of IE dynamics, bridge structural and coevolution views, support IE creation/orchestration.	Use a mix of empirical and theoretical approach with multiple case studies and expert workshops. The system theoretic approach of Phillips and Ritala (2019) is used to find main variables creating dynamics in IEs. IEs are modelled as complex adaptive systems, inter-organisational innovation, knowledge-based innovation.	Ecosystem actors, properties, environment/outcomes are key factors. Good orchestration substantially speeds up innovation outcomes by promoting openness and knowledge flow. Co-development reinforces itself through pilots, attractiveness, firm entry, research capacity. Attractiveness can decrease if the innovation is overhyped. Private finance responds to market/pilots and public finance strategic. Shorter, substantial funding is better. Model captures non-linear dynamics, uncertainties, tipping points.
Samara et al.	2023	Greece (Central and Western Macedonia)	Study impact of ICT on regional development using SD, develop framework-guidance tool for what-if scenarios.	what-if scenarios applied to an SD model built with previously analysed in-depth literature review on the need to use smart technologies as a key component of a regional innovation system and their impact on regional development. It divides RIS components (Product/Process Innovation, Knowledge Network, Institutional Conditions, Market Conditions, ICT Capacity, R&D activities).	Digital technology significantly impacts regional development. Central Macedonia shows better growth rates and reaches equilibrium sooner due to higher initial ICT levels and population. Western Macedonia needs more time. ICT indicators related to infrastructure improve slower. Model can be adapted to other regions.
Samara et al.	2024	Greece (Western and Central Macedonia)	Amalgamate systemic approach with computer modelling for RIS, explore smart tech impact on regional development via SD model as 'experimental tool'.	Literature study of RIS influential components informs the SD modelling. RIS as six subsystems (ICT Capacity, Innovation & Regional Development, Institutional Framework, Knowledge Implementation/Capitalisation, Knowledge Networking, Knowledge Production/Dissemination). Numerical experimentation with regional data informs model results.	Smart tech significantly enhances regional development; optimal combinations vary by region/initial conditions. Western Macedonia needs ICT programs, Central Macedonia needs PC usage/ICT specialists at high internet penetration. Impact is high but takes time.
Hou et al.	2024	China	Explore internal causes/symptoms of "dualisation" effect in regional	Modelling informed by literature with four subsystems: innovation efficiency, science & technology innovation,	Growth rate of industrial enterprises and R&D expenditure intensity are key factors for both city types. Central cities and non-central cities show divergent trends in innovation development. Innovation policy-guided and innovation

			innovation, propose optimisation paths.	innovation culture, innovation policy. Scenario analysis to understand system behaviour.	culture-catalysed capabilities are weaker, especially in non-central cities. Optimisation paths are proposed, prioritised factors differ for central and non-central cities.

Table 14:Overview of Agglomeration Studies in Innovation Systems.

Author(s)	Date	Localisation	Research Objective	Method (including concepts/theories used)	Results
Nielsen et al.	2021	Denmark (93 municipalities)	To examine factors determining subnational geographic location of multinational enterprise (MNE) investments, comparing Marshallian and Jacobian agglomeration mechanisms to understand micro-location patterns of domestic and foreign firms.	Empirical study; Conditional logit model; Marshallian agglomeration (intra-industry knowledge spillovers, labour market pooling, input-output linkages); Jacobian agglomeration (inter-industry knowledge diversity, cross-industry knowledge spillovers, industry-agnostic suppliers, competition for general factors); Agglomeration externalities (knowledge spillovers, market transactions, competition); Controls for global connectivity, education, population density, unemployment.	Agglomeration systematically relates to both foreign and domestic location patterns, with relationships varying by agglomeration type and firm ownership. Foreign firms are located in municipalities with consistently higher agglomeration levels (all types) and are more globally connected. Foreign and domestic firms exhibit diverging locational patterns.
Antonelli et al.	2017	214 regions in 27 European Union member states (1994-2008)	To analyse the role of regional knowledge stock composition in explaining innovation performance, specifically investigating the relevance of Jacobs knowledge externalities.	Econometric analysis; Hidalgo-Hausmann (HH) methodology (measures of knowledge base: variety, ubiquity, complexity); Jacobs knowledge externalities; Marshallian externalities; Recombinant knowledge generation; Knowledge variety, interrelatedness, coherence, rarity; Patent data (Revealed Technological Advantage - RTA index).	Characterisation of regional knowledge base via HH indicators provides insights into its composition and its role as a provider of Jacobs knowledge externalities. Jacobs knowledge externalities account for regional innovative performance dynamics. High variety with rare knowledge items leads to strong Jacobs externalities, while low variety with ubiquitous items leads to weak effects. Excess diversification can limit positive effects.
Beaudry & Schiffauerova	2009	Global (meta-analysis of 67 articles)	To survey scholarly contributions on Marshall or Jacobs theories regarding specialisation or diversity effects on economic performance of regions and identify measurement and methodological issues causing lack of resolution in the debate.	Meta-analysis (census of 67 regression-based studies); Marshall-Arrow-Romer (MAR) model (specialisation, intra-industry spillovers, local monopoly); Jacobs theory (diversity, cross-sectoral spillovers, cities as innovation source, local competition); Porter externalities (competition); Knowledge externalities; Urban product cycles. Analyses industrial and geographical aggregation levels, performance measures, and indicator choices.	Mixed results, with both specialised and diversified structures promoting performance. Measurement and methodological issues (industrial/geographical aggregation, performance measures, indicator choice) are primary causes for inconclusive debate. Jacobs externalities more impactful on economic growth; Marshall's theory more supported for productivity and innovation. Effects vary by industrial aggregation, geographical scale, firm level vs. regional level, and firm size.

de Vor, & de Groot	2010	Amsterdam, Netherlands (68 industrial sites)	To determine the extent to which industrial site performance is affected by local economic structure and accessibility, by testing relationships between agglomeration externalities, accessibility, and employment growth.	Empirical study; Applies Glaeser et al. (2000) methodology; Marshall-Arrow-Romer (MAR) externalities (localisation, labour market pooling, input-output linkages, knowledge spillovers); Jacobs externalities (diversity, cross-industry knowledge spillovers); Porter externalities (competition); Employment growth rate (dependent variable); Specialisation index (Location Quotient - LQ); Relative Diversity Index (RDI); Competition (establishments per employee); Controls for accessibility (highway proximity, harbour area).	At the site-industry level, specialisation hampers growth (negative MAR effect). Industrial sites with easy highway access and those in the Amsterdam harbor area experience relatively fast employment growth.
de Groot et al.	2016	Global (meta-analysis of 73 articles)	To revisit the discussion on agglomeration externalities (specialisation, diversity, competition) contributing to innovation, productivity, and urban employment growth, drawing more robust conclusions from a larger sample.	Meta-analysis of 73 articles (787 estimates); Ordered probit analysis and weighted least squares regression; MAR externalities (industrial concentration, specialisation); Jacobs externalities (economic/social diversity, cross-sectoral spillovers); Porter externalities (intensity of competition); Agglomeration economies. Examines influence of dependent variable measure, service sector inclusion, specialisation/diversity measures, population density, GDP, year of data, country, etc.	Significant heterogeneity among studies, partially accounted for. Evidence of publication bias (more recent studies favor specialisation, less diversity). Overall, competitive forces show most positive impact; specialisation has mixed positive/negative impacts; diversity shows positive impact. Specialisation impacts positively on lower density places and when growth is measured by output or patents/innovations. Diversity impacts positively on urban growth, especially in Asia.
Yangjun et al.	2019	China (30 provinces, 2008-2016)	To analyze the impact of producer services agglomeration on green economic efficiency and its spatial spillover effects, introducing spatial effects into the analysis framework.	Empirical research; Panel data; Spatial autocorrelation test (Moran's I); Spatial econometric models (Spatial Lag Model - SLM, Spatial Error Model - SEM, Spatial Durbin Model - SDM); Super Slacks-based Measure (SBM)-DEA model for Green Economic Efficiency (GEE); Marshallian agglomeration (specialised agglomeration); Jacobs externalities (diversified agglomeration).	China's regional green economic efficiency shows significant positive spatial dependence. Producer services specialised agglomeration inhibits local GEE and has negative spatial spillover effects on adjacent areas. Producer services diversified agglomeration only enhances local GEE (no significant spatial spillover). Regional differences exist: Eastern region consistent with national findings; Central region benefits only from specialised agglomeration; Western region not significantly affected by agglomeration mode.
Neffke et al.	2011	Sweden (12 manufacturing industries, 1974-2004)	To investigate the changing roles of agglomeration externalities along the industry life cycle. It is argued that industries have different agglomeration needs in different stages of their life cycles because their mode of competition, innovation intensity, and learning opportunities change over time.	Empirical study; Cobb-Douglas-inspired production function; Marshall-Arrow-Romer (MAR) externalities (intra-industry knowledge spillovers, specialised labor force, access to specialised clients/suppliers, joint innovation efforts); Jacobs' externalities (inter-industry knowledge spillovers, benefits from industrial diversity, stable demand, wide range of local input substitutes, love of variety); Industry life cycle theory (young, intermediate, mature stages).	MAR externalities steadily increase with the maturity of industries. Jacobs' externalities are positive for young industries, but decline and even become negative for more mature industries.

Antonelli & Colombelli	2015	European financial markets (panel of companies listed in UK, Germany, France, Italy, Netherlands, 1995-2006)	To explore the role of internal and external knowledge in the generation of new technological knowledge, implementing the notion of recombinant knowledge generation function.	Econometric analysis (simultaneous equations, recursive model, Heckman Two-Step, Negative Binomial/Zero-Inflated Negative Binomial); Concepts: Knowledge Generation Function, Recombinant Knowledge Generation, Complementarity of Internal and External Knowledge, Knowledge Indivisibility, Cumulability, Non-exhaustibility, Cognitive Distance; Data: IPER database, Thomson Datastream, AMADEUS, OECD REGPAT (patent data).	R&D efforts and external knowledge are indispensable inputs. External knowledge (both local and inter-regional) significantly contributes to new knowledge generation. Multiplicative complementarity exists between internal R&D/knowledge stock and external knowledge. Firms focusing search in knowledge space close to their competencies are more likely to generate new knowledge.
Bergek et al.	2015	Global (conceptual paper on Technological Innovation Systems)	To strengthen the Technological Innovation System (TIS) framework by a more elaborated conceptualisation of TIS context structures and TIS-context interactions.	Conceptual paper; Literature review; Technological Innovation System (TIS) framework; Context structures (technological, sectorial, geographical, political); Structural couplings; Multi-scalarity.	Identifies and discusses four important types of context structures (technological, sectorial, geographical, political) that interact with a focal TIS. Emphasizes that TIS elements are embedded in pre-existing territorial structures, and TIS boundaries often coincide with territorial limits. Highlights multi-scalarity, where TIS processes can run across pre-set territorial boundaries, and the need for analysts to carefully set technological and territorial boundaries.

Table 15:Analysis of institutions, actors and relations in agglomeration mechanics of Regional Innovation Systems according to Williamson's Institutional Layer (2000)

Mechanism	Agglomeration externality	Definition	Institutions and Layer	Actor	Relations
Cultural/Cognitive Homogeneity	MAR	Deep-seated cultural preferences or shared cognitive frameworks within a specific industry foster strong intra-industry ties and knowledge transfer, potentially leading to "groupthink" but reinforcing specialised learning.	Cultural Preferences and informal institutions - Layer 1	Firms within a specialised industry, individuals (workers, entrepreneurs).	Firms and individuals *utilize* shared cultural preferences and cognitive frameworks (informal institutions) to facilitate intra-industry knowledge transfer and specialised learning. This homogeneity reduces communication barriers and fosters trust, reinforcing the specialised cluster.
Traditional Industry Focus	MAR	Historical development of a region around a particular industry embeds norms and traditions that favour continued specialisation and resist diversification.	Norms and traditions linked to history – Layer 1	Local communities, established firms, regional authorities (influenced by local sentiment).	Local communities and established firms *adhere to* historical norms and traditions that prioritize a specific industry. This informal institutional inertia can lead regional authorities to implicitly or explicitly favour continued specialisation, potentially hindering diversification efforts.
Industry-Specific Regulations/Standards	MAR	Formal legal frameworks that support or standardize practices within a specific industry, reinforcing specialisation (e.g., specialised licensing, quality controls).	Laws – Layer 2	Government bodies (regulators), specialised firms, industry associations.	Government bodies *implement* formal legal frameworks and standards tailored to specific industries. Specialised firms *comply with* and *benefit from* these regulations, which reinforce their specialised activities and can create barriers to entry for non-specialised firms, thus solidifying the specialised cluster.

Strong IPR Protection for Specialised Knowledge	MAR	Robust intellectual property rights (IPR) protection incentivizes R&D and innovation within specialised fields by allowing innovators to appropriate returns, though excessive protection can hinder knowledge diffusion.	Property rights – Layer 2	Innovating firms (within a specialised industry), legal system, government (IPR offices).	Innovating firms *rely on* formal IPR laws to protect their specialised technological knowledge. The legal system *enforces* these rights, allowing firms to appropriate returns from their R&D, which incentivizes further investment in their specific domain.
Labor Laws for Specialised Skills	MAR	Regulations that facilitate the mobility and training of specialised labour within an industry, supporting labour market pooling.	Laws – Layer 2	Specialised firms, labour unions, government (labour departments).	Specialised firms and labour unions *operate within* labour laws that facilitate the mobility and training of specialised workers. These formal rules support the efficient functioning of a specialised labour market pool.
Industry Associations & Networks	MAR	Formal and informal networks within a specialised industry facilitate knowledge exchange, joint R&D efforts, and collective action, forming strong "structural couplings."	Private alignment for knowledge exchange in specialised industries – Layer 3	Firms within a specialised industry, industry associations, research consortia.	Firms *participate in* and *govern* formal and informal industry-specific networks and associations. These governance structures facilitate knowledge exchange, joint R&D, and collective action, reinforcing specialised learning and competitive advantage within the cluster.
Specialised Training Programs	MAR	Industry-led or government-supported vocational training programs tailored to the needs of a specific sector, ensuring a continuous supply of specialised labour.	Educational structures and resources (studies, training programs…) – Layer 3	Industry associations, vocational schools, specialised firms, government (education/labour departments).	Industry associations and vocational schools, often with government support, *design and implement* training programs tailored to a specific sector's needs. Specialised firms *employ* graduates from these programs, ensuring a continuous supply of specialised labour.
Vertical Integration/Collaboration	MAR	Governance structures promoting close collaboration or vertical integration within a specialised value chain, reducing transaction costs and enhancing efficiency.	Private and public supply chain agreements within firms in the same sector – Layer 3	Firms along a specialised value chain (suppliers, producers, distributors).	Firms *establish* formal agreements and collaborative governance structures (e.g., joint ventures, long-term contracts) to promote close collaboration or vertical integration within a specialised value chain. This reduces transaction costs and enhances efficiency within the specialised industry
Intra-industry Knowledge Spillovers	MAR	Direct, continuous flow of specialised knowledge within an industry, reducing individual R&D costs and increasing the quantity of specialised innovations.	Private incentives for informal interactions and collaboration – Layer 4	Firms within the same industry, employees (moving between firms).	Firms *benefit from* the continuous, often unintended, flow of specialised knowledge through informal interactions, employee mobility, and joint projects. This reduces individual R&D costs and increases the quantity of specialised innovations, directly impacting their incentives for R&D investment.
Specialised Labor Market Pooling	MAR	Continuous matching of specialised labour supply and demand, reducing search costs and increasing labour availability for firms in the same industry.	Private resource allocations and employment – Layer 4	Specialised firms, specialised workers.	Specialised firms *access* a readily available pool of specialised labour, and workers *find* employment opportunities within their niche. This continuous matching reduces search costs for firms and increases labour availability, directly impacting the cost and quantity of labour for continuous production.
Specialised Input/Output Linkages	MAR	Ongoing reduction of transaction and transportation costs due to proximity to specialised suppliers and buyers, directly impacting production costs and efficiency.	Private supply chain transactions within firms in the same sector – Layer 4	Specialised firms (buyers and suppliers) within the same value chain.	Firms *engage in* continuous transactions with proximate specialised suppliers and buyers. This reduces transaction and transportation costs, directly impacting the prices and quantities of inputs and outputs, leading to cost efficiencies in continuous operations.

