

Inter-firm Network Resilience under Flood Shocks

Evidence from a Dynamic Network

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by

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Preface

Before you start reading my thesis, I would like to reflect on these past couple of months. Last November, I first reached out to Tatiana regarding a potential thesis subject. The subject appealed to me because of the combination of climate change-related shocks and the use of ABM. The description explained that I would be working with an existing ABM and extending and adapting it, which was a different approach than I was used to.

After the initial meeting with Tatiana and Joos, I quickly realized that the topic would be quite challenging, not only because of the complexity of the climate change macroeconomic subject itself, but also due to the many different directions I could take and the complexity of the EMERGO model I was going to use. Nevertheless, I was determined to take on this challenge.

Forming a concrete proposal turned out to be a challenge in itself. Narrowing the different directions down was not straightforward. With the help of Tatiana and Joos, I eventually decided to focus on including different sectors based on input-output data, where the relationships between these sectors would form the network that exists between firms. To this, I added the aim of investigating how such a network becomes resilient after a flood shock, and what firm behavior contributes to this resilience.

However, it soon became clear that all of these elements together were too ambitious for a master's thesis. Understanding how the EMERGO model worked, on a code level, already took a significant amount of time, and adding all sectors introduced more complexity than the scope of the project could accommodate. As a result, certain elements had to be removed, without changing the overall direction of the research.

Going through this process taught me to be flexible and that even when an initial plan cannot be fully carried out, it is still possible to form a well-constructed research.

*Larissa Amirjalali
Delft, July 2026*

Acknowledgements

Dear reader,

I would like to take a moment to thank the people who have supported me throughout this process.

I would like to thank Tatiana for guiding me throughout this process. From the beginning, she has helped me in shaping my thesis topic and navigating the complexity of choosing a clear and meaningful direction. Her expertise in the subject has been valuable, especially given the challenging nature of the climate change macroeconomic theme and the different paths the research could have taken. I also appreciate her support in dealing with the more practical and operational aspects that followed from this thesis. In particular, at the beginning of the process, when I was still organizing my thesis committee and running into various administrative challenges, her understanding and flexibility made a difference.

Moreover, I would like to express my appreciation to Joos, who has been a great help throughout the modeling part of this thesis in EMERGO. While I enjoy working with models, I found that the modeling component of the thesis proved to be more complex than initially anticipated. Joos helped me work through various challenges and was always willing to think along when I got stuck or needed clarification on more technical aspects.

I would also like to thank Roman, my second reader. As mentioned earlier, I experienced some difficulties at the beginning in establishing my thesis committee. I therefore especially appreciate his willingness to step in and support the process at a later stage. Thank you for the time you have taken to read and review my thesis, and for your involvement during the formal moments.

Lastly, I am grateful that you all encouraged me not to take the easy route, but instead to engage with the more complex and demanding aspects of the research. This has pushed me to learn more and develop my work in a more meaningful direction.

Larissa

Summary

Floods are among the climate change effects most likely to intensify, and they account for a disproportionate share of climate-related economic losses in the EU. Economic production is organized around complex, interconnected supply chains where sectors continuously buy from one another. Through buyer-supplier relationships, disruptions propagate to firms that were never directly exposed. Ignoring these inter-firm and inter-sectoral dependencies, therefore, risks underestimating the true economic burden of floods. This makes it important for both firms and policymakers to understand not just how individual firms adapt, but how the network of interdependent firms as a whole regains its resilience after a shock.

While flood adaptation research has examined post-shock firm behaviors, these studies did not focus on how the network structure evolves because of it. The literature examines the changing network structure following a shock and the firm-level behaviors that influence it. However, it emphasizes the opportunity of researching what the restructuring of the network does to the long-term resilience of the network. From the knowledge gap, the following research question is addressed: How do firm-level rewiring behaviors, including those exhibiting path dependency through firms' memory of past shocks, reshape the inter-firm network structure and affect its resilience following a flood shock?

To address this gap, the EMERGO model developed within the NWO VIDI project "Social Tipping Points for Transformational Climate Change Adaptation" (grant number 191.015) was extended in three steps. First, a new sectoral interdependency structure was introduced between the capital goods, consumer goods, and consumer services sectors, capturing the intermediate goods and services dependencies that were previously only implicit in the model (SQ1). Second, this was used to structure an explicit, dynamic inter-firm network in which supplier relationships evolve over time as firms enter, exit, and switch suppliers (SQ2). Third, several rewiring behaviors were implemented and tested in simulation experiments: probabilistic rewiring based on competitiveness, rewiring toward market leaders, risk-averse rewiring based on suppliers' past disruption history (including memory of past shocks), and combinations of these. Each scenario was run 30 times and subjected to two sequential flood shocks, after which network-structure metrics and resilience metrics (based on the absorb-adapt-restore framework) were calculated and compared (SQ3, SQ4). This approach contributes to the first dynamic, multi-sector inter-firm network implemented within EMERGO, and links micro-level rewiring decisions directly to macro-level network structure and resilience outcomes, addressing the knowledge gap.