Intra-industry Competition	MAR	Continuous rivalry within a specialised industry, driving firms to innovate and improve efficiency to maintain market share.	Private incentives for resource allocation – Layer 4	Firms within a specialised industry.	Firms *compete* fiercely within their concentrated industry. This continuous rivalry drives them to innovate and improve efficiency to maintain market share, influencing their incentives for continuous innovation and their profitability.
Industry Life Cycle Effects	MAR	As industries mature, the benefits from intra-industry spillovers (MAR) steadily increase, influencing continuous resource allocation towards specialisation.	Private resource allocation – Layer 4	Mature industries, firms within those industries	Firms in mature industries *experience* increasing benefits from intra-industry spillovers. This influences their incentives to continue specialising and the efficiency gains from specialisation, impacting continuous resource allocation towards established practices.
Congestion Costs	MAR	Continuous increase in land rents, wages, and other costs due to high concentration, potentially offsetting benefits and influencing firms' location decisions.	Private resource costs from agglomeration – Layer 4	Firms, workers, property owners, local government.	Firms and workers *face* increased costs (e.g., higher land rents, wages) due to high concentration. These costs directly impact the prices of key resources, increasing operational costs and potentially reducing profitability, influencing continuous resource allocation and location decisions.
Culture of Openness/Experimentation	Jacobs	Underlying societal values encourage cross-disciplinary collaboration, experimentation, and the recombination of diverse ideas, fostering a "science base" for innovation	Cultural Preferences and informal institutions - Layer 1	Entrepreneurs, diverse firms, research institutions, individuals (e.g., "solar civic associations").	Entrepreneurs, diverse firms, and research institutions *leverage* a societal culture that values cross-disciplinary collaboration and experimentation (informal institutions). This culture fosters the recombination of diverse ideas and encourages new firm formation, enabling a dynamic innovation ecosystem. Individuals build on established trust relationships within their communities to facilitate knowledge exchange.
Cognitive Diversity Acceptance	Jacobs	Societal norms that value and integrate diverse knowledge items, including "rare knowledge," are crucial for strong Jacobs externalities.	Norms and traditions linked to history – Layer 1	Firms, researchers, local communities.	Firms and researchers *benefit from* societal norms that accept and integrate diverse knowledge, including "rare knowledge." This informal institution enhances their "absorptive capacity" for external knowledge, allowing them to effectively combine varied inputs for innovation.
Entrepreneurial Spirit	Jacobs	A cultural emphasis on new firm formation and risk-taking, often linked to diverse knowledge spillovers.	Cultural Preferences and informal institutions - Layer 1	Aspiring entrepreneurs, new firms, local investors.	Aspiring entrepreneurs and new firms *are encouraged by* a cultural emphasis on risk-taking and new business creation (informal institution). This spirit facilitates the formation of new ventures that can leverage diverse knowledge spillovers.
General Competition Laws	Jacobs	Formal rules promoting competition across industries, which Jacobs argues is beneficial for growth and innovation by incentivising firms to innovate and speed up technology adoption.	Laws – Layer 2	All firms (across diverse industries), government (competition authorities).	All firms *operate under* formal competition laws enforced by the government. These laws *incentivize* innovation and efficiency across diverse sectors by preventing monopolies and fostering a competitive environment.
Broad Innovation Policies	Jacobs	Legal and administrative frameworks designed to support innovation across a wide range of sectors, rather than favouring specific industries.	Policies – Layer 2	Government (policy-makers), diverse firms, research institutions.	Government *designs and implements* formal policies (e.g., R&D tax credits, funding for general research) that support innovation across a wide range of sectors. Diverse firms and research institutions *utilize* these policies to foster cross-sectoral knowledge recombination and new technological development.

Open Access to Public Knowledge	Jacobs	Policies and legal frameworks ensuring broad access to public research and knowledge bases, facilitating cross-sectoral knowledge recombination.	Law and Polity – Layer 2	Public research institutions (universities, government labs), firms, researchers, government (funding agencies, regulatory bodies).	Public research institutions *generate* knowledge, and government *establishes* formal rules (e.g., open science policies) that ensure broad access to this knowledge. Firms and researchers *leverage* this open access to facilitate cross-sectoral knowledge recombination.
Regulatory Framework for Digital Economy	Jacobs	Policies supporting the development of digital infrastructure and e-skills across the economy, enabling broader knowledge sharing and networking.	Polity, formal rule of the game – Layer 2	Government (regulators), ICT firms, businesses across all sectors, citizens.	Government *establishes* formal regulatory frameworks that support the development of digital infrastructure and e-skills. ICT firms and businesses *operate within* and *benefit from* these rules, which enable broader knowledge sharing, networking, and overall efficiency across diverse innovation systems.
Cross-Sectoral Innovation Platforms	Jacobs	Governance mechanisms actively promote collaboration and knowledge exchange between diverse industries.	Play of the game – Layer 3	Diverse firms, research institutions, universities, government agencies, orchestrators.	Diverse actors *participate in* and *co-govern* platforms (e.g., innovation hubs, incubators) that actively promote collaboration and knowledge exchange across different industries. "Orchestrators" guide these interactions and ensure "openness of knowledge flow."
Public-Private Partnerships for General Infrastructure	Jacobs	Governance arrangements for developing infrastructure (e.g., digital networks, transportation) that benefits a wide array of industries.	Aligning governance structures – Layer 3	Government agencies, private companies (e.g., telecom providers, construction firms), diverse industries.	Government and private companies *form* partnerships to develop general infrastructure (e.g., digital networks, transportation systems) that benefits a wide array of industries. These governance arrangements foster general agglomeration economies by providing shared resources.
Flexible Resource Allocation Mechanisms	Jacobs	Governance models allowing dynamic reallocation of resources (e.g., funding, talent) across emerging and declining sectors.	Transactions aligned with governance structure – Layer 3	Regional development agencies, venture capitalists, diverse firms, startups.	Regional development agencies and investors *implement* governance mechanisms that allow for dynamic reallocation of resources (e.g., funding, talent) across emerging and declining sectors. This supports adaptability and diversification within the regional economy.
Orchestration of Innovation Ecosystems	Jacobs	Active coordination and guidance of actors within diverse innovation ecosystems to promote shared goals, openness, and knowledge flow.	Aligning governance structures – Layer 3	Designated orchestrators (e.g., keystone actors, specialised consultants, research organisations), ecosystem actors (firms, research partners, customers, regulators).	Orchestrators *actively coordinate and guide* the diverse actors within innovation ecosystems through established governance rules and agreements. This promotes shared goals, openness, and knowledge flow, which is crucial for successful systemic innovation and value co-creation.
Inter-industry Knowledge Spillovers	Jacobs	Continuous cross-fertilisation of ideas across diverse industries, leading to novel combinations and breakthrough innovations.	Knowledge resource allocation – Layer 4	Diverse firms, researchers across different sectors, individuals.	Diverse firms and researchers *benefit from* the continuous cross-fertilisation of ideas across different industries, leading to novel combinations and breakthrough innovations. This influences the quantity and quality of new products or processes for continuous innovation.
General Labor Market Pooling	Jacobs	Diverse industries create demand for highly skilled general labour, leading to a larger, more flexible general labour market.	Employment – Layer 4	Diverse firms, general skilled workers (e.g., managers, accountants).	Diverse firms *access* a broad pool of general skilled labour, and workers *find* varied employment opportunities. This continuous access to diverse human capital

					influences the availability and cost of labour for firms' ongoing operations across various sectors.
Access to Industry-Agnostic Suppliers	Jacobs	Proximity to diverse advanced producer services (e.g., finance, legal, consulting) that serve multiple industries.	Resource alignment – Layer 4	Diverse firms, advanced producer service providers (e.g., finance, legal, consulting).	Diverse firms *utilize* the continuous availability of specialised services that cater to multiple industries. This reduces transaction costs and improves access to essential, non-specialised inputs, enhancing the efficiency of firms' continuous operations.
Inter-industry Competition	Jacobs	Competition for shared resources like physical space and general talent across diverse industries.	Private incentives for resource allocation – Layer 4	Diverse firms, local government (managing shared resources).	Diverse firms *compete* for shared resources like physical space and general talent. This continuous competition affects the prices of these resources and influences firms' strategic decisions regarding resource allocation and location, impacting continuous operational costs.
Qualified Variety of Knowledge	Jacobs	High variety with rare knowledge items in the regional knowledge base enhances Jacobs externalities, leading to more effective recombinant knowledge generation.	Varied resource quantity – Layer 4	Firms, researchers, knowledge institutions (universities, research centers).	Firms and researchers *leverage* a regional knowledge base characterised by high variety with rare knowledge items. This continuous recombination leads to strong Jacobs externalities, reducing absorption costs for new knowledge and influencing the quantity of new knowledge produced.
Industry Life Cycle Effects (Young)	Jacobs	Jacobs externalities (benefits from diversity) are positive for young industries but decline and can become negative for more mature industries.	Time-based incentive alignment – Layer 4	Young industries, firms within those industries.	Firms in young industries *experience* positive benefits from local diversity. This influences their incentives to locate in diverse environments and the efficiency gains from diversity, impacting continuous resource allocation towards exploration.
Excess Diversification/ Lack of Focus	Jacobs	Too much diversity or "unqualified variety" can limit the positive effects of recombination, lead to a lack of focus, or reduce the benefits of knowledge generation and exploitation.	Resource incentive alignments – Layer 4	Firms, regional policymakers.	Firms *may experience* reduced benefits from innovation if diversification is "unqualified" or too dispersed. This can hinder the efficiency of continuous innovation and resource allocation, potentially leading to suboptimal quantities of new knowledge or products.
Green Economic Efficiency	Jacobs	Diversified agglomeration can enhance green economic efficiency locally, while specialised agglomeration can inhibit it and have negative spatial spillover effects.	Resource allocation incentives – Layer 4	Producer service firms, local/regional governments, industries.	Producer service firms *contribute to* diversified agglomeration, which can enhance green economic efficiency locally. This influences resource allocation decisions towards more sustainable practices, impacting the quantity and quality of green outputs

Appendix B: Data Addendum

Table 16: Exogenous variable parametrisation for the Ile-de-France Region (FR10) and Bretagne (FRH)

	Exogenous Variable	Description	FR10 Value	FRH Value	Source	Date
Regional	Average Mortality Rate of Children	Rate of deaths per year for the region	0.0041	0.0033	INSEE	2015-2021
	Average Fertility per Woman	Average number of children per woman	1.823	1.639	INSEE	2015-2021
	Average Mortality Rate Of Adults	Computed as the number of total deaths minus the number of infant deaths over the total number of adults in the region	0.0016	0.002	INED	2021
	Average Mortality Rate Of Elders	Computed as the total number of +65 deaths over the total number of +65 population	0.037	0.04	INED	2021
	Initial Children from 0 to 17	Number of children 0-18 in the national population over total national population times the regional population	2 911 380	736353	INSEE	2021
	Young Adults from 18 to 24	All adults in region enrolled in higher education institutes or professionals	1 139 937	261077	INSEE	2021
	Adults 25 to 45	All adults in region looking for work or professionals between ages 25 to 45	5 259 690	1276100	INSEE	2021
	Adults In The Workforce	All adults after studies in working age 45-60	1 770 820	205692	INSEE	2021
	Adults after retirement	All adults after 60 in the region	2 561 681	680791	INSEE	2021
	Public-Private Collaboration Per person	Number of public-private co-publications per region per person	402,7	188.734	EU RIS data	2021
	Innovative SMEs Collaborating With Others	Meant to represent the degree to which SMEs are involved in cooperation, indicator limited to measuring the collaboration between SMEs in % of all SMEs because large firms are usually involved in innovation cooperation	0.617	0.531	EU RIS data	2021
	Workforce Hiring And Training Time in Years	Based on a DARES survey for engineering roles, time for hiring and training personnel in R&D	2	2	DARES	2021
	Percentage Of workforce wanting to work in Private R&D Sector	Number taken from the proportion of graduates from the Grandes Ecoles going to public sector	0.7	0.7	Fondation MMA	2018
	Percentage Of Workforce Going to R&D After Studies	Number taken from the proportion of graduates from the Grandes Ecoles going to private sector	0.4	0.4	Fondation MMA	2018
Sectorial	Initial Employed Workforce In Sector	Number of R&D employees in the sector in 2013 over the national sector R&D employees in 2013 times the national sector R&D employees in 2021	4880.52, 2143.43, 10162, 11580.6,4646, 6352.73, 5728, 5250, 4973, 2005	1093, 988	OPEN DATA MENESR	2013/2021
	Attrition Rate In Sector	Based on national CEREQ 2006 data, compared with DARES 2019-2030 regional data to estimate the current rate	0.037, 0.025, 0.03, 0.0158, 0.025, 0.025, 0.025, 0.243, 0.025, 0.025	0.025	CEREQ, DARES	2006/2019-2030
	Initial Knowledge Specialisation In Sector	Number of patents in sector in region for year 2021 based on the INPI database	3490,430,15951,710,230,6310, 1210,4730,811,491	199, 7	INPI	2021

	Exogenous Variable	Description	FR10 Value	FRH Value	Source	Date
	Knowledge Obsolescence Time	Based on the useful duration of a patent cross-references with academic literature, is set at 10 years	10	10	Hubert, 1991	1991
	Average Time To Market In Sector in Years	Average from sector based literature	12, 10, 6, 2, 15, 5,5,2,4,3	5, 5	Belay et al. (2011)	1991
	Initial Added Value In Sector	The national sector added value proportional to the number of employees in the region's sector	2.699,3.4e9,10.88e9,21.08e9,1.4e9,2.6e9,2e9,4.3e9,1.4e9,5.5e9	3e9,2e9	CCFA	2021
	Percentage Of Profit In Sector	Based on the national average	0.471, 0.459, 0.4105, 0.4155, 0.275,0.314,0.437,0.415,0.275, 0.791	0.405, 0.346	CCFA	2021
	Public Funding For Private R&D In Sector in proportion to total budget	Average amount from the 2011 to the 2022 period proportional to the region's employees in sector	0.0137,0.0363,0.0083,0.0477,0.2709,0.1069,0.2113,0.0402,0.2587,0.0174	0.0137, 0.0137	OPEN DATA MENESR	2011-2022
	Percentage Of R&D Budget on Total Budget In Sector	R&D spendings over total spending in sector at national level	0.3465,0.1841,0.1981,0.0654,0.971,0.3938,0.239,0.1322,0.3233,0.0765	0.3218	OPEN DATA MENESR	2021
	Government Funding for Public R&D In Sector	Average of the R&D spendings in public domain per sector in from 2001 to 2013	8e8	24390000	OPEN DATA MENESR	2001-2013
	Public R&D Expenditure Per Personnel in Sector	Public R&D spending in sector over public R&D employees per sector	334128,40523.1,103778,142497,393604,1.29275e+06,127634, 40523.1,40523.1,40523.1	147657	OPEN DATA MENESR	2021
	Relatedness	The relatedness is obtained from the relatedness scope with NACE rev. 2 sectors	See Table 19	1, 1	Balland et al.	2016
Academic	Initial Students in Studies	Total students enrolled in studies in the region depending on program	25323,6171,632,65597,3993,11891,44976,3882,7588,7344	2335.64	OPEN DATA MENESR	2021
	Percentage Of Adults Enrolling in Studies	Proportion of students enrolled in study over total regional population of 18-25	0.00125182, 5.60557e-4, 7.1057e-5, 0.00173781, 0.00156237, 0.00180536, 0.00557575, 4.23708e-4, 7.14075e-4, 0.000888646	0.00894616	OPEN DATA MENESR, INSEE	2021
	Initial Workforce After Studies	Population from the study having graduated and in the workforce	9090,2037,670,15865,1320,11765,57939,2295,2920,5890	1965	OPEN DATA MENESR	2021
	Initial public researchers in the region	Number of public researchers in the region, independent of the sector.	34715	16715	OPEN DATA MENESR	2021

Table 17: Summary of the typical graduate-level subjects studies expected for a research/R&D position in France, by industry (APEC, 2025).

Industry	Expected Subject of Graduate Studies
Automotive	Mechanics; Electronics, electrical engineering; Computer science; Mathematics; Technology and industrial sciences; Process engineering; Physics
Pharmaceutical	Pharmacy; Chemistry; Life sciences; Process engineering; Multidisciplinary life, health, earth and universe sciences
ICT (Information & Services)	Computer science; Electronics, electrical engineering; Information and communication sciences; Mathematics; Technology and industrial sciences
Aerospace Construction & Engineering	Mechanics, Electronics, electrical engineering; Physics; Mathematics; Technology and industrial sciences; Computer science; Process engineering

Specialistic Technical & Scientific Activities (metrology, testing, R&D consultancy, etc.)	Physics; Chemistry; Mathematics; Electronics, electrical engineering; Multidisciplinary fundamental sciences and applications; Technology and industrial sciences; Computer Science; Process engineering
Manufacturing of Measurement Instruments, Navigation & Watchmaking	Electronics, electrical engineering; Mechanics; Physics; Mathematics; Technology and industrial sciences; Computer Science; Process engineering
Chemical Industry	Chemistry; Process engineering; Technology and industrial sciences; Mathematics
Editing, Audiovisual & Diffusion (publishing, film, media, streaming)	Arts; Information and communication sciences; Foreign languages and literatures; French Languages and Literature; Electronics, electrical engineering; Computer science
Manufacturing of Communication Equipment (telecoms, networks)	Electronics, electrical engineering; Computer science; Information and communication sciences; Physics; Mechanics, mechanical engineering; Mathematics; Process engineering; Technology and industrial sciences
Production & Distribution of Gas, Vapour & Air-Conditioning	Process engineering; Mechanics, mechanical engineering; Physics; Technology and industrial sciences; Mathematics
Telecommunications	Electronics, electrical engineering; Computer science; Information and communication sciences; Physics; Mechanics, mechanical engineering; Mathematics; Process engineering; Technology and industrial sciences

Table 18: Listing of the CIB patenting codes by industry (CIB, 2025).

Industry	CIB
Automotive	B60P 3/07, G08G 1/00, B60W 60/00, B60V 3/02, G08G 1/015, B60W 50/00, B60W 40/00, B60W 30/00, B60N 2/38, B60W 30/18, A63H 17/14, B60W 30/02, B60W 40/103, B60W 40/10, B60W 30/16, B60W 40/12, B60W 20/00, B62D 53/00, B60W 30/165, B60W 30/17
Pharmaceutical	A61J 1/00, A61K 6/69, A61J 3/00, A61J 7/00, A61J 7/04, A61P 3/04, A61H 15/02, A61P 3/00, A61P 17/00, A61P 19/00, A61P 27/00, A61P 5/00, A61P 9/00, A61P 11/00, A61P 13/00, A61P 25/00, A61P 37/00, A61P 5/44, A61P 7/12, A61P 9/14
ICT (Information & Services)	G16Y 10/75, H04K 1/00, G06Q 50/00, H04K 3/00, H04L 51/10, H04W 4/48, H04N 21/643, H04L 51/58, H04L 61/5069, H04L 69/24, H04B 10/118, H04B 10/70, H04W 72/566, H04L 41/0853, H04B 10/116, H04L 51/043, H04H 20/55, H04L 67/2869, H04B 1/56, H04B 10/03
Aerospace Construction & Engineering	B64G 1/14, B64G 1/68, B64G 1/56, B64G 1/22, B64G 1/64, B64G 1/00, B64G 6/00
Specialistic Technical & Scientific Activities (metrology, testing, R&D consultancy, etc.)	G06Q 50/10 G06Q 50/26 H04W 4/50 H04W 4/024 G06Q 50/18 H04H 60/63 H04W 28/24 H04L 67/50 H04L 45/0377 H04W 4/02 H04W 4/10 H04W 4/029 H04W 4/021 G06Q 30/012 H04W 72/30 H04L 67/562 H04W 4/06 A47F 10/06 H04L 67/53 H04L 67/55 H04L 67/56 H04H 20/83 H04L 41/5019 H04W 52/26 G06Q 30/014 G06Q 50/60 H04L 41/5051 H04L 67/567 H04L 61/4541 H04L 65/40
Manufacturing of Measurement Instruments, Navigation & Watchmaking	G01C 23/00 G04C 13/04 G01C 21/00 G01C 21/20 G01C 21/24 G04C 13/00 G01C 21/28 G01C 21/12 G01C 21/16 G01C 21/26 G04C 13/02 G04C 1/00 G04C 15/00 G04C 13/08 G04D 7/12 G16Y 40/60 G04B 21/12 G04B 25/02 G01C 17/00 F21W 111/043 G04C 10/00 G04C 11/00 G06F 1/06 G04B 19/14 G01C 1/00 G04C 13/03 G06F 1/10 G06F 1/12 G04B 19/26 G04C 21/14
Chemical Industry	G16C 20/60 G16C 10/00 C40B 50/04 G16C 20/40 G16C 20/10 G16C 20/20 G16C 20/30 C40B 60/00 B01J 13/00 C06C 9/00 B01B 1/04 C14C 3/02 A24B 15/28 C40B 70/00 G21G 5/00 C08J 7/12 C23F 1/04 C03C 25/68 C23F 14/02 B01J 19/00 G16C 20/00 C07B 63/02 C40B 80/00 A23B 7/022 A23B 7/05 A62D 3/30 G16C 60/00 D01F 11/16 C14C 7/00 A23B 5/025
Editing, Audiovisual & Diffusion (publishing, film, media, streaming)	H04L 65/611 C23C 10/32 B01D 17/09 B01D 59/16 C30B 31/08 C23C 10/54 F04F 9/00 G03C 8/06 C23C 10/08 C23C 10/20 C23C 10/26 C23C 10/36 C23C 12/02 G01K 11/322 G01K 11/324 B01D 59/12 C23C 10/14 C23C 10/16 C23C 10/52 C23C 10/58
Manufacturing of Communication Equipment (telecoms, networks)	H04M 3/62 H04W 36/36 H04W 4/48 B63C 11/26 H04K 1/00 B63C 11/02 H04M 1/17 G06F 9/54 H04M 9/02 F27D 3/15 B23Q 16/02 H04M 1/00 H04N 21/643 H04M 1/72484 H04M 1/72513 H04W 4/46 B63C 11/32 H04M 11/00 H04K 3/00 B63C 9/23
Production & Distribution of Gas, Vapour & Air-Conditioning	B64D 13/06 F24F 13/32 B63J 2/02 F24F 5/00 B64D 13/08 F24F 13/00 F24H 4/06 F24H 15/204 F24H 15/208 F24H 3/00 F24H 9/1854 F24F 3/12 F24F 1/00 F24F 12/00 F02C 7/08 F24F 3/00 F24F 1/0003 F24F 1/02 C10J 1/20 B07B 11/02 F02M 21/04 F24F 110/52 F24F 110/12 F24F 110/22 F24F 110/32 F24F 11/74 F24F 6/00 F24F 3/153 F24F 3/052 B60H 1/18

Telecommunications	H01F 17/08 H04W 28/18 G06Q 20/16 G01S 19/12 G06Q 50/50 H04W 4/00 H04W 48/18 H04W 92/00 H02G 15/18 G04R 20/14 H04L 41/052 H04W 88/00 H04W H02G

Table 19: Relatedness Matrix amongst sectors within Ile-de-France with Jaccard Method (Boschma et al., 2014, 2015). The sectors are coded from I1 to I10 respectively as Pharmaceutical Industry, Chemical industry, Automotive industry, ICT information and services, Aerospace construction and engineering, Specialistic Technical and scientific activities, Manufacturing of measurement instruments of navigation and Watchmaking, Editing audiovisual and diffusion, Manufacturing of communication equipment, Production and distribution of gas vapour and AC

	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10
I1	0	0.297297	0.027778	0.08	0.090909	0	0.083333	0	0.052632	0
I2	0.297297	0	0.027778	0.038462	0.028571	0	0.083333	0	0.052632	0.137931
I3	0.027778	0.027778	0	0.04878	0.190476	0.210526	0.037037	0	0	0
I4	0.08	0.038462	0.04878	0	0.076923	0.025641	0.046512	0.322581	0.15	0
I5	0.090909	0.028571	0.190476	0.076923	0	0.047619	0	0	0	0
I6	0	0	0.210526	0.025641	0.047619	0	0.041667	0	0	0.1875
I7	0.083333	0.083333	0.037037	0.046512	0	0.041667	0	0	0.148148	0.043478
I8	0	0	0	0.322581	0	0	0	0	0.038462	0
I9	0.052632	0.052632	0	0.15	0	0	0.148148	0.038462	0	0.041667
I10	0	0.137931	0	0	0	0.1875	0.043478	0	0.041667	0

Table 20: Time Series of Set-Up Parameters for Model Look Up Table per region

Parameters	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Fertility per woman Bretagne	1.92	1.9	1.93	1.94	1.94	2.04	2	2.04	2.02	2.03	2.01	2	1.95	1.93	1.86	1.83	1.8	1.79	1.77	1.73	1.78
Fertility per woman Ile-de-France	1.92	1.93	1.93	1.95	1.96	2.03	1.99	2.01	2.02	2.05	2.03	2.02	2.01	2.04	2	1.98	1.95	1.94	1.94	1.88	1.86
Public R&D expense for the ICT sector in Bretagne (€M)	13	16.46	19.24	10.18	13.31	17.36	22.78	19.9	28.75	25.45	23.49	24.39	24.93								
Public R&D expense for the Pharmaceutical sector in Ile-de-France (€M)	224.14	237.98	240.63	260.43	276.76	485.01	523.86	540.67	594.14	628.65	636.29	676.27	684.3								
Public R&D researchers in ICT in full-time work	175.6	146.6	203.4	194.2	201.6	212.72	229.49	263.24	271.06	182.2	184.24	165.18	175.6								
Public R&D researchers in Pharmaceutical in full-time work	1414.7	1487.5	1463.9	1447.9	1512.3	1549.5	1756.06	1817.06	1913.3	1955	1929.4	1982.72	2048.02								

Table 21:Parametrisation Data for the Ile-de-France region for all the sector subscripts in 2021

Exogenous Variable	Automotive Industry	Pharmaceutical	ICT	Aerospace Construction & Engineering	Specialistic Technical & Scientific Activities	Manufacturing of Measurement Instruments, Navigation & Watchmaking	Chemical Industry	Editing, Audiovisual & Diffusion	Manufacturing of Communication Equipment	Production & Distribution of Gas, Vapour & Air-Conditioning
Initial Employed R&D Workforce In Sector (in full time employees)	11168	4373	17181	5116	11484	6138	2593	8385	5650	2208
Retention Rate In Sector	3%	3.7%	1.58%	2.5%	2.5%	2.5%	2.5%	2.43	2.5%	2.5%
Initial Knowledge Specialisation In Sector (in patents)	15951	3490	710	230	6310	1210	430	4730	811	491
Average Time To Market In Sector (in years)	6	12	2	15	5	5	10	2	4	3
Initial Added Value In Sector (in €B)	5.7	2.6	15.7	1.4	2.6	2	3.4	4.3	1.4	5.5
Percentage Of Profit In Sector (%)	41.05	47.1	41.55	27.5	31.4	43.7	45.9	41.5	27.5	79.1
Public Funding For Private R&D In Sector (as percentage of total private R&D spending)	0.83	1.37	4.77	27.09	10.69	21.13	3.63	4.02	25.87	1.74
Percentage Of R&D Budget on Total Budget In Sector (%)	19.81	34.65	6.54	97.1	39.38	23.9	18.41	13.22	32.33	7.65

Exogenous Variable	Automotive Industry	Pharmaceutical	ICT	Aerospace Construction & Engineering	Specialistic Technical & Scientific Activities	Manufacturing of Measurement Instruments, Navigation & Watchmaking	Chemical Industry	Editing, Audiovisual & Diffusion	Manufacturing of Communication Equipment	Production & Distribution of Gas, Vapour & Air-Conditioning
Innovation Expenditure Per Person Employed in Innovation in Sector (in € per researcher)	4486316	300134	112260.3	208088.7	112260.3	142732.2	363440.8	122792.4	118865.9	253022.4
Government Funding for Public R&D In Sector (in €M)	30.27	684.3	92.78	229.58	1023.61	16.72	266.86	266.86	266.86	266.86
Public R&D Expenditure Per Personnel in Sector (in € per researcher)	103778.11	334127.59	142497.31	393603.54	1292754	127633.58	40523.11	40523.11	40523.11	40523.11

Table 22: Parametrisation Data for the Ile-de-France region for all the studies subscripts in 2021

	Audiovisual	Health	Multidisciplinary Sciences	Digital	Industry	Mechanics	Physics	Chemistry	Process Engineering	Information and communication studies
Initial Students in Studies	65597	25323	3993	11891	44976	3882	7588	6171	632	7344
Percentage Of Adults Enrolling in Studies	5.85%	2.26%	0.36%	1.06%	4.01%	0.35%	0.68%	0.55%	0.06%	0.65%
Initial Workforce After Studies	15865	9090	1320	11765	57939	2295	2920	2037	670	5890

Table 23: Validation Data for the Ile-de-France region for the Pharmaceutical sector subscripts from 2001-2022

	2001	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**
Regional Population	11102824	11185563	11270074	11350290	11442143	11532398	11598866	11659260	11728240	11786234	11852851
Children	2911377	2929778	2948556	2970969	2992114	3008457	3021977	3029354	3042263	3056145	3071017
Young Adults	1160937	1163147	1165227	1164616	1165149	1169601	1167765	1166478	1167801	1167475	1164346
Adults in the workforce	5259687	5311172	5354974	5393074	5431018	5473161	5474460	5464992	5465730	5460201	5459916

	2012	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**
Regional Population	11898502	11959807	12027565	12082144	12117132	12174880	12213447	12262544	12271794	12317279	11185563
Children	3081236	3093352	3107383	3127492	3132488	3146029	3155638	3164236	3137668	3117685	2929778
Young Adults	1159941	1154412	1148858	1144519	1141782	1142935	1143197	1133676	1132579	1139937	1163147
Adults in the workforce	5466261	5473536	5489139	5488863	5484001	5488695	5487895	5485109	5475711	5497976	5311172

Adults after retirement	1770823	1781466	1801317	1821631	1853862	1881179	1934664	1998436	2052446	2102413	2157572	2191064	2238507	2282185	2321270	2358861	2397221	2426717	2479523	2525836	2561681	1781466
Regional birth rate	0,0155	0,0155	0,0153	0,0154	0,0154	0,0158	0,0154	0,0154	0,0154	0,0156	0,0153	0,0152	0,015	0,0152	0,0149	0,0147	0,0144	0,0143	0,0142	0,0137	0,0135	0,0131
Workforce employed in knowledge intensive activities in sector	4663	4921	5353	NA	5016	4977	5133,09	4772	4726	4557,88	4687,97	4794,35	4880,52	4511,94	4635,13	4743,22	4842,36	4733,83	4733,14	4503,42	4380,92	4304,56
Internal knowledge generation	645	658	556	676	671	614	606	625	619	602	547	518	542	377	376	390	495	419	310	401	535	501
Innovation expenditure per person employed in innovation in sector	303058,117	297266,8	288550,3	NA	284718,9	319746,8	311243,3	333015,5	330188,3	314832,8	310366,7	314518,1	300134	330367.7	320956.5	314669	301648.7	299453.9	289716.1	301059.8	311325.5	351964.8
R&D expenditure in Sector	1413160000	1462850000	1544610000	NA	1428150000	1591380000	1597640000	1589150000	1560470000	1434970000	1454990000	1507910000	1464810000	1439093298	1436272130	1440974155	1410221040	1368582208	1323885135	1273345373	1316764363	1462703220
Students	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	19126	20893	20202	20296	22338	23388	24180	26157
Percentage of adults enrolling in studies	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	1.67	1.68	1,67	1,67	1,69	1,69	1,68	1,64
Knowledge workforce in public R&D	1414,7	1487,5	1463,9	1447,9	1512,3	1549,5	1756,06	1817,06	1913,3	1955	1929,4	1982,72	2048,0	NA	NA	NA	NA	NA	NA	NA	NA	NA

Table 24: Data comparison between model run and data collection for the Pharmaceutical sector from 2001 to 2022.

	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Regional Population	11102824	11185563	11270074	11350290	11442143	11532398	11598866	11659260	11728240	11786234	11852851	11898502	11959807	12027565	12082144	12117132	12174880	12213447	12262544	12271794	12317279	11185563

Regional Population : model	11102800	11152000	11200600	11247400	11294300	11340900	11387800	11429000	11467300	11503000	11536200	11562900	11584600	11601400	11615500	11623000	11624500	11619800	11611000	11597100	11575500	11548500
Children	2911377	2929778	2948556	2970969	2992114	3008457	3021977	3029354	3042263	3056145	3071017	3081236	3093352	3107383	3127492	3132488	3146029	3155638	3164236	3137668	3117685	2929778
Children : model	2911380	2921910	2932590	2942500	2953740	2966420	2981550	2993260	3004730	3016370	3028330	3036720	3042840	3046860	3050750	3050400	3046340	3038270	3027950	3014260	2994650	2971240
Young Adults	1160937	1163147	1165227	1164616	1165149	1169601	1167765	1166478	1167801	1167475	1164346	1159941	1154412	1148858	1144519	1141782	1142935	1143197	1133676	1132579	1139937	1163147
Young adults : model	1160940	1117570	1074610	1034660	1000300	972668	951694	936640	926528	920375	917309	916607	917695	920119	923511	927572	932058	936763	941506	946120	950453	954369
Adults in the workforce	5259687	5311172	5354974	5393074	5431018	5473161	5474460	5464992	5465730	5460201	5459916	5466261	5473536	5489139	5488863	5484001	5488695	5487895	5485109	5475711	5497976	5311172
Adults in the workforce : model	5259690	5322540	5384940	5444350	5498270	5545640	5586620	5622030	5652920	5680330	5705160	5728160	5749910	5770850	5791310	5811550	5831740	5852010	5872440	5893090	5913970	5935080
Adults after retirement	1770823	1781466	1801317	1821631	1853862	1881179	1934664	1998436	2052446	2102413	2157572	2191064	2238507	2282185	2321270	2358861	2397221	2426717	2479523	2525836	2561681	1781466
Adults after retirement : model	1770820	1790020	1808450	1825900	1841950	1856130	1867970	1877070	1883130	1885940	1885380	1881420	1874110	1863570	1849950	1833460	1814330	1792800	1769130	1743580	1716410	1687850
Workforce employed in knowledge intensive activities in sector	4663	4921	5353		5016	4977	5133.09	4772	4726	4557.88	4687.97	4794.35	4880.52	4511.94	4635.13	4743.22	4842.36	4733.83	4733.14	4503.42	4380.92	4304.56
Workforce employed	4663	4492.06	4327.4	4168.76	4015.95	3868.73	3726.91	3590.29	3458.68	3331.89	3209.75	3092.09	2978.74	2869.55	2764.36	2663.02	2565.4	2471.36	2380.76	2293.49	2212.4	2174.7

in knowledge intensive activities[Pharmaceutical Industry] : model																						
Internal knowledge generation	645	658	556	676	671	614	606	625	619	602	547	518	542	377	376	390	495	419	310	401	535	501
internal knowledge generation[Pharmaceutical Industry] : model	405	405	405	405	405.92	408	411.03	416	424	436	451	470.84	496	527	563	605	653	706.6	766	832	902	976
R&D expenditure in Sector	1413160000	1462850000	1544610000		1428150000	1591380000	1597640000	1589150000	1560470000	1434970000	1454990000	1507910000	1464810000	1439093298	1436272130	1440974155	1410221040	1368582208	1323885135	1273345373	1316764363	1462703220
R&D expenditure in Sector[Pharmaceutical Industry] : model	1425100000	1458400000	1491640000	1524310000	1555770000	1585580000	1613730000	1640670000	1667260000	1694710000	1724550000	1758660000	1799160000	1848290000	1908180000	1980850000	2068120000	2171680000	2293080000	2433720000	2594610000	2775990000
Students	19445.69475	19482.71225	19517.55225	19507.318	19516.24575	19590.81675	19560.06375	19538.5065	19560.66675	19555.20625	19502.7955	19429.01175	19336.401	19243.3715	19126	20893	20202	20296	22338	23388	24180	26157
Students[Health] : model	19445	20992.5	22348.5	23422.7	24150.3	24541.3	24656.9	24578.1	24382.8	24135.1	23881.2	23651.1	23461.5	23319.5	23225.6	23176.5	23166.7	23189.8	23239.2	23308.6	23391.9	23483.8
Knowledge workforce	1414.7	1487.5	1463.9	1447.9	1512.3	1549.5	1756.06	1817.06	1913.3	1955	1929.4	1982.72	2048									

in public R&D																						
knowledge workforce in public R&D[Pharmaceutical Industry] : model	1238.51	1487.51	1463.91	1447.9	1512.3	1549.5	1756.06	1817.06	1913.3	1955	1929.4	1982.73	2048.02	2048.02	2048.02	2048.02	2048.02	2048.02	2048.02	2048.02	2048.02	2048.02

Table 25: Validation Data for the Bretagne region for the Telecommunication sector subscripts from 2001-2012

Parameters	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
Regional Population	2954324	2981765	3009249	3037077	3066585	3094534	3120288	3149701	3175064	3199066	3217767	3237097
Children	736353	738672	741681	748027	753913	757353	762853	767672	773652	777642	780408	781997
Young Adults	261077	261122.6	261055.3	259746	258567	258776.3	257019.3	256835.3	256010.3	254220	252368	250020
Adults in the workforce	1276102	1299275	1318796	1334115	1350370	1367992	1370809	1375193	1373499	1372196	1370917	1370123
Adults after retirement	680791	682695	687717	695189	703735	710413	729607	750001	771903	795008	814074	834957
Adults after retirement: model	680791	623410	573891	531371	495071	464289	438391	416808	399029	384595	373096	364163
Workforce employed in knowledge intensive activities in sector	1093	1265	1272		1552	1480	1602	1579	1386	1433	1426	1656
Internal knowledge size	199	218	240	261	289	315	333	357	375	391	406	423
R&D expenditure in Sector	1.93E+08	1.99E+08	1.84E+08		2.00E+08	2.09E+08	2.27E+08	2.43E+08	1.87E+08	1.78E+08	2.57E+08	1.84E+08
Students	2335.64	2336.0453	2335.443	2323.729	2313.182	2315.055	2299.336	2297.69	2290.31	2274.293	2257.725	2236.719
Knowledge workforce in public R&D	175.6	146.6	203.4	194.2	201.6	212.72	229.49	263.24	271.06	182.2	184.24	165.18

Table 26: Data comparison between model run and data collection for the Telecommunication sector from 2001 to 2012.