The key findings show two distinct patterns of network structure evolution: scenarios driven by competitiveness-based rewiring centralized gradually, while scenarios including market leader-based rewiring centralized rapidly early on. These structural differences mattered for resilience: the gradually centralizing scenarios showed better absorptive, adaptive, and restorative capacity after the first shock, while continuous rewiring improved resilience across all scenarios by the second shock. Firms' memory of past shocks did not produce a visible difference in network structure, but it did improve restorative capacity under repeated shocks. This suggests resilience operates through two separate dimensions: a structural one, where the speed and pattern of network centralization shape resilience to the first shock, and a behavioral one, where memory of past disruptions improves recovery without changing the network structure itself, pointing to a form of path dependency in supplier-selection decisions. Resilience effects were also uneven across markets: clearest for the consumer goods sub-network, more limited for consumer services, and inconclusive for capital goods, whose inventory dynamics were too volatile to retrieve reliable resilience metrics.

These findings carry several policy implications. Excessive concentration around dominant suppliers, as seen in the pure Market Leader scenario, removes network redundancy and increases vulnerability to cascading failures, whereas performance-based rewiring, applied without such concentration, gradually strengthens resilience — suggesting continuous, competitiveness-driven supplier diversification is preferable to static, long-term contracts. Risk-averse, memory-based switching improves recovery

but not initial shock absorption, indicating it should complement rather than replace other resilience measures. Because resilience effects differ by sector, policy should be sector-specific rather than uniform, and given the volatility observed in capital goods, sufficient inventory buffers appear especially important for capital-intensive sectors.

The study has several limitations. Attempts for the sensitivity analysis revealed extreme sensitivity to the capital goods and intermediates utilization parameters. Moreover, the model showed no sensitivity to switching weight parameters and moderate sensitivity to supplier range parameters. Taken together, the model shows selective robustness. Resilience could only reliably be assessed through inventory levels, meaning the analysis effectively measures inventory resilience rather than broader economic resilience, and conclusions are linked to the most sensitive parameters in the model. The strength of inter-sectoral dependencies modeled (the intermediate input coefficient) is also constrained to a relatively low, stable value, meaning the results reflect weaker interdependencies than may exist in practice. The capital goods sub-network's resilience metrics could not be meaningfully interpreted due to high volatility.

Based on these findings, the thesis offers several policy recommendations, which need to be interpreted cautiously given the model's limitations. First, policymakers could discourage rapid, excessive supplier concentration around market leaders, since this increases network vulnerability, and instead encourage performance-based supplier selection, which produces a more distributed and resilient structure. Second, since risk-averse rewiring improved restorative capacity, there is value in improving the availability of flood-risk information at the industry level, for example, through databases on firm-level flood exposure, coordinated by regional water authorities and national disaster management organizations, to support firms in making better-informed supplier decisions, though such measures would need to be extended with structural steps to address the initial impact of a disruption. Third, since the resilience benefits of rewiring were found to differ across sectors, and inventory buffers played an important role in absorbing disruptions in capital-intensive sectors, a uniform resilience policy is unlikely to be effective, however, further research into what drives these sector-specific differences is needed before concrete, differentiated policy requirements can be formulated.

Moreover, future research should explore the effect of a longer sequence of repeated shocks to determine what level of resilience ultimately emerges from continuous rewiring. It should also investigate the role of memory of past shocks at the individual firm level rather than only through aggregate network metrics, to better understand the causal link between rewiring behavior and resilience. Future work could also explore a less radical implementation of market leader preferences, since the version used in this study led to rapid and excessive market concentration. Combining risk-averse rewiring with explicit firm-level adaptation actions (firms take measures to reduce their own vulnerability after repeated damage) would offer a more realistic representation of path dependency, and applying the full set of resilience metrics proposed Bruckler et al. (2024), rather than the three used here, would give a more complete picture of network resilience. In addition, future work could extend the model to include switching behavior from the supplier's perspective, since the current model only captures switching decisions made by buying firms. Finally, future research could examine whether the model's shock mechanism generalizes to other climate-related hazards beyond flooding, which would require reconsidering the spatial concentration of the shock used in this study.