Parameters	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
Regional Population	2954324	2981765	3009249	3037077	3066585	3094534	3120288	3149701	3175064	3199066	3217767	3237097
Regional Population: model	2954320	2965760	2976450	2986770	2996510	3006300	3015880	3024520	3032620	3039750	3045910	305100
Children	736353	738672	741681	748027	753913	757353	762853	767672	773652	777642	780408	781997
Children: mode	736353	747621	757344	766220	774532	782790	790610	797436	803777	809547	814674	818718
Young Adults	261077	261122.6	261055.3	259746	258567	258776.3	257019.3	256835.3	256010.3	254220	252368	250020

Young adults: mode	261077	253316	247527	243286	240277	238253	237038	236431	236291	236498	236966	237594
Adults in the workforce	1276102	1299275	1318796	1334115	1350370	1367992	1370809	1375193	1373499	1372196	1370917	1370123
Adults in the workforce: model	1276102	1261570	1246440	1231080	121579	1200780	1186200	1172190	1158810	1146110	1134130	1122860
Adults after retirement	680791	682695	687717	695189	703735	710413	729607	750001	771903	795008	814074	834957
Adults after retirement: model	680791	623410	573891	531371	495071	464289	438391	416808	399029	384595	373096	364163
Workforce employed in knowledge intensive activities in sector	1093	1265	1272		1552	1480	1602	1579	1386	1433	1426	1656
Workforce employed in knowledge intensive activities[Telecommunication]: model	1093	1069.95	1085.93	1152.51	1267.35	1451.42	1726.08	2037.25	2308.95	2505.26	2637.59	2758.77
Internal knowledge size	199	218	240	261	289	315	333	357	375	391	406	423
Industry knowledge size[Telecommunication]: current MAR	199	203.194	207.391	211.689	216.354	221.816	228.684	237.753	249.998	266.552	288.688	347.843
R&D expenditure in Sector	192.98e6	199.27e6	1.84E+08		2.00E+08	2.09E+08	2.27E+08	2.43E+08	1.87E+08	1.78E+08	2.57E+08	1.84E+08
R&D expenditure in Sector[Telecommunication]: current MAR	1.92E+08	1.97E+08	1.99E+8	202.69e6	2.08E+08	2.14E+08	2.21E+08	2.29E+08	2.40E+08	2.56E+08	2.77E+08	3.07E+08
Students	2335.64	2336.0453	2335.443	2323.729	2313.182	2315.055	2299.336	2297.69	2290.31	2274.293	2257.725	2236.719
Students: model	2335.64	2336.0453	2335.443	2184.57	2159.51	2142.96	2133.39	2129.06	2128.74	2131.38	2136.23	2142.42
Knowledge workforce in public R&D	175.6	146.6	203.4	194.2	201.6	212.72	229.49	263.24	271.06	182.2	184.24	165.18
knowledge workforce in public R&D: model	175.602	146.6	203.402	194.201	201.603	212.722	229.491	263.241	271.06	182.201	184.241	162.18

Regional Population

The regional population is seen as increasing at a higher rate than the model for both Bretagne and Ile-de-France regions. It shows a steady growth from 11.10 million in 2001 to a peak of approximately 12.32 million in 2021, then a slight dip back to 11.19 million in 2022 for the Ile-de-France region. Comparatively, the model curvature is also rising, but from 11.10 million to only approximately 11.57 million by 2021, and under-shoots the 2022 drop to 11.55 million. The model quantitatively underestimates population by approximately 0.2 to 0.6 million, with the gap widening over time. The 28 000 differences in 2002 increases to 62 000 over two decades. It fails to capture the late-stage deceleration and slight reversal seen in 2022. These differences are also present in Bretagne's results, where the actual population goes from around 3 million in 2001 to 4 million in 2012, while the model shows a slower growth averaging around 3 million.
Finally, the model has not been coded to recognise or implement shocks, which might be the cause of the abrupt decline in population in 2022 compared to 2021.

The historical trend shows the number of children in the region experiencing a gradual increase from 2.91 million to 3.15 million by 2018, a slight dip to 3.12 million in 2021, then down to 2.93 million in 2022 for Ile-de-France simulations. In the MAR model, the results are very proximal to the empirical data measured by showing a constant increasing curve from 0.7 million to 0.9 million. The model here follows this dynamic more accurately for both Jacobs and MAR regions for this population group than for the rest of the groups, with a remaining small difference. In Ile-de-France, it rises more slowly, from 2.911 million to 3.05 million in 2018, then also declines steadily to 2.97 million by 2021 and approximately the same value in 2022. The model underestimates the children cohort by 10 000 to 50 000 people annually in Ile-de-France, while this amount is lower in Bretagne. It also overstates the pace of decline post-2015: historical children plateau around 3.15 million, whereas the model peaks at only 3.05 million before reversing. Nonetheless, its dynamics remain more accurate for this section of the population compared to the overall trend.

The same finding is observed for young adults, which the model is underestimating in a lower scale. The historical data analysis for young adults reflects a stable evolution around 1.16 million until 2007, then a slow decline to 1.13 million in 2020, finally rebounding to 1.16 million in 2022 in Ile-de-France. On the other hand, the model predicts a sharp fall from 1.16 million in 2001 to just around 0.95 million by 2007, then a very gradual recovery back to 1 million by 2022. The same observation is deductible from the MAR regional model, where the model slightly underestimates young adults from the 2002 onwards. However, it manages to reproduce the historical mid-period stabilisation and late recovery, even if at a slower rate it projects a monotonic decline then stagnation. With a children population that progressively becomes lower than the registered one, this difference is expected to happen and possibly exacerbate already existing inaccuracies. Despite the differing amounts, the dynamics of the system are properly simulated, showing a slowing decrease.

From the registered data, the adult population in the workforce in Ile-de-France reaches a steady rise from 5.26 million in 2001 to 5.50 million in 2013, then a plateau around 5.49 million to 5.48 million through 2021, dipping slightly to 5.31 million in 2022. The model matches early growth, then overshoots, projecting continual growth to 5.93 million by 2022. After 2007 the model begins to overestimate the workforce by 60 thousand and that bias grows to 620 thousand by 2022, failing to capture the late-period plateau and slight decline. The opposite case is observable in the MAR region of Bretagne, which largely underestimates the output variable. The difference is as significant in the Bretagne model output as it is for the Ile-de-France (around 500 000) and the trend has an opposite direction than the empirical time series. This variable is however the one with the largest timespan before the entering value begins to decrease. The time delay for change is of 40 years, also signifying that any change in population within those years that does not include aging is not recognised. It might be the case that each year there is brain drain occurring, pushing part of the qualified workforce to leave the region and seek opportunities elsewhere. In this sense, if the region is very prone to migration dynamics, it is more likely that they are empirically measured in this age group given the larger sample size.

The number of adults after retirement in Ile-de-France historically rises from 1.77 million in 2001 to 2.53 million in 2020, then decreases back to 1.78 million in 2022 as if the data appeared reset in 2022. The model shows a growth that is in line with the historical trend from 1.77 million in 2001 until 2007 then to a maximum 1.95 million in 2011, then declines steadily to 1.69 million by 2022 to approximate the final number of aging population. The model underestimates retirees after 2007, projects a faster post-2011 decline than the shock induced by what could be the covid period, which is did not account for as it is not parametrised for it. The retiree underestimation is valid for the data points from Bretagne as well. The model predicts declining retirees compared to an actual increasing amount. The shape of the curve follows the same one as the curve for adults in the workforce, suggesting that this inaccurate model output is linked to the inaccuracy of the previous stock. Finally, it reflects the historical aging-driven accumulation up to 2020 to a lesser extent. This might be because the model has been programmed with life expectancy as a constant value. Not modelling the increase in life expectancy over the last two decades might explain the lower number of retirees by the shorter time delay in the stock before the outflow.
From a modelling perspective, this could mean that to improve output accuracy, we could consider migratory flows that impact the older subscripts of population. This would then ensure that this fertile portion of the population is also accounted for the fertility and demographic growth of the region. That being said, the previous hypothesis remains valid for Children, as migratory flows could account for the difference in population increase, and the recent covid shock could explain the abrupt decrease in children at the end of the decade.

Students

Students in Pharmaceutical Higher studies demonstrate a behaviour with little variation until 2016. The number of students keeps constant at 19 450 in 2001 to 2014, then abruptly jumps to 20 893 in 2016, and a further rise to 26 157 by 2022. The model predicts a smoother upward drift from 19 445 in 2001 to 23 384 in 2022. It does not show the sudden mid-decade jump of 1 400 students in 2016 but rather smoothly reaches that estimate over time. Given that is has not been coded to handle the 2016 shock, it anticipates it with a smooth dynamic, reaching the expected result. In the MAR region, a similar case is observed where data points suddenly decrease around 2004 with a progressive increase. The model output does not abruptly decrease but shows convergence towards the values from the historical dataset.

Knowledge Workforce in Public R&D

The number of researchers in public R&D rises from 1 415 in 2001 to 2 048 by 2012, then data stops. The model infallibly matches early values through 2013, then flattens at 2 048 from 2013 onward as the data to generate different values is absent. The model captures the upward trend until 2012 but thereafter does not to project further growth; it holds the workforce constant, whereas historical likely continued evolving. Nonetheless, due to data restrictions this could not have been modelled.

Workforce Employed in Knowledge-Intensive Activities

Despite the differences in certain categories of the population, the R&D workforce in both regional models shows a behaviour that is in line with the trend from historical data. The R&D workforce in the private sector in Ile-de-France shows a rise from 4 663 in 2001 to 5 353 in 2004, then gradual fall to 4 381 by 2021 and 4 305 by 2022. The model peaks at 5 353 in 2003 as well, but then declines more steeply, down to 2 174 by 2022. While timing of the peak aligns, the model overstates the subsequent decline, underestimating by 200–500 in early years and by over 2 000 by 2021. While the R&D in this sector in the region is in decline, in the MAR region of Bretagne, R&D workers are following an S shaped curve, which seemingly is an amplification of the S curve from historical data points. While the increasing behaviour is properly present through both real data and modelled data, the model anticipates the speed of growth which lead to be up to 1000 employees higher than measured. This might suggest adjusting hiring and training time or attrition rate to be more representative of the region and sector dynamics.

R&D Expenditure in Sector

The R&D expenditure in the pharmaceutical sector grows from €1.41 billion in 2001 to a plateau around €1.59 to 1.64 billion in 2006–2008, then modestly declines to €1.27 billion by 2020, before jumping back to €1.46 billion in 2022. The model however projects continuous acceleration, from €1.43 billion in 2001 to €2.78 billion in 2022.
The model is bound to projecting an increasing rise in R&D expenditure in the sector given the positively reinforcing loops stemming from knowledge generation. The more patents a firm has, the more it can commercialise on those patents, therefore increasing their sales, profits and budget commitments for the following year, allowing the sector to expand and hire more R&D staff to generate more knowledge. Hence, the knowledge generation over the previous years keeps accumulating to generate more financial capital. The telecommunication sector in Bretagne observes oscillations in R&D expenditure from historical data. These oscillations are not replicated by the model which aligns with the upper peaks of the oscillations and shows growth.

Internal Knowledge

The internal knowledge generation represents the number of patents published per year in the pharmaceutical sector for Ile-de-France. This number is seen as fluctuating between 556 and 676 in the 2001–2007 year span, then drifts down to a low of 310 in 2019 before rebounding to 535 by 2021 and 501 by 2022. The model on the other hand holds almost flat at 600 from 2001 to 2022 with only a low oscillation, then a slight decrease in 2022, replicating the historical patent decrease in that same year. The model does not reproduce the knowledge volatility since it is not tuned to possible industry shocks but depicts a period of stabilisation that is expected is by averaging the peaks and declines of the knowledge generation.
In the Telecommunication sector for Bretagne, the final knowledge output size is compared given the difference in the availability of data with Ile-de-France. What can be firstly noticed is the strong alignment on both initial and final values of the model. However, the modelled curve represented by the dashed line appears to more convex than the real values, underestimating them by at most 40 patents

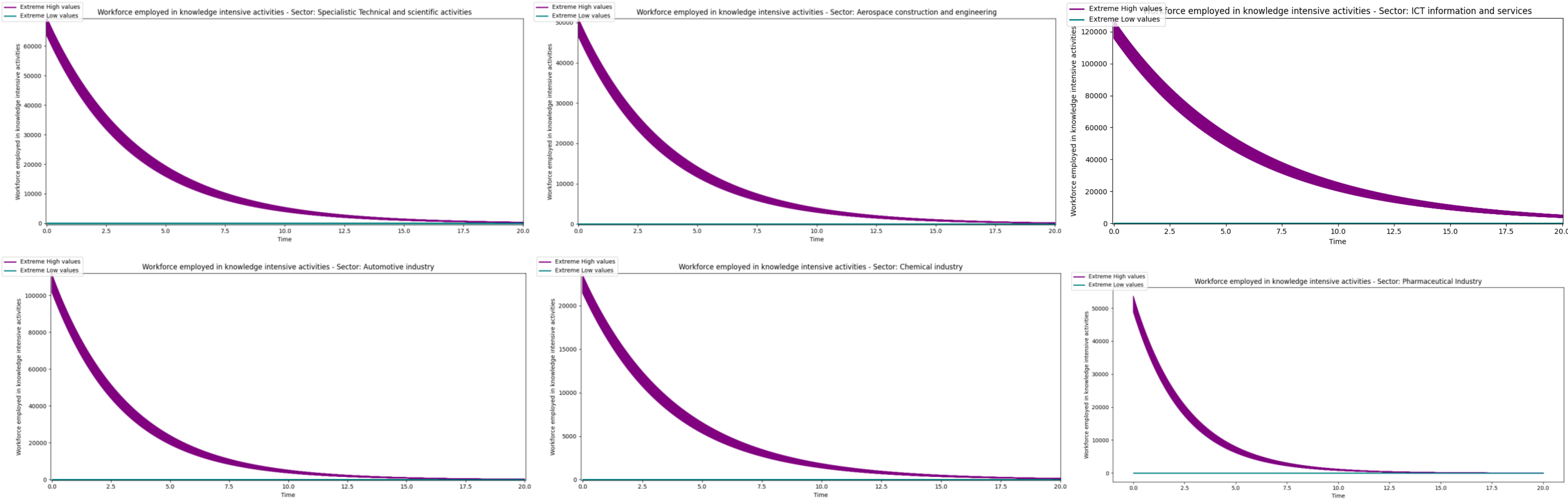

Figure 46: Extreme Values Test R&D Workforce Results for Jacobs Region Ile-de-France

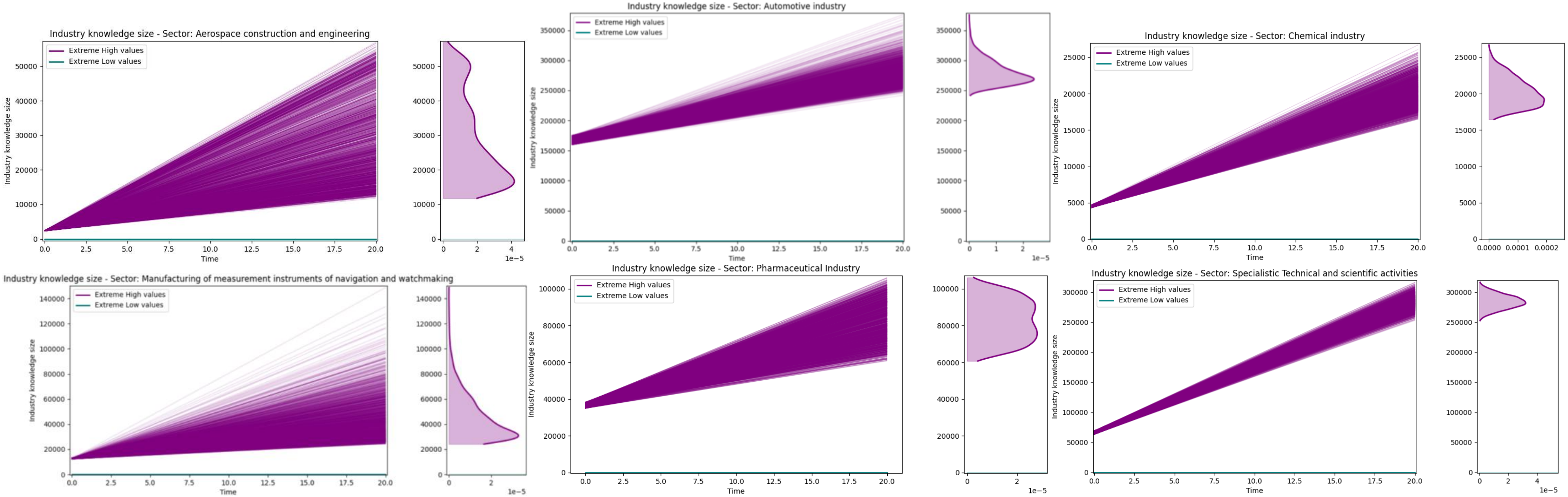

Figure 47: Extreme Values Test Knowledge Size Results for Jacobs Region Ile-de-France

Table 27: Expert Validation Questions

Model Focus	Question
Structure	Is the causal loop diagram structure consistent with reality?
	Do you think the model structure (sub-models) are consistent with reality?
	Do you think the model (variables, stocks and flows) are consistent with reality?
	Do you see any parameter as being unrealistic/not-existent?
Behaviour	Does the model appear to you like it endogenously generates the characteristics the real system behaviour?
	Do you think anomalies occur in the model behaviour?
	Do you think anomalies would occur if the assumptions got removed?
	Does the model seem to you like it represents the behaviour at different instances of the sectors when their input parameters have been entered?
	Does this model seem to represent dynamics not explored in previous models?
	Does the model seem able to identify “new” behaviour that has not been known in the real system?
	Does the model behave properly when extreme input values are entered?
	Does the model seem sensitive to reliable changes in parameters?
	Does the model outputs have the same statistical characteristics as the real system output?

Policy Effect/Contextual	Does the model represent correctly the results of specialisation/diversification dynamics?
	Are the policy recommendations sensitive to the addition or the change of structure which allow for possible alternative theories?
	Are the policy recommendations sensitive to reliable changes of parameters?

Table 28: Mapping of lever to number for the Sobol sensitivity analysis of the Jacobs regional model.

Lever	**Lever_no**
Relative share women in fertile age	215
Relatedness[Specialistic Technical and scientific activities,Specialistic Technical and scientific activities]	214
Relatedness[Specialistic Technical and scientific activities,Production and distribution of gas vapour and AC]	213
Relatedness[Specialistic Technical and scientific activities,Pharmaceutical Industry]	212
Relatedness[Specialistic Technical and scientific activities,Manufacturing of measurement instruments of navigation and watchmaking]	211
Relatedness[Specialistic Technical and scientific activities,Manufacturing of communication equipment]	210
Relatedness[Specialistic Technical and scientific activities,ICT information and services]	209
Relatedness[Specialistic Technical and scientific activities,Editing audiovisual and diffusion]	208
Relatedness[Specialistic Technical and scientific activities,Chemical industry]	207
Relatedness[Specialistic Technical and scientific activities,Automotive industry]	206
Relatedness[Specialistic Technical and scientific activities,Aerospace construction and engineering]	205
Relatedness[Production and distribution of gas vapour and AC,Specialistic Technical and scientific activities]	204
Relatedness[Production and distribution of gas vapour and AC,Production and distribution of gas vapour and AC]	203
Relatedness[Production and distribution of gas vapour and AC,Pharmaceutical Industry]	202
Relatedness[Production and distribution of gas vapour and AC,Manufacturing of measurement instruments of navigation and watchmaking]	201
Relatedness[Production and distribution of gas vapour and AC,Manufacturing of communication equipment]	200
Relatedness[Production and distribution of gas vapour and AC,ICT information and services]	199
Relatedness[Production and distribution of gas vapour and AC,Editing audiovisual and diffusion]	198
Relatedness[Production and distribution of gas vapour and AC,Chemical industry]	197
Relatedness[Production and distribution of gas vapour and AC,Automotive industry]	196
Relatedness[Production and distribution of gas vapour and AC,Aerospace construction and engineering]	195
Relatedness[Pharmaceutical Industry,Specialistic Technical and scientific activities]	194
Relatedness[Pharmaceutical Industry,Production and distribution of gas vapour and AC]	193
Relatedness[Pharmaceutical Industry,Pharmaceutical Industry]	192
Relatedness[Pharmaceutical Industry,Manufacturing of measurement instruments of navigation and watchmaking]	191
Relatedness[Pharmaceutical Industry,Manufacturing of communication equipment]	190

Relatedness[Pharmaceutical Industry,ICT information and services]	189
Relatedness[Pharmaceutical Industry,Editing audiovisual and diffusion]	188
Relatedness[Pharmaceutical Industry,Chemical industry]	187
Relatedness[Pharmaceutical Industry,Automotive industry]	186
Relatedness[Pharmaceutical Industry,Aerospace construction and engineering]	185
Relatedness[Manufacturing of measurement instruments of navigation and watchmaking,Specialistic Technical and scientific activities]	184
Relatedness[Manufacturing of measurement instruments of navigation and watchmaking,Production and distribution of gas vapour and AC]	183
Relatedness[Manufacturing of measurement instruments of navigation and watchmaking,Pharmaceutical Industry]	182
Relatedness[Manufacturing of measurement instruments of navigation and watchmaking,Manufacturing of measurement instruments of navigation and watchmaking]	181
Relatedness[Manufacturing of measurement instruments of navigation and watchmaking,Manufacturing of communication equipment]	180
Relatedness[Manufacturing of measurement instruments of navigation and watchmaking,ICT information and services]	179
Relatedness[Manufacturing of measurement instruments of navigation and watchmaking,Editing audiovisual and diffusion]	178
Relatedness[Manufacturing of measurement instruments of navigation and watchmaking,Chemical industry]	177
Relatedness[Manufacturing of measurement instruments of navigation and watchmaking,Automotive industry]	176
Relatedness[Manufacturing of measurement instruments of navigation and watchmaking,Aerospace construction and engineering]	175
Relatedness[Manufacturing of communication equipment,Specialistic Technical and scientific activities]	174
Relatedness[Manufacturing of communication equipment,Production and distribution of gas vapour and AC]	173
Relatedness[Manufacturing of communication equipment,Pharmaceutical Industry]	172
Relatedness[Manufacturing of communication equipment,Manufacturing of measurement instruments of navigation and watchmaking]	171
Relatedness[Manufacturing of communication equipment,Manufacturing of communication equipment]	170
Relatedness[Manufacturing of communication equipment,ICT information and services]	169
Relatedness[Manufacturing of communication equipment,Editing audiovisual and diffusion]	168
Relatedness[Manufacturing of communication equipment,Chemical industry]	167
Relatedness[Manufacturing of communication equipment,Automotive industry]	166
Relatedness[Manufacturing of communication equipment,Aerospace construction and engineering]	165
Relatedness[ICT information and services,Specialistic Technical and scientific activities]	164
Relatedness[ICT information and services,Production and distribution of gas vapour and AC]	163
Relatedness[ICT information and services,Pharmaceutical Industry]	162
Relatedness[ICT information and services,Manufacturing of measurement instruments of navigation and watchmaking]	161
Relatedness[ICT information and services,Manufacturing of communication equipment]	160
Relatedness[ICT information and services,ICT information and services]	159
Relatedness[ICT information and services,Editing audiovisual and diffusion]	158
Relatedness[ICT information and services,Chemical industry]	157
Relatedness[ICT information and services,Automotive industry]	156
Relatedness[ICT information and services,Aerospace construction and engineering]	155

Relatedness[Editing audiovisual and diffusion,Specialistic Technical and scientific activities]	154
Relatedness[Editing audiovisual and diffusion,Production and distribution of gas vapour and AC]	153
Relatedness[Editing audiovisual and diffusion,Pharmaceutical Industry]	152
Relatedness[Editing audiovisual and diffusion,Manufacturing of measurement instruments of navigation and watchmaking]	151
Relatedness[Editing audiovisual and diffusion,Manufacturing of communication equipment]	150
Relatedness[Editing audiovisual and diffusion,ICT information and services]	149
Relatedness[Editing audiovisual and diffusion,Editing audiovisual and diffusion]	148
Relatedness[Editing audiovisual and diffusion,Chemical industry]	147
Relatedness[Editing audiovisual and diffusion,Automotive industry]	146
Relatedness[Editing audiovisual and diffusion,Aerospace construction and engineering]	145
Relatedness[Chemical industry,Specialistic Technical and scientific activities]	144
Relatedness[Chemical industry,Production and distribution of gas vapour and AC]	143
Relatedness[Chemical industry,Pharmaceutical Industry]	142
Relatedness[Chemical industry,Manufacturing of measurement instruments of navigation and watchmaking]	141
Relatedness[Chemical industry,Manufacturing of communication equipment]	140
Relatedness[Chemical industry,ICT information and services]	139
Relatedness[Chemical industry,Editing audiovisual and diffusion]	138
Relatedness[Chemical industry,Chemical industry]	137
Relatedness[Chemical industry,Automotive industry]	136
Relatedness[Chemical industry,Aerospace construction and engineering]	135
Relatedness[Automotive industry,Specialistic Technical and scientific activities]	134
Relatedness[Automotive industry,Production and distribution of gas vapour and AC]	133
Relatedness[Automotive industry,Pharmaceutical Industry]	132
Relatedness[Automotive industry,Manufacturing of measurement instruments of navigation and watchmaking]	131
Relatedness[Automotive industry,Manufacturing of communication equipment]	130
Relatedness[Automotive industry,ICT information and services]	129
Relatedness[Automotive industry,Editing audiovisual and diffusion]	128
Relatedness[Automotive industry,Chemical industry]	127
Relatedness[Automotive industry,Automotive industry]	126
Relatedness[Automotive industry,Aerospace construction and engineering]	125
Relatedness[Aerospace construction and engineering,Specialistic Technical and scientific activities]	124
Relatedness[Aerospace construction and engineering,Production and distribution of gas vapour and AC]	123
Relatedness[Aerospace construction and engineering,Pharmaceutical Industry]	122

Relatedness[Aerospace construction and engineering,Manufacturing of measurement instruments of navigation and watchmaking]	121
Relatedness[Aerospace construction and engineering,Manufacturing of communication equipment]	120
Relatedness[Aerospace construction and engineering,ICT information and services]	119
Relatedness[Aerospace construction and engineering,Editing audiovisual and diffusion]	118
Relatedness[Aerospace construction and engineering,Chemical industry]	117
Relatedness[Aerospace construction and engineering,Automotive industry]	116
Relatedness[Aerospace construction and engineering,Aerospace construction and engineering]	115
Percentage of workforce wanting to go the private sector	114
Percentage of profit from revenue in Sector[Specialistic Technical and scientific activities]	113
Percentage of profit from revenue in Sector[Production and distribution of gas vapour and AC]	112
Percentage of profit from revenue in Sector[Pharmaceutical Industry]	111
Percentage of profit from revenue in Sector[Manufacturing of measurement instruments of navigation and watchmaking]	110
Percentage of profit from revenue in Sector[Manufacturing of communication equipment]	109
Percentage of profit from revenue in Sector[ICT information and services]	108
Percentage of profit from revenue in Sector[Editing audiovisual and diffusion]	107
Percentage of profit from revenue in Sector[Chemical industry]	106
Percentage of profit from revenue in Sector[Automotive industry]	105
Percentage of profit from revenue in Sector[Aerospace construction and engineering]	104
Percentage of innovative SMEs collaborating with others	103
Percentage of adults enrolling in studies[Process Engineering18to24]	102
Percentage of adults enrolling in studies[Physics18to24]	101
Percentage of adults enrolling in studies[Multidisciplinary Sciences18to24]	100
Percentage of adults enrolling in studies[Mechanics18to24]	99
Percentage of adults enrolling in studies[Information and communication studies18to24]	98
Percentage of adults enrolling in studies[Industry18to24]	97
Percentage of adults enrolling in studies[Health18to24]	96
Percentage of adults enrolling in studies[Digital18to24]	95
Percentage of adults enrolling in studies[Chemistry18to24]	94
Percentage of adults enrolling in studies[Audiovisual18to24]	93
Number of years for knowledge commercialisation	92
Knowledge obsolescence time	91
Hiring and training time of employees	90
External investments	89
Average mortality per age[twentyfiveto45]	88
Average mortality per age[fortyfiveto65]	87
Average mortality per age[Zeroto17]	86

Average mortality per age[Process Engineering45to65]	85
Average mortality per age[Process Engineering25to45]	84
Average mortality per age[Process Engineering18to24]	83
Average mortality per age[Physics45to65]	82
Average mortality per age[Physics25to45]	81
Average mortality per age[Physics18to24]	80
Average mortality per age[Multidisciplinary Sciences45to65]	79
Average mortality per age[Multidisciplinary Sciences25to45]	78
Average mortality per age[Multidisciplinary Sciences18to24]	77
Average mortality per age[Mechanics45to65]	76
Average mortality per age[Mechanics25to45]	75
Average mortality per age[Mechanics18to24]	74
Average mortality per age[Information and communication studies45to65]	73
Average mortality per age[Information and communication studies25to45]	72
Average mortality per age[Information and communication studies18to24]	71
Average mortality per age[Industry45to65]	70
Average mortality per age[Industry25to45]	69
Average mortality per age[Industry18to24]	68
Average mortality per age[Health45to65]	67
Average mortality per age[Health25to45]	66
Average mortality per age[Health18to24]	65
Average mortality per age[Eighteento24]	64
Average mortality per age[Digital45to65]	63
Average mortality per age[Digital25to45]	62
Average mortality per age[Digital18to24]	61
Average mortality per age[Chemistry45to65]	60
Average mortality per age[Chemistry25to45]	59
Average mortality per age[Chemistry18to24]	58
Average mortality per age[Audiovisual45to65]	57
Average mortality per age[Audiovisual25to45]	56
Average mortality per age[Audiovisual18to24]	55
Average mortality per age[Above65]	54
Average Time to Market in Sector[Specialistic Technical and scientific activities]	53

Average Time to Market in Sector[Production and distribution of gas vapour and AC]	52
Average Time to Market in Sector[Pharmaceutical Industry]	51
Average Time to Market in Sector[Manufacturing of measurement instruments of navigation and watchmaking]	50
Average Time to Market in Sector[Manufacturing of communication equipment]	49
Average Time to Market in Sector[ICT information and services]	48
Average Time to Market in Sector[Editing audiovisual and diffusion]	47
Average Time to Market in Sector[Chemical industry]	46
Average Time to Market in Sector[Automotive industry]	45
Average Time to Market in Sector[Aerospace construction and engineering]	44
Attrition rate in sector[Specialistic Technical and scientific activities]	43
Attrition rate in sector[Production and distribution of gas vapour and AC]	42
Attrition rate in sector[Pharmaceutical Industry]	41
Attrition rate in sector[Manufacturing of measurement instruments of navigation and watchmaking]	40
Attrition rate in sector[Manufacturing of communication equipment]	39
Attrition rate in sector[ICT information and services]	38
Attrition rate in sector[Editing audiovisual and diffusion]	37
Attrition rate in sector[Chemical industry]	36
Attrition rate in sector[Automotive industry]	35
Attrition rate in sector[Aerospace construction and engineering]	34
"Public-private collaboration per person"	33
"Public R&D expenditure per personel"[Specialistic Technical and scientific activities]	32
"Public R&D expenditure per personel"[Production and distribution of gas vapour and AC]	31
"Public R&D expenditure per personel"[Pharmaceutical Industry]	30
"Public R&D expenditure per personel"[Manufacturing of measurement instruments of navigation and watchmaking]	29
"Public R&D expenditure per personel"[Manufacturing of communication equipment]	28
"Public R&D expenditure per personel"[ICT information and services]	27
"Public R&D expenditure per personel"[Editing audiovisual and diffusion]	26
"Public R&D expenditure per personel"[Chemical industry]	25
"Public R&D expenditure per personel"[Automotive industry]	24
"Public R&D expenditure per personel"[Aerospace construction and engineering]	23
"Public Funding for Private R&D in Sector"[Specialistic Technical and scientific activities]	22
"Public Funding for Private R&D in Sector"[Production and distribution of gas vapour and AC]	21
"Public Funding for Private R&D in Sector"[Pharmaceutical Industry]	20
"Public Funding for Private R&D in Sector"[Manufacturing of measurement instruments of navigation and watchmaking]	19
"Public Funding for Private R&D in Sector"[Manufacturing of communication equipment]	18
"Public Funding for Private R&D in Sector"[ICT information and services]	17

"Public Funding for Private R&D in Sector"[Editing audiovisual and diffusion]	16
"Public Funding for Private R&D in Sector"[Chemical industry]	15
"Public Funding for Private R&D in Sector"[Automotive industry]	14
"Public Funding for Private R&D in Sector"[Aerospace construction and engineering]	13
"Percentage of workforce wanting to go to R&D"	12
"Percentage of R&D budget on total budget in Sector"[Specialistic Technical and scientific activities]	11
"Percentage of R&D budget on total budget in Sector"[Production and distribution of gas vapour and AC]	10
"Percentage of R&D budget on total budget in Sector"[Pharmaceutical Industry]	9
"Percentage of R&D budget on total budget in Sector"[Manufacturing of measurement instruments of navigation and watchmaking]	8
"Percentage of R&D budget on total budget in Sector"[Manufacturing of communication equipment]	7
"Percentage of R&D budget on total budget in Sector"[ICT information and services]	6
"Percentage of R&D budget on total budget in Sector"[Editing audiovisual and diffusion]	5
"Percentage of R&D budget on total budget in Sector"[Chemical industry]	4
"Percentage of R&D budget on total budget in Sector"[Automotive industry]	3
"Percentage of R&D budget on total budget in Sector"[Aerospace construction and engineering]	2
"Government funding for public R&D in sector"	1

Table 29: Mapping of lever to number for the Sobol sensitivity analysis of the MAR regional model.