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Nomenclature

Abbreviations

Table 1: Overview of abbreviations

Definition	Abbreviation
Emergent Macro-Economic dynamics in Regional economies Governed by climatic shOcks	EMERGO
Capital goods	KG
Consumer goods	CG
Consumer services	CS
Intermediate goods	IG
Intermediate services	IS
Households	HH
Exposed region	E
Non-exposed region	NE

Introduction

1.1. Social Relevance

By continuing the century-long trend of rising greenhouse gas emissions (UN Environment Programme, 2025b), UN research shows that a significant increase in global temperature remains inevitable (UN Environment Programme, 2025a). With the increasing temperatures and the extreme weather that goes along with that, floods are the climate change effects most likely to intensify (Fatica et al., 2024). This trend is already visible in the EU, where the past thirty years have been the most flood-prone of the last five centuries (Fatica et al., 2024), and the spatial extent of floods increases (Fang et al., 2024). Between 1980 and 2024, economic losses in the EU due to climate-related hazards were estimated at €822 billion, with floods accounting for the largest share at 47%, compared to 27% for meteorological hazards, 18% for heatwaves, and 8% for droughts and wildfires (European Environment Agency, 2025), 27% for meteorological hazards, and 8% for droughts and wildfires. The combination of floods' increased likelihood of intensifying and their disproportionate contribution to the climate-related economic burden makes floods a particularly relevant focus for this study.

The economic burden of floods creates an incentive for both private firms and the government to protect business activity from flood shocks. Private firms seek to safeguard their assets and minimize costs to maintain their business operations (Cortés Arbués et al., 2025). Governments have the responsibility of protecting their citizens, but also benefit from a strong private sector through gaining tax revenues and the functioning of critical infrastructure (Cortés Arbués et al., 2025).

A strong private sector does not consist of individually operating firms; rather, it is an interconnected network of firms that are interdependent because sectors continuously supply and consume one another's goods and services. Bijnens et al. (2024) argue that economic production is structured around complex supply chains. Consequently, when a shock occurs, firms are affected not only directly through damage to their own production but also indirectly through disruptions affecting upstream suppliers and downstream customers (Bijnens et al., 2024). This means that ignoring sectoral interdependencies may underestimate the broader economic impacts of floods, as disruptions in one sector can propagate through supply chains and affect output in other connected sectors. Therefore, sectoral interdependencies can serve as a means of structuring an inter-firm network. When a flood occurs, non-resilient firms can disrupt the supply chain, thereby indirectly affecting initially unaffected firms and increasing the economic burden (Grover & Kahn, 2024; Wu et al., 2025; Ye & Abe, 2012).

This underscores the importance for policymakers to understand how firm-level decisions following a flood influence one another and shape overall resilience in the network of firms. These decisions are essential for building a resilient firm network, especially for firms critical to regional economic stability (Akkerman et al., 2026; Baghersad & Zobel, 2015).

The present study examines the behavior that exists within an interdependent, multi-sector network of firms following a flood shock. Here, adaptation emerges from interacting firm behaviors and shapes the network's resilience. It will use and extend the EMERGO model (ABM) introduced in Akkerman

et al. (2026), where the impact of a flood shock on aggregated economic dynamics is simulated. The results will inform policy advice on how networks of firms recover after a flood, creating opportunities to support and accelerate this recovery.

1.2. Scientific Relevance

While research on flood adaptation exists, firm-level flood adaptation remains underdeveloped, particularly in terms of regaining inter-firm network resilience, which is defined as the resilience of networks consisting of interconnected firms. Past research provided insights about the differences in how sectors are affected by floods (Cortés Arbués et al., 2024), how public and private investments in adaptation measures are distributed over economic sectors (Cortés Arbués et al., 2024), and what specific adaptation measures are that firms could take to deal with the financial burden of floods (De Carolis & Peters, 2025; Fatica et al., 2024; Sakai & Yao, 2023; Wutzler et al., 2022). However, there remains ambiguity regarding the firm-level behaviors that drive the recovery of a resilient multi-sector network of interdependent firms after a flood shock.

Therefore, this study focuses on the dynamic behavior involved in restoring the disrupted network that exists between firms in the aftermath of a flood, where the interdependencies between sectors are taken into account. This contribution will benefit the climate adaptation community and, in particular, the flood risk management community. It advances the field by shifting attention from isolated firm-level adaptation measures toward understanding how adaptive processes emerge through interactions of firm behavior, which is essential for designing effective and systemic flood adaptation policies.

1.3. Past literature

Rather than challenging EMERGO's core assumptions, this research adopts EMERGO as a foundational modeling framework and builds upon this to extend EMERGO's capacity to analyze post-shock recovery dynamics in an inter-firm network context. The current model does not focus on the network that exists among firms. The current EMERGO model has indirectly modeled a simple network (Akkerman et al., 2026), but modeling an explicit network where firms in different sectors buy from one another is essential for analyzing shock propagation and recovery dynamics within a network. An elaborate explanation of the current EMERGO model and the changes made for this thesis research can be found in Chapter 2.1.