Lever	**Lever_no**
Relative share women in fertile age	29
Percentage of workforce wanting to go the private sector	28
Percentage of profit from revenue in Sector[Telecommunication]	27
Percentage of profit from revenue in Sector[Manufacturing of communication equipment]	26
Percentage of innovative SMEs collaborating with others	25
Percentage of adults enrolling in studies	24
Knowledge obsolescence time	23
Hiring and training time of employees	22
External investments	21
Average mortality per age[Students]	20
Average mortality per age[Graduates45to65]	19
Average mortality per age[Graduates25to45]	18
Average mortality per age[Age65toLifeExpectancy]	17

Average mortality per age[Age45to65]	16
Average mortality per age[Age25to45]	15
Average mortality per age[Age18to24]	14
Average mortality per age[Age0to17]	13
Average Time to Market in Sector[Telecommunication]	12
Average Time to Market in Sector[Manufacturing of communication equipment]	11
Attrition rate in sector[Telecommunication]	10
Attrition rate in sector[Manufacturing of communication equipment]	9
"Public-private collaboration per academic"	8
"Public R&D expenditure per personel"	7
"Public Funding for Private R&D in Sector"[Telecommunication]	6
"Public Funding for Private R&D in Sector"[Manufacturing of communication equipment]	5
"Percentage of workforce wanting to go to R&D"	4
"Percentage of R&D budget on total budget in Sector"[Telecommunication]	3
"Percentage of R&D budget on total budget in Sector"[Manufacturing of communication equipment]	2
"Government funding for public R&D in sector"	1

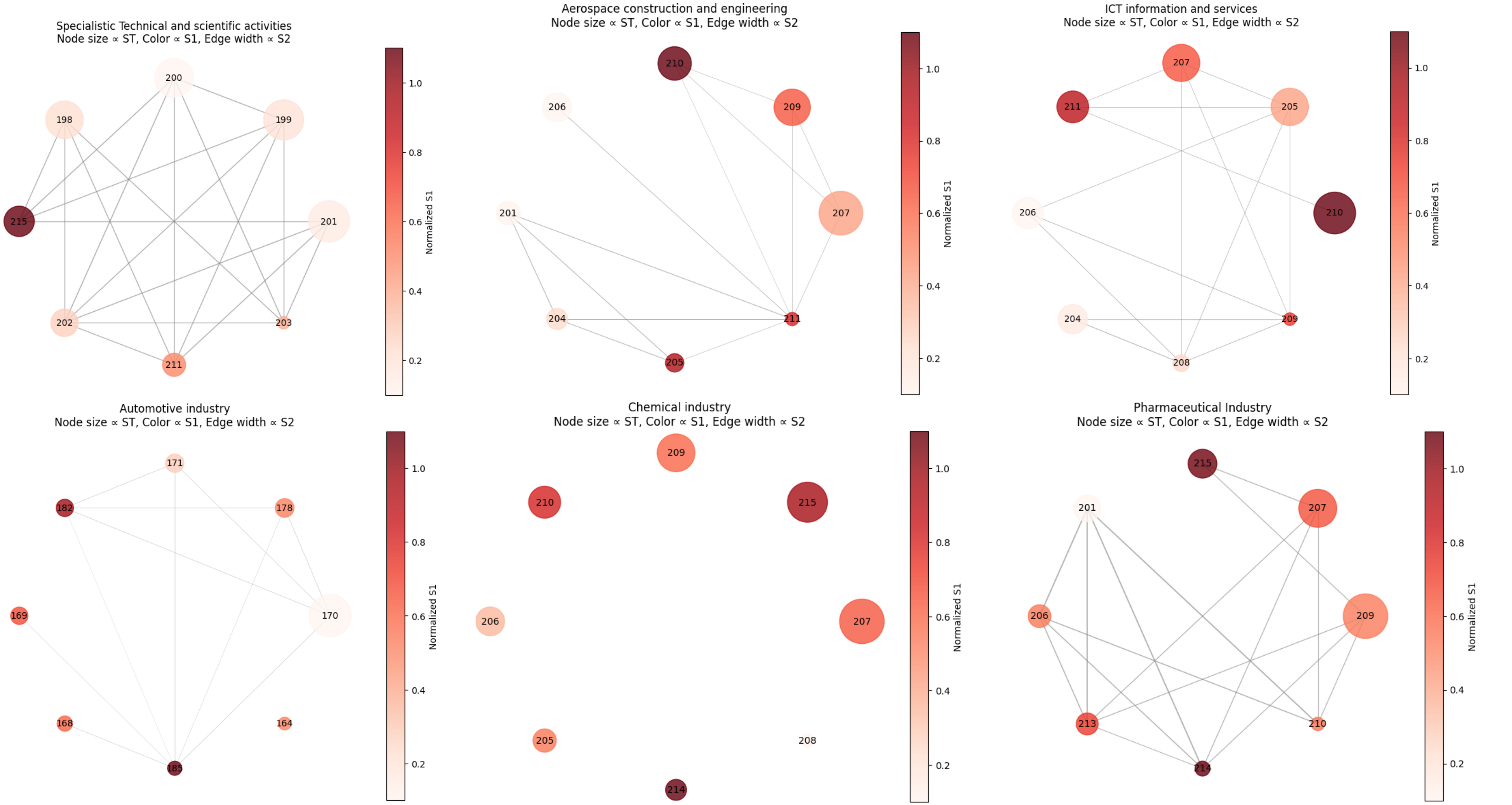

Figure 48: Network graph of top eight Sobol scores for Ile-de-France Jacobs region sectors with relatedness.

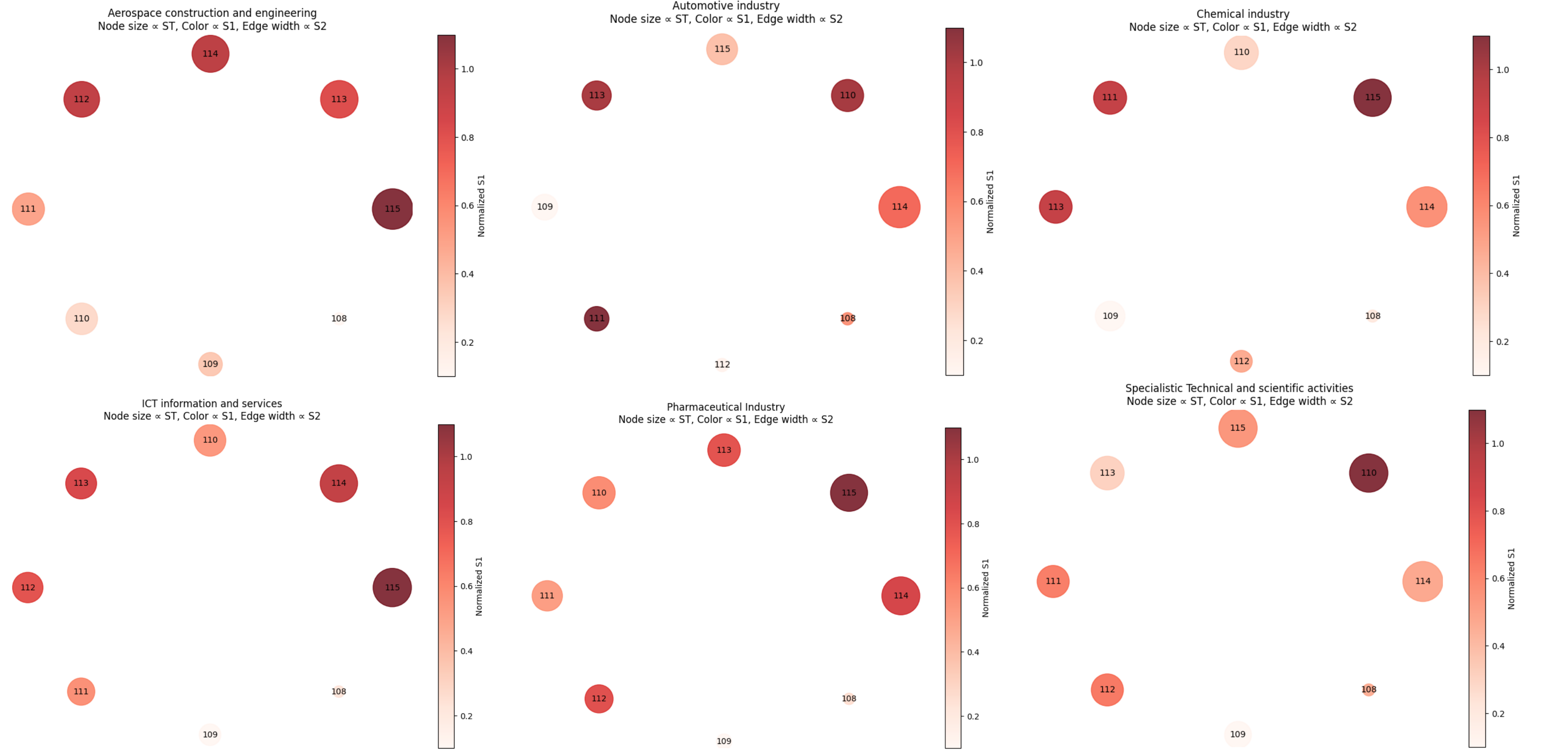

Figure 49: Network graph of top eight Sobol scores for Ile-de-France Jacobs region sectors without relatedness.

Appendix C: Code Addendum

Code for Sector Analysis from NAF rev. 2: Sorting-NAF-rev-2-sectors.R

```
library(tidyverse)

library(readxl)
library(data.tree)
library(collapsibleTree)

# Read Excel file
df <- read_excel("NACE rev 2.xlsx") # contains Code and Name

# Step 1: Identify code level and extract numeric part
df <- df %>%
  mutate(
    level = case_when(
      str_detect(Code, "^\\d+$") ~ "group",
      str_detect(Code, "^\\d+\\.\\d+$") ~ "subgroup",
      TRUE ~ NA_character_
    ),
    group_num = as.numeric(str_extract(Code, "^\\d+"))
  )

# Step 2: Manually assign section based on group_num
df <- df %>%
  mutate(
    section_fixed = case_when(
      group_num >= 1 & group_num < 5 ~ "SECTION A",
      group_num >= 5 & group_num < 10 ~ "SECTION B",
      group_num >= 20 & group_num < 40 ~ "SECTION C",
      group_num >= 40 & group_num < 44 ~ "SECTION D",
      group_num >= 45 & group_num < 48 ~ "SECTION G",
      group_num >= 49 & group_num < 55 ~ "SECTION H",
      group_num >= 55 & group_num < 65 ~ "SECTION J",
      group_num >= 70 & group_num < 75 ~ "SECTION M",
      group_num >= 76 & group_num < 80 ~ "SECTION N",
      group_num >= 80 & group_num < 100 ~ "SECTION S",
      TRUE ~ NA_character_
    )
  )

# Step 3: Fill down group/subgroup names to help build paths
df <- df %>%
  mutate(
    group_name = if_else(level == "group", NAFrev2, NA_character_),
    subgroup_name = if_else(level == "subgroup", NAFrev2, NA_character_)
  ) %>%
  fill(section_fixed, group_name, subgroup_name, .direction = "down")

# Step 4: Build pathString based on level
df_tree <- df %>%
```

```
  mutate(
    pathString = case_when(
      level == "group" ~ paste("Sectors", section_fixed, group_name, sep = "/"),
      level == "subgroup" ~ paste("Sectors", section_fixed, group_name, subgroup_name,
sep = "/")
    )
  ) %>%
  filter(!is.na(pathString))

# Step 5: Create the data.tree structure
tree <- as.Node(df_tree)
print(tree, "name")

#Function to print the tree in a HTML file
# collapsibleTree(
# df_tree,
# hierarchy = c("section_fixed", "group_name", "subgroup_name"),
# root = "Sectors",
# fontSize = 8, # Smaller font size
# width = 800,
# zoomable = TRUE
# )

##
levelName
## 1 Sectors
## 2 ¦--SECTION A
## 3 ¦ °--NA
## 4 ¦ °--Cultivation of spice, aromatic, medicinal and pharmaceutical plants
## 5 ¦--SECTION B
## 6 ¦ °--NA
## 7 ¦ ¦--Extraction of natural gas
## 8 ¦ °--Extraction of chemical minerals and mineral fertilisers
## 9 ¦--SECTION C
## 10 ¦ ¦--Chemical industry
## 11 ¦ ¦ °--Manufacture of industrial gases
## 12 ¦ ¦--Manufacture of pharmaceuticals
## 13 ¦ ¦ °--Manufacture of steam generators, except central heating boilers
## 14 ¦ ¦--Manufacture of computer, electronic and optical products
## 15 ¦ ¦ ¦--Manufacture of communications equipment
## 16 ¦ ¦ ¦--Manufacture of instruments and appliances for measuring, testing and
navigation; watches and clocks
## 17 ¦ ¦ ¦--Manufacture of electric motors, generators, transformers and electri
city distribution and control apparatus
## 18 ¦ ¦ °--Manufacture of other specialised machinery
## 19 ¦ °--Manufacture of motor vehicles
## 20 ¦ ¦--Manufacture of automotive equipment
## 21 ¦ ¦--Manufacture of aircraft and spacecraft
## 22 ¦ ¦--Manufacture of medical and dental instruments and supplies
## 23 ¦ °--Repair and maintenance of aircraft and spacecraft
## 24 ¦--SECTION D
## 25 ¦ °--Specialised construction work
## 26 ¦ °--Installation of water and gas in all premises
## 27 ¦--SECTION G
## 28 ¦ °--Sale and repair of motor vehicles and motorbikes
## 29 ¦ ¦--Agents involved in the sale of fuels, metals, minerals and chemical p
roducts
## 30 ¦ ¦--Wholesale of perfume and cosmetics
## 31 ¦ ¦--Wholesale of pharmaceutical products
```

```
## 32 ¦ ¦--Wholesale of watches, clocks and jewellery
## 33 ¦ ¦--Wholesale of information and communication equipment
## 34 ¦ ¦--Wholesale of chemical products
## 35 ¦ ¦--Retail sale of information and communication equipment in specialise
d shops
## 36 ¦ ¦--Retail sale of audio
## 37 ¦ ¦ °--video equipment in specialised shops
## 38 ¦ ¦--Retail sale of pharmaceutical products in specialised shops
## 39 ¦ °--Retail sale of medical and orthopaedic goods in specialised shops
## 40 ¦--SECTION H
## 41 ¦ ¦--Sale and repair of motor vehicles and motorbikes
## 42 ¦ ¦ °--Other passenger land transport
## 43 ¦ °--Air transport
## 44 ¦--SECTION J
## 45 ¦ ¦--Publishing
## 46 ¦ ¦--Motion picture, video and television programme production; sound recordi
ng and music publishing
## 47 ¦ ¦--Programming and broadcasting
## 48 ¦ ¦--Telecommunications
## 49 ¦ ¦ °--Satellite telecommunications
## 50 ¦ ¦--Programming, consulting and other IT activities
## 51 ¦ °--Information services
## 52 ¦--SECTION M
## 53 ¦ °--Information services
## 54 ¦ °--Motor vehicle roadworthiness testing
## 55 ¦--SECTION N
## 56 ¦ °--Information services
## 57 ¦ ¦--Renting and leasing of cars and light motor vehicles
## 58 ¦ °--Rental and leasing of air transport equipment
## 59 °--SECTION S
## 60 °--Information services
## 61 °--Repair of computers and communications equipment
## n
ame
## 1 S
ectors
## 2 S
ECTION A
## 3 N
A
## 4 Cultivation of spice, aromatic, medicinal
and pharmaceutical plants
## 5 S
ECTION B
## 6 N
A
## 7 E
xtraction of natural gas
## 8 Extraction of chemical minera
ls and mineral fertilisers
## 9 S
ECTION C
## 10 C
hemical industry
## 11 Manuf
acture of industrial gases
## 12 Manu
```

```
facture of pharmaceuticals
## 13 Manufacture of steam generators, exce
pt central heating boilers
## 14 Manufacture of computer, elect
ronic and optical products
## 15 Manufacture o
f communications equipment
## 16 Manufacture of instruments and appliances for measuring, testing and nav
igation; watches and clocks
## 17 Manufacture of electric motors, generators, transformers and electricity distrib
ution and control apparatus
## 18 Manufacture of o
ther specialised machinery
## 19 Man
ufacture of motor vehicles
## 20 Manufactu
re of automotive equipment
## 21 Manufacture
of aircraft and spacecraft
## 22 Manufacture of medical and denta
l instruments and supplies
## 23 Repair and maintenance
of aircraft and spacecraft
## 24 S
ECTION D
## 25 Spe
cialised construction work
## 26 Installation of wat
er and gas in all premises
## 27 S
ECTION G
## 28 Sale and repair of mot
or vehicles and motorbikes
## 29 Agents involved in the sale of fuels, metals, min
erals and chemical products
## 30 Wholesal
e of perfume and cosmetics
## 31 Wholesale
of pharmaceutical products
## 32 Wholesale of wat
ches, clocks and jewellery
## 33 Wholesale of information a
nd communication equipment
## 34 Whol
esale of chemical products
## 35 Retail sale of information and communication equ
ipment in specialised shops
## 36 R
etail sale of audio
## 37 video equi
pment in specialised shops
## 38 Retail sale of pharmaceutical pro
ducts in specialised shops
## 39 Retail sale of medical and orthopaedic
goods in specialised shops
## 40 S
ECTION H
## 41 Sale and repair of mot
```

```
or                       vehicles                            and                        motorbikes
## 42                                                                                         Othe
r                       passenger                            land                        transport
## 43                                                                                            A
ir                                                                                       transport
## 44                                                                                            S
ECTION                                                                                           J
## 45                                                                                            P
ublishing
## 46             Motion picture, video and television programme production; sound rec
ording                    and                            music                          publishing
## 47                                                                                           Pr
ogramming                               and                                           broadcasting
## 48                                                                                            T
elecommunications
## 49                                                                                           Sa
tellite                                                                         telecommunications
## 50                                                                         Programming, consulti
ng                 and                   other                   IT                     activities
## 51                                                                                            I
nformation                                                                                services
## 52                                                                                            S
ECTION                                                                                           M
## 53                                                                                            I
nformation                                                                                services
## 54                                                                                   Motor vehi
cle                                  roadworthiness                                        testing
## 55                                                                                            S
ECTION                                                                                           N
## 56                                                                                            I
nformation                                                                                services
## 57                                                                  Renting and leasing of car
s                 and                   light                   motor                     vehicles
## 58                                                                          Rental and leasing
of                       air                        transport                            equipment
## 59                                                                                            S
ECTION                                                                                           S
## 60                                                                                            I
nformation                                                                                services
## 61                                                                      Repair of computers an
d communications equipment
```

Code for Relatedness Matrix Computation: Relatedness-Code.R

```
# +eval=FALSE
```

Compute the relatedness between entities (industries, technologies, …) from their co-occurence matrix

This function computes the relatedness between entities (industries, technologies, …) from their co-occurence (adjacency) matrix. Different normalisation procedures are proposed following van Eck and Waltman (2009): association strength, cosine, Jaccard, and an adapted version of the association strength that we refer to as probability index. @param mat An adjacency matrix of co-occurences between entities (industries, technologies, cities…) @param method Which normalisation method should be used to compute relatedness? Defaults to “prob”, but it can be “association”, “cosine” or “Jaccard” @keywords relatedness @export @examples ## generate an industry - industry matrix in which cells give the number of co-occurences ## between two industries

```
set.seed(31)
mat <- matrix(
  data = c(0, 11, 1, 4, 3, 0, 3, 0, 2, 0,
           0, 0, 1, 2, 1, 0, 3, 0, 2, 4,
           0, 0, 0, 2, 4, 4, 1, 0, 0, 0,
           0, 0, 0, 0, 3, 1, 2, 10, 6, 0,
           0, 0, 0, 0, 0, 1, 0, 0, 0, 0,
           0, 0, 0, 0, 0, 0, 1, 0, 0, 3,
           0, 0, 0, 0, 0, 0, 0, 0, 4, 1,
           0, 0, 0, 0, 0, 0, 0, 0, 1, 0,
           0, 0, 0, 0, 0, 0, 0, 0, 0, 1), # Elements of the matrix
  nrow = 10, # Number of rows
  ncol = 10, # Number of columns
  byrow = TRUE # Fill matrix by rows
)

## Warning in matrix(data = c(0, 11, 1, 4, 3, 0, 3, 0, 2, 0, 0, 0, 1, 2, 1, : data
## length differs from size of matrix: [90 != 10 x 10]

mat[lower.tri(mat, diag = TRUE)] <- t(mat)[lower.tri(t(mat), diag = TRUE)]
rownames(mat) <- c ("I1", "I2", "I3", "I4", "I5", "I6", "I7", "I8", "I9", "I10")
colnames(mat) <- c ("I1", "I2", "I3", "I4", "I5", "I6", "I7", "I8", "I9", "I10")


"relatedness" <- function(mat, method = "prob") {
  method <- tolower(method)

  Cij = mat
  diag(Cij) <- 0
  Si <- colSums(Cij)
  Sj <- colSums(Cij)
  Si <- matrix(Si,nrow=length(Si),ncol=length(Si),byrow=TRUE)
  Sj <- matrix(Sj,nrow=length(Sj),ncol=length(Sj),byrow=FALSE)
  T<-(sum(Cij))
  if (method == "prob") {
    SM <- Cij/(((Si/T)*(Sj/(T-Si))+(Sj/T)*(Si/(T-Sj)))*(T/2))
    SM[is.na(SM)] <- 0
    diag(SM) <- 0
    return(SM)
  } else if (method == "association") {
    SA <- (Cij/T)/ ((Si/T) * (Sj/T))
    SA[is.na(SA)] <- 0
    diag(SA) <- 0
    return(SA)
  } else if (method == "cosine") {

    SC <- (Cij)/ sqrt (Si * Sj)
    SC[is.na(SC)] <- 0
    diag(SC) <- 0
    return(SC)
  } else if (method == "jaccard") {
    SJ <- (Cij)/ (Si + Sj - Cij)
    SJ[is.na(SJ)] <- 0
```

```r
    diag(SJ)                                          <-                                              0
    return(SJ)

  }                                              else                                                 {
    stop("Unknown            value          for           argument            'method'")

  }


}
relatedness (mat)
```

```
##              I1         I2         I3         I4         I5         I6         I7
## I1    0.0000000  2.6736111  0.4656798  0.7607461  1.5182648  0.0000000  1.2029988
## I2    2.6736111  0.0000000  0.4656798  0.3803731  0.5060883  0.0000000  1.2029988
## I3    0.4656798  0.4656798  0.0000000  0.7281691  3.8845731  4.6918537  0.7691966
## I4    0.7607461  0.3803731  0.7281691  0.0000000  1.1869464  0.4776852  0.6271221
## I5    1.5182648  0.5060883  3.8845731  1.1869464  0.0000000  1.2749455  0.0000000
## I6    0.0000000  0.0000000  4.6918537  0.4776852  1.2749455  0.0000000  1.0097250
## I7    1.2029988  1.2029988  0.7691966  0.6271221  0.0000000  1.0097250  0.0000000
## I8    0.0000000  0.0000000  0.0000000  4.3294267  0.0000000  0.0000000  0.0000000
## I9    0.7494213  0.7494213  0.0000000  1.7581560  0.0000000  0.0000000  2.4749719
## I10  0.0000000  2.7244193  0.0000000  0.0000000  0.0000000  5.1499461  1.1254873
##                           I8                  I9                  I10
##         I1           0.0000000           0.7494213           0.000000
##         I2           0.0000000           0.7494213           2.724419
##         I3           0.0000000           0.0000000           0.000000
##         I4           4.3294267           1.7581560           0.000000
##         I5           0.0000000           0.0000000           0.000000
##         I6           0.0000000           0.0000000           5.149946
##         I7           0.0000000           2.4749719           1.125487
##         I8           0.0000000           0.8548777           0.000000
##         I9           0.8548777           0.0000000           1.051522
## I10 0.0000000 1.0515218 0.000000
```

```r
relatedness (mat, method = "association")
```

```
##              I1         I2         I3         I4         I5         I6         I7
## I1    0.0000000  3.1319444  0.5256410  0.9111111  1.7083333  0.0000000  1.3666667
## I2    3.1319444  0.0000000  0.5256410  0.4555556  0.5694444  0.0000000  1.3666667
## I3    0.5256410  0.5256410  0.0000000  0.8410256  4.2051282  5.0461538  0.8410256
## I4    0.9111111  0.4555556  0.8410256  0.0000000  1.3666667  0.5466667  0.7288889
## I5    1.7083333  0.5694444  4.2051282  1.3666667  0.0000000  1.3666667  0.0000000
## I6    0.0000000  0.0000000  5.0461538  0.5466667  1.3666667  0.0000000  1.0933333
## I7    1.3666667  1.3666667  0.8410256  0.7288889  0.0000000  1.0933333  0.0000000
## I8    0.0000000  0.0000000  0.0000000  4.9696970  0.0000000  0.0000000  0.0000000
## I9    0.8541667  0.8541667  0.0000000  2.0500000  0.0000000  0.0000000  2.7333333
## I10  0.0000000  3.0370370  0.0000000  0.0000000  0.0000000  5.4666667  1.2148148
##                           I8                  I9                  I10
##         I1           0.0000000           0.8541667           0.000000
##         I2           0.0000000           0.8541667           3.037037
##         I3           0.0000000           0.0000000           0.000000
##         I4           4.9696970           2.0500000           0.000000
##         I5           0.0000000           0.0000000           0.000000
##         I6           0.0000000           0.0000000           5.466667
##         I7           0.0000000           2.7333333           1.214815
##         I8           0.0000000           0.9318182           0.000000
```

```
## I9 0.9318182 0.0000000 1.138889
## I10 0.0000000 1.1388889 0.000000
```

```
relatedness (mat, method = "cosine")
```

```
##              I1         I2         I3         I4         I5         I6
##   I1 0.00000000 0.45833333 0.05661385 0.14907120 0.17677670 0.00000000
##   I2 0.45833333 0.00000000 0.05661385 0.07453560 0.05892557 0.00000000
##   I3 0.05661385 0.05661385 0.00000000 0.10127394 0.32025631 0.35082321
##   I4 0.14907120 0.07453560 0.10127394 0.00000000 0.15811388 0.05773503
##   I5 0.17677670 0.05892557 0.32025631 0.15811388 0.00000000 0.09128709
##   I6 0.00000000 0.00000000 0.35082321 0.05773503 0.09128709 0.00000000
##   I7 0.15811388 0.15811388 0.07161149 0.09428090 0.00000000 0.08164966
##   I8 0.00000000 0.00000000 0.00000000 0.55048188 0.00000000 0.00000000
##   I9 0.10206207 0.10206207 0.00000000 0.27386128 0.00000000 0.00000000
##   I10 0.00000000 0.27216553 0.00000000 0.00000000 0.00000000 0.31622777
##                    I7         I8         I9        I10
##      I1    0.15811388 0.00000000 0.10206207 0.00000000
##      I2    0.15811388 0.00000000 0.10206207 0.27216553
##      I3    0.07161149 0.00000000 0.00000000 0.00000000
##      I4    0.09428090 0.55048188 0.27386128 0.00000000
##      I5    0.00000000 0.00000000 0.00000000 0.00000000
##      I6    0.08164966 0.00000000 0.00000000 0.31622777
##      I7    0.00000000 0.00000000 0.25819889 0.08606630
##      I8    0.00000000 0.00000000 0.07537784 0.00000000
##      I9    0.25819889 0.07537784 0.00000000 0.08333333
## I10 0.08606630 0.00000000 0.08333333 0.00000000
```

```
relatedness (mat, method = "Jaccard")
```

```
##              I1         I2         I3         I4         I5         I6
##   I1 0.00000000 0.29729730 0.02777778 0.08000000 0.09090909 0.00000000
##   I2 0.29729730 0.00000000 0.02777778 0.03846154 0.02857143 0.00000000
##   I3 0.02777778 0.02777778 0.00000000 0.04878049 0.19047619 0.21052632
##   I4 0.08000000 0.03846154 0.04878049 0.00000000 0.07692308 0.02564103
##   I5 0.09090909 0.02857143 0.19047619 0.07692308 0.00000000 0.04761905
##   I6 0.00000000 0.00000000 0.21052632 0.02564103 0.04761905 0.00000000
##   I7 0.08333333 0.08333333 0.03703704 0.04651163 0.00000000 0.04166667
##   I8 0.00000000 0.00000000 0.00000000 0.32258065 0.00000000 0.00000000
##   I9 0.05263158 0.05263158 0.00000000 0.15000000 0.00000000 0.00000000
##   I10 0.00000000 0.13793103 0.00000000 0.00000000 0.00000000 0.18750000
##                    I7         I8         I9        I10
##      I1    0.08333333 0.00000000 0.05263158 0.00000000
##      I2    0.08333333 0.00000000 0.05263158 0.13793103
##      I3    0.03703704 0.00000000 0.00000000 0.00000000
##      I4    0.04651163 0.32258065 0.15000000 0.00000000
##      I5    0.00000000 0.00000000 0.00000000 0.00000000
##      I6    0.04166667 0.00000000 0.00000000 0.18750000
##      I7    0.00000000 0.00000000 0.14814815 0.04347826
##      I8    0.00000000 0.00000000 0.03846154 0.00000000
##      I9    0.14814815 0.03846154 0.00000000 0.04166667
## I10 0.04347826 0.00000000 0.04166667 0.00000000
```

@author Pierre-Alexandre Balland   Joan Crespo   Mathieu Steijn @seealso , @references van Eck, N.J. and Waltman, L. (2009) How to normalize cooccurrence data? An analysis of some well-known similarity measures, (8): 1635-1651 Boschma, R., Heimeriks, G. and Balland, P.A. (2014) Scientific Knowledge Dynamics and Relatedness in Bio-Tech Cities, (1): 107-114 Hidalgo, C.A., Klinger, B., Barabasi, A. and Hausmann, R. (2007) The product space conditions the development of nations, : 482-487 Balland, P.A. (2016) Relatedness and the Geography of Innovation, in: R.

Shearmur, C. Carrincazeaux and D. Doloreux (eds) Handbook on the Geographies of Innovation. Northampton, MA: Edward Elgar   Steijn, M.P.A. (2017) Improvement on the association strength: implementing probability measures based on combinations without repetition,

Code for the Vensim Model

```
Absorption Capacity[Sectors,OtherSectors]=Percentage of innovative SMEs collaborating with others
   *Relatedness[Sectors,OtherSectors]*Industry knowledge size[OtherSectors]*(
   Workforce employed in knowledge intensive activities[OtherSectors]/Workforce employed in knowledge intensive activities
   [Sectors])
   Units: patent/Year

Addtional mortality rate of old people=0.037
Units: Dmnl/Year

Adults after retirement= INTEG (Aging of adults-Further aging-Mortality of adults after fertile ages
,
      1.77082e+06
      )
Units: people

Adults in the workforce= INTEG (Aging of Young adults-Aging of adults-mortality in worforce
,
      5.25969e+06
      )
Units: people

Age of ageing of adults=65
Units: Year

Age of entering higher education=18
Units: Year

Age of entering the workforce=24
Units: Year

Age of further ageing=83
Units: Year

Aging[Studies]= DELAY N ( Graduating in studies[Studies] , Amount of years being in the workforce in Sector
 , Workforce from studies[Studies]/Amount of years being in the workforce in Sector
   -Yearly mortality rate of adults*Workforce from studies[Studies], 3 )
Units: people/Year

Aging of adults= DELAY N ( Aging of Young adults , Amount of years being a young adult in the workforce
 , Adults in the workforce
   /Amount of years being a young adult in the workforce
   -mortality in worforce , 3 )
Units: people/Year

Aging of Young adults= DELAY N ( Becoming Adult, Amount of years being in higher education
 , Young adults/Amount of years being in higher education
```

-Mortality of young adults , 3)
Units: people/Year

Amount of years being a child=Age of entering higher education
Units: Year

Amount of years being a young adult in the workforce=Age of ageing of adults
-Age of entering the workforce
Units: Year

Amount of years being adult after fertile ages=Age of further ageing-Age of ageing of adults
Units: Year

Amount of years being in higher education=Age of entering the workforce-Age of entering higher education
Units: Year

Amount of years being in the workforce in Sector=Age of ageing of adults-Age of entering the workforce
Units: Year

Attrition rate in sector[Sectors]=0.037, 0.025, 0.03, 0.0158, 0.025, 0.025,
0.025, 0.243, 0.025, 0.025
Units: Dmnl/Year

Average knowledge commercialisation[Sectors]=Initial Added Value in Sector[
Sectors]/Initial knowledge specialisation in Sector[Sectors]/(Number of years for knowledge commercialisation
)
Units: $/patent/Year

Average regional knowledge generation per capita in sector[Sectors]=Initial knowledge specialisation in Sector
[Sectors]/Number of years in the sector/"Initial Employed R&D Workforce in Sector"
[Sectors]
Units: patent/people/Year

Average Time to Market in Sector[Sectors]=12, 10, 6, 2, 15, 5,5,2,4,3
Units: Year [0,50]

Becoming Adult= DELAY N (Births , Amount of years being a child , Children
/Amount of years being a child
-Mortality of Children , 3)
Units: people/Year

Births=Regional Birth Rate*Regional Population
Units: people/Year

Children= INTEG (Births-Becoming Adult-Mortality of Children,
Initial Children)
Units: people

Commercial expenditure[Sectors]=Commercial Sales[Sectors]*Percentage of profit from revenue in Sector
[Sectors]/100
Units: $/Year

Commercial Sales[Sectors]= Average knowledge commercialisation

[Sectors]*Industry knowledge size[Sectors]
Units: $/Year

Delay order 1=3
Units: Dmnl

Delay order 2=3
Units: Dmnl [0,5]

Delay order 3=3
Units: Dmnl [0,5]

"Demand for private R&D workforce in sector"[Chemistry,Sectors from Chemistry
]="Percentage of workforce wanting to go to the private R&D"
/10000*Workforce from studies[Chemistry]*Industry attractiveness[Sectors from Chemistry
]/(SUM (Industry attractiveness[Sectors from Chemistry
!]))
"Demand for private R&D workforce in sector"[Health,Sectors from Health]="Percentage of workforce wanting to go to the private R&D"
/10000*Workforce from studies[Health]*Industry attractiveness[Sectors from Health
]/(SUM (Industry attractiveness[Sectors from Health
!]))
"Demand for private R&D workforce in sector"[Process Engineering,Sectors from Process Engineering
]=
"Percentage of workforce wanting to go to the private R&D"
/10000*Workforce from studies[Process Engineering]*Industry attractiveness
[Sectors from Process Engineering]/(SUM
(Industry attractiveness[Sectors from Process Engineering!]))
"Demand for private R&D workforce in sector"[Multidisciplinary Sciences,Sectors from Multidisciplinary Sciences
]=
"Percentage of workforce wanting to go to the private R&D"
/10000*Workforce from studies[Multidisciplinary Sciences]*Industry attractiveness
[Sectors from Multidisciplinary Sciences]/(SUM (Industry attractiveness[Sectors from Multidisciplinary Sciences
!]))
"Demand for private R&D workforce in sector"[Mechanics,Sectors from Mechanics
]=
"Percentage of workforce wanting to go to the private R&D"
/10000*Workforce from studies[Mechanics]*Industry attractiveness[Sectors from Mechanics
]/(SUM (Industry attractiveness[Sectors from Mechanics
!]))
"Demand for private R&D workforce in sector"[Industry,Sectors from Industry
]=
"Percentage of workforce wanting to go to the private R&D"
/10000*Workforce from studies[Industry]*Industry attractiveness[Sectors from Industry
]/(SUM (Industry attractiveness[Sectors from Industry
!]))
"Demand for private R&D workforce in sector"[Physics,Sectors from Physics]=
"Percentage of workforce wanting to go to the private R&D"
/10000*Workforce from studies[Physics]*Industry attractiveness[Sectors from Physics
]/(SUM (Industry attractiveness[Sectors from Physics
!]))
"Demand for private R&D workforce in sector"[Digital,Sectors from Digital]=
"Percentage of workforce wanting to go to the private R&D"

/10000*Workforce from studies[Digital]*Industry attractiveness[Sectors from Digital
]/(SUM (Industry attractiveness[Sectors from Digital
!]))
"Demand for private R&D workforce in sector"[Information and communication studies
,Sectors from ICT studies]=
"Percentage of workforce wanting to go to the private R&D"
/10000*Workforce from studies[Information and communication studies]*Industry attractiveness
[Sectors from ICT studies]/(SUM (Industry attractiveness[Sectors from ICT studies
!]))
"Demand for private R&D workforce in sector"[Audiovisual,Sectors from Audiovisual
]=
"Percentage of workforce wanting to go to the private R&D"
/10000*Workforce from studies[Audiovisual]*Industry attractiveness[Sectors from Audiovisual
]/(SUM (Industry attractiveness[Sectors from Audiovisual
!]))
Units: people