The literature has focused on different behaviors as a reaction to a shock in an inter-firm network (Brown & Dawson, 2016; Khanna et al., 2022; Marzano, 2025; Son et al., 2021). Brown and Dawson (2016) and Marzano (2025) describe strategies to make a network resilient after a flood, including the diversification of the supply chain and the reduction of sectoral clustering. However, having a dependent set of suppliers is crucial in a strong supply chain network, as suppliers act as the link that guarantees the flow of materials needed for production (Lo et al., 2024). Moreover, supply disruptions are mostly associated with issues with suppliers (Lo et al., 2024), making firm-level behaviors related to restoring disrupted supplier links an interesting focus for this study.

The importance of these 'rewiring' behaviors is also emphasized by Reisch et al. (2026). The paper employs a statistical generative network model that reproduces the structural characteristics of a Hungarian supply chain network. It argues that high rewiring rates within the network reflect its adaptive capacity, enhancing post-shock recovery and resilience. However, rewiring can also indicate potential instability within the network (Reisch et al., 2026).

Ersahin et al. (2024) and Khanna et al. (2022) focus on these rewiring behaviors and argue that firms prefer industry leaders as new suppliers. Moreover, Khanna et al. (2022) discuss that firms seek new partners that are highly connected within the network. The underlying rationale is that highly connected firms are better positioned to withstand shocks because of their central role within the network. This is in line with Reggiani (2022), who emphasizes the potential of network connectivity to absorb shocks. In this view, hubs, nodes characterized by a high degree of interconnectedness, enable networks to adapt by redistributing flows, thereby allowing resilience to emerge (Reggiani, 2022). Firms' preference to rewire with industry leaders and highly connected firms may be related, as industry leaders typically have more connections because they have more buyers.

On the other hand, risk also plays an important role in buyer–supplier relationships. Zsidisin et al. (2004) argue that all buying firms are exposed to supply risk due to their connections within the supply chain network. Furthermore, the literature shows that suppliers facing high environmental risk, including risks associated with climate change, are less likely to attract buyers (Banerjee et al., 2014). This is in line with Lo et al. (2024), which discusses natural disasters as one of the most critical risk factors that could impact the supply chain. The paper emphasizes that firms need to identify the risk associated with their suppliers and try to mitigate this to prevent disruptions in the network. These findings suggest that rewiring with suppliers that are less vulnerable to disruptions, such as flooding, would benefit the supply chain network more.

Taken together, the literature suggests that firms adapt their supplier relationships after disruptions through rewiring behaviors. While existing studies provide insights into the determinants of rewiring decisions and their role in short-term recovery, less attention has been paid to the consequences of these decisions for the long-term evolution of the network. Son et al. (2021) examines how network structures change following a shock and highlights the need for further research into how such restructuring processes affect the long-term resilience of supply chain networks.

1.4. Knowledge Gap

While past studies have examined post-shock firm behaviors, these studies did not focus on how the network structure evolves because of it. Son et al. (2021) examines the changing network structure following a shock and the firm-level behaviors that influence it. However, the paper emphasizes the opportunity of researching what the restructuring of the network does to the long-term resilience of the network.

Moreover, Akkerman et al. (2026) introduce the EMERGO agent-based model to explore firm-level differences in recovery from flood shocks. However, EMERGO does not incorporate an explicit network that exists between firms. Here, the challenge lies in using the EMERGO model and extending it to incorporate the inter-firm network. This feature will greatly increase the complexity of the EMERGO model because introducing interdependencies between firms requires introducing sector interdependencies and remodeling existing supplier-buyer relationships. The remodeling will result in a dynamic inter-firm network within a macro-economic environment.

This gap in the literature underscores the need for further research into the behavior behind regaining a resilient dynamic inter-firm network after a flood shock, framing the systemic recovery as a form of adaptation in itself. Introducing the feature of an inter-firm network within EMERGO will enable us to examine the propagation of shocks and recovery dynamics across a dynamic network, rather than between isolated firms, making EMERGO usable for the purpose of this study. Addressing this gap is important for advancing scientific understanding of how micro-level firm interactions and firm interdependencies gain system-level resilience. Understanding these dynamics can inform more effective flood adaptation strategies and reduce economic losses.

1.5. Scope & Research Question

The goal of this thesis is to analyze how micro-level firm behaviors shape the recovery of inter-firm links after a flood and, in doing so, determine how resilience re-emerges in disrupted dynamic inter-firm networks. Therefore, the main result will be a dynamic inter-firm network within an agent-based model that policymakers can use to understand how firm decisions and interactions influence network-wide recovery dynamics and how targeted interventions can accelerate network resilience after a flood.

This study focuses specifically on flood shocks. Floods are well suited