Employee turnover[Sectors]=Workforce employed in knowledge intensive activities
[Sectors]*Attrition rate in sector[Sectors]
Units: people/Year

Entering higher education[Studies]=Young adults*Percentage of adults enrolling in studies
[Studies]
Units: people/Year

External investments=10000
Units: $/Year [0,1e+09]

"Foreign R&D workforce"[Sectors]=IF THEN ELSE (("Human capital need in R&D"
[Sectors]-Workforce employed in knowledge intensive activities
[Sectors])<0 , 0, ("Human capital need in R&D"[Sectors]-Hires[Sectors]))
Units: people

Further aging= DELAY N (Aging of adults , Amount of years being adult after fertile ages
, Adults after retirement/Amount of years being adult after fertile ages
-Mortality of adults after fertile ages, 3)
Units: people/Year

"Government funding for public R&D in sector"=8e+08
Units: $

Graduating in studies[Studies]= DELAY N (Entering higher education[Studies
] , Amount of years being in higher education , Students[Studies]/Amount of years being in higher education
-Yearly mortality rate of adults*Students[Studies], 3)
Units: people/Year

Hires[Sectors]=MIN (
("Human capital need in R&D"[Sectors]
-Workforce employed in knowledge intensive activities
[Sectors]),
("Private R&D workforce in sector"[Sectors])
)
Units: people

Hiring and training time of employees=2
Units: Year [0,3]

Hiring of new employees[Sectors]= DELAY N (
IF THEN ELSE ((Hires[Sectors]>=0) , Hires[Sectors]/Hiring and training time of employees
, 0) , Hiring and training time of employees , 0 , Delay order 1)
Units: people/Year

"Human capital need in R&D"[Sectors]="R&D expenditure in Sector"[Sectors]/Innovation expenditure per person employed in innovation in Sector
[Sectors]
Units: people

Industry attractiveness[Sectors]=Innovation expenditure per person employed in innovation in Sector
[Sectors]/"Total R&D expenditure"[Sectors]
Units: Dmnl

Industry knowledge size[Sectors]= INTEG (internal knowledge generation[Sectors
]-knowledge expiry[Sectors],
Initial knowledge specialisation in Sector[Sectors])
Units: patent

Initial Added Value in Sector[Sectors]=2.6e+09,3.4e+09,1.088e+10,2.108e+10,
1.4e+09,2.6e+09,2e+09,4.3e+09,1.4e+09,5.5e+09
Units: $

Initial Children=2.91138e+06
Units: people

"Initial Employed R&D Workforce in Sector"[Sectors]=4880.52, 2143.43, 10162
, 11580.6,4646, 6352.73, 5728, 5250, 4973, 2005
Units: people [0,120000]

Initial knowledge specialisation in Sector[Sectors]=3490,430,23720,1710,230
,6310,1210,4730,1940,17140
Units: patent

Initial researchers in the region=34715
Units: people

Initial students in studies[Studies]=25323,6171,632,65597,3993,11891,44976,
3882,7588,7344
Units: people

Initial Workforce after studies[Studies]=9090,2037,670,15865,1320,11765,57939
,2295,2920,5890
Units: people

Innovation expenditure per person employed in innovation in Sector[Sectors]
=300134,
363441,
222900,

```
    112260,
    208089,
    135521,
    118866,
    122792,
    118866,
    253022
Units: $/(people*Year)

"Inter-sector knowledge spillover"[Sectors]=SUM ( Absorption Capacity[Sectors
,OtherSectors!] )*Sector attractiveness[Sectors]
Units: patent/Year

internal knowledge generation[Sectors]= DELAY N (  Average regional knowledge generation per capita in sector
    [Sectors]
    *Workforce employed in knowledge intensive activities[Sectors]+Knowledge Spillover
[Sectors], Average Time to Market in Sector
    [Sectors] ,  Average regional knowledge generation per capita in sector
    [Sectors]
    *Workforce employed in knowledge intensive activities[Sectors]+Knowledge Spillover
[Sectors], Delay order 3 )
Units: patent/Year

knowledge expiry[Sectors]= DELAY N ( internal knowledge generation[Sectors]
 , Knowledge obsolescence time , Industry knowledge size
    [Sectors]/(Time+Number of years in the sector)
     , Delay order 2 )
Units: patent/Year

Knowledge obsolescence time=10
Units: Year

Knowledge Spillover[Sectors]="Public-private collaboration per academic"[Sectors
]*"knowledge workforce in public R&D"[Sectors]+"Inter-sector knowledge spillover"
[Sectors]
Units: patent/Year

"knowledge workforce in public R&D"[Pharmaceutical Industry]=
    MIN ( SUM ( "Workforce wanting to work in academia & public research"[To pharmaceutical
!,Pharmaceutical Industry])  , "Government funding for public R&D in sector"
/"Public R&D expenditure per personel"[Pharmaceutical Industry] )
"knowledge workforce in public R&D"[Chemical industry]=
        MIN ( SUM ( "Workforce wanting to work in academia & public research"[To chemical
    !,Chemical industry])  , "Government funding for public R&D in sector"/"Public R&D expenditure per personel"
    [Chemical industry])
"knowledge workforce in public R&D"[Specialistic Technical and scientific activities
    ]=
        MIN ( SUM ( "Workforce wanting to work in academia & public research"["To Spec. Serv. Act."
    !,Specialistic Technical and scientific activities])  , "Government funding for public R&D in sector"
    /"Public R&D expenditure per personel"[Specialistic Technical and scientific activities
    ])
"knowledge workforce in public R&D"[Production and distribution of gas vapour and AC
    ]=
```

MIN (SUM ("Workforce wanting to work in academia & public research"["To Prod. Gas"
!,Production and distribution of gas vapour and AC]) , "Government funding for public R&D in sector"
/"Public R&D expenditure per personel"[Production and distribution of gas vapour and AC
])
"knowledge workforce in public R&D"[Automotive industry]=
MIN (SUM ("Workforce wanting to work in academia & public research"[To Automotive
!,Automotive industry]) , "Government funding for public R&D in sector"/"Public R&D expenditure per personel"
[Automotive industry])
"knowledge workforce in public R&D"[Manufacturing of measurement instruments of navigation and watchmaking
]=
MIN (SUM ("Workforce wanting to work in academia & public research"[To Navigation
!,Manufacturing of measurement instruments of navigation and watchmaking])
, "Government funding for public R&D in sector"/"Public R&D expenditure per personel"
[Manufacturing of measurement instruments of navigation and watchmaking])
"knowledge workforce in public R&D"[Aerospace construction and engineering]
=
MIN (SUM ("Workforce wanting to work in academia & public research"[To Aerospace
!,Aerospace construction and engineering]) , "Government funding for public R&D in sector"
/"Public R&D expenditure per personel"[Aerospace construction and engineering
])
"knowledge workforce in public R&D"[Manufacturing of communication equipment
]=
MIN (SUM ("Workforce wanting to work in academia & public research"[To Communication Equipment
!,Manufacturing of communication equipment]) , "Government funding for public R&D in sector"
/"Public R&D expenditure per personel"[Manufacturing of communication equipment
])
"knowledge workforce in public R&D"[Editing audiovisual and diffusion]=
MIN (SUM ("Workforce wanting to work in academia & public research"[To Editing
!,Editing audiovisual and diffusion]) , "Government funding for public R&D in sector"
/"Public R&D expenditure per personel"[Editing audiovisual and diffusion])
"knowledge workforce in public R&D"[ICT information and services]=
MIN (SUM ("Workforce wanting to work in academia & public research"[To ICT
!,ICT information and services]) , "Government funding for public R&D in sector"
/"Public R&D expenditure per personel"[ICT information and services])
Units: people

mortality in worforce=Adults in the workforce*Yearly mortality rate of adults
Units: people/Year

Mortality of adults after fertile ages=Adults after retirement *(Addtional mortality rate of old people
+Yearly mortality rate of adults)
Units: people/Year

Mortality of Children=Children*Yearly Mortality Rate
Units: people/Year

Mortality of young adults=Young adults*Yearly mortality rate of adults
Units: people/Year

Number of years for knowledge commercialisation=1
Units: Year

Number of years in the sector=10

Units: Year [0,100]

Percentage of adults enrolling in studies[Studies]=0.00125182,
0.000560557,
7.1057e-05,
0.00173781,
0.00156237,
0.00180536,
0.00557575,
0.000423708,
0.000714075,
0.000888646
Units: Dmnl/Year

Percentage of innovative SMEs collaborating with others=0.613
Units: Dmnl/Year

Percentage of profit from revenue in Sector[Sectors]=47.1, 45.9, 41.05, 41.55
, 27.5,31.4,43.7,41.5,27.5,79.1
Units: Dmnl [0,100]

"Percentage of R&D budget on total budget in Sector"[Sectors]=34.65,18.41,19.81
,6.54,97.1,39.38,23.9,13.22,32.33,7.65
Units: Dmnl [0,100]

Percentage of workforce wanting to go the private sector=70
Units: Dmnl [0,100]

"Percentage of workforce wanting to go to R&D"=40
Units: Dmnl [0,100]

"Percentage of workforce wanting to go to the private R&D"=Percentage of workforce wanting to go the private sector
*"Percentage of workforce wanting to go to R&D"
Units: Dmnl

"Percentage of workforce wanting to work in public R&D"=(100-Percentage of workforce wanting to go the private sector
)*"Percentage of workforce wanting to go to R&D"
Units: Dmnl

"Private R&D workforce in sector"[Pharmaceutical Industry]=SUM ("Demand for private R&D workforce in sector"
[To pharmaceutical!,Pharmaceutical Industry])
"Private R&D workforce in sector"[Chemical industry]=SUM ("Demand for private R&D workforce in sector"
[To chemical!,Chemical industry])
"Private R&D workforce in sector"[Specialistic Technical and scientific activities
]=SUM ("Demand for private R&D workforce in sector"["To Spec. Serv. Act."
!,Specialistic Technical and scientific activities])
"Private R&D workforce in sector"[Production and distribution of gas vapour and AC
]=SUM ("Demand for private R&D workforce in sector"["To Prod. Gas"!,Production and distribution of gas vapour and AC
])
"Private R&D workforce in sector"[Aerospace construction and engineering]=SUM
("Demand for private R&D workforce in sector"[To Aerospace!,Aerospace construction and engineering
])
"Private R&D workforce in sector"[Automotive industry]=SUM ("Demand for private R&D workforce in sector"

[To Automotive!,Automotive industry])
"Private R&D workforce in sector"[Manufacturing of measurement instruments of navigation and watchmaking
]=SUM ("Demand for private R&D workforce in sector"[To Navigation!,Manufacturing of measurement instruments of navigation and watchmaking
])
"Private R&D workforce in sector"[Manufacturing of communication equipment]
=SUM ("Demand for private R&D workforce in sector"[To Communication Equipment
!,Manufacturing of communication equipment])
"Private R&D workforce in sector"[ICT information and services]=SUM ("Demand for private R&D workforce in sector"
[To ICT!,ICT information and services])
"Private R&D workforce in sector"[Editing audiovisual and diffusion]=SUM (
"Demand for private R&D workforce in sector"[To Editing!,Editing audiovisual and diffusion
])
Units: people

Profit[Sectors]= INTEG (Commercial Sales[Sectors]-Commercial expenditure[Sectors
],
Initial Added Value in Sector[Sectors]*Percentage of profit from revenue in Sector
[Sectors]/100)
Units: $

"Public Funding for Private R&D in Sector"[Sectors]=1.37,3.63,0.83,4.77,27.09
,10.69,21.13,4.02,25.87,1.74
Units: Dmnl [0,100]

"Public R&D expenditure per personel"[Sectors]=334128,40523.1,103778,142497
,393604,1.29275e+06,127634,40523.1,40523.1,40523.1
Units: $/people

"Public-private collaboration per academic"[Sectors]="Public-private collaboration"
/Initial researchers in the region
Units: patent/Year/people

"Public-private collaboration per million population"=30
Units: patent/(Year*people)

"Public-private collaboration"=Regional Population*"Public-private collaboration per million population"
/1e+06
Units: patent/Year

"R&D expenditure in Sector"[Sectors]="Percentage of R&D budget on total budget in Sector"
[Sectors]/100*(Commercial expenditure[Sectors]+External investments)+"Public Funding for Private R&D in Sector"
[Sectors]/100*Commercial expenditure[Sectors]
Units: $/Year

Regional Birth Rate=0.0135
Units: Dmnl/Year [0,1]

Regional Population=Young adults+Adults in the workforce+Children+Adults after retirement
Units: people

Relatedness[Sectors,OtherSectors]=0, 0.297297, 0.0277778, 0.08, 0.0909091,
0, 0.0833333, 0, 0.0526316, 0;

0.297297, 0, 0.0277778, 0.0384615, 0.0285714, 0, 0.0833333, 0, 0.0526316,
0.137931;
0.0277778 ,0.0277778, 0 ,0.0487805, 0.190476, 0.210526, 0.037037, 0 ,0, 0;
0.08 ,0.0384615, 0.0487805, 0 ,0.0769231 ,0.025641, 0.0465116, 0.322581 ,0.15
,0;
0.0909091 ,0.0285714, 0.190476, 0.0769231, 0, 0.047619 ,0 ,0 ,0, 0;
0 ,0, 0.210526 ,0.025641, 0.047619 ,0, 0.0416667, 0 ,0, 0.1875;
0.0833333 ,0.0833333, 0.037037, 0.0465116, 0, 0.0416667, 0, 0 ,0.148148 ,0.0434783
;
0 ,0, 0, 0.322581, 0, 0 ,0, 0 ,0.0384615, 0;
0.0526316, 0.0526316, 0, 0.15, 0, 0 ,0.148148, 0.0384615 ,0, 0.0416667;
0, 0.137931, 0, 0, 0, 0.1875 ,0.0434783, 0 ,0.0416667, 0;
Units: Dmnl [0,1]

Sector attractiveness[Sectors]=Industry knowledge size[Sectors]/Total Regional Industrial Knowledge
Units: Dmnl

Students[Studies]= INTEG (Entering higher education[Studies]-Graduating in studies
[Studies],
Initial students in studies[Studies])
Units: people

"Total R&D expenditure"[Sectors]=SUM (Innovation expenditure per person employed in innovation in Sector
[Sectors!])
Units: $/(people*Year)

Total Regional Industrial Knowledge=SUM (Industry knowledge size[Sectors!]
)
Units: patent

Workforce employed in knowledge intensive activities[Sectors]= INTEG (Hiring of new employees
[Sectors]-Employee turnover[Sectors],
"Initial Employed R&D Workforce in Sector"[Sectors])
Units: people

Workforce from studies[Studies]= INTEG (Graduating in studies[Studies]-Aging
[Studies],
Initial Workforce after studies[Studies])
Units: people

"Workforce wanting to work in academia & public research"[Chemistry,Sectors from Chemistry
]="Percentage of workforce wanting to work in public R&D"/10000*Workforce from studies
[Chemistry]*Industry attractiveness[Sectors from Chemistry]/(SUM (Industry attractiveness
[Sectors from Chemistry
!]))
"Workforce wanting to work in academia & public research"[Process Engineering
,Sectors from Process Engineering]=
"Percentage of workforce wanting to work in public R&D"/10000
*Workforce from studies[Process Engineering]*Industry attractiveness[Sectors from Process Engineering
]/(SUM (Industry attractiveness[Sectors from Process Engineering
!]))
"Workforce wanting to work in academia & public research"[Mechanics,Sectors from Mechanics
]="Percentage of workforce wanting to work in public R&D"/10000

*Workforce from studies[Mechanics]*Industry attractiveness[Sectors from Mechanics
]/(SUM (Industry attractiveness[Sectors from Mechanics
!]))
"Workforce wanting to work in academia & public research"[Health,Sectors from Health
]=
"Percentage of workforce wanting to work in public R&D"/10000*Workforce from studies
[Health]*Industry attractiveness[Sectors from Health]/(SUM (Industry attractiveness
[Sectors from Health
!]))
"Workforce wanting to work in academia & public research"[Multidisciplinary Sciences
,Sectors from Multidisciplinary Sciences]=
"Percentage of workforce wanting to work in public R&D"/10000*Workforce from studies
[Multidisciplinary Sciences]*Industry attractiveness[Sectors from Multidisciplinary Sciences
]/(SUM (Industry attractiveness[Sectors from Multidisciplinary Sciences
!]))
"Workforce wanting to work in academia & public research"[Industry,Sectors from Industry
]=
"Percentage of workforce wanting to work in public R&D"/10000*Workforce from studies
[Industry]*Industry attractiveness[Sectors from Industry]/(SUM (Industry attractiveness
[Sectors from Industry
!]))
"Workforce wanting to work in academia & public research"[Physics,Sectors from Physics
]=
"Percentage of workforce wanting to work in public R&D"/10000*Workforce from studies
[Physics]*Industry attractiveness[Sectors from Physics]/(SUM (Industry attractiveness
[Sectors from Physics
!]))
"Workforce wanting to work in academia & public research"[Digital,Sectors from Digital
]=
"Percentage of workforce wanting to work in public R&D"/10000*Workforce from studies
[Digital]*Industry attractiveness[Sectors from Digital]/(SUM (Industry attractiveness
[Sectors from Digital
!]))
"Workforce wanting to work in academia & public research"[Information and communication studies
,Sectors from ICT studies]=
"Percentage of workforce wanting to work in public R&D"/10000*Workforce from studies
[Information and communication studies]*Industry attractiveness[Sectors from ICT studies
]/(SUM (Industry attractiveness[Sectors from ICT studies
!]))
"Workforce wanting to work in academia & public research"[Audiovisual,Sectors from Audiovisual
]=
"Percentage of workforce wanting to work in public R&D"/10000*Workforce from studies
[Audiovisual]*Industry attractiveness[Sectors from Audiovisual]/(SUM (Industry attractiveness
[Sectors from Audiovisual
!]))
Units: people
Yearly Mortality Rate=0.004
Units: Dmnl/Year
Yearly mortality rate of adults=0.002
Units: Dmnl/Year
Young adults= INTEG (Becoming Adult-Aging of Young adults-Mortality of young adults
1.13994e+06)
Units: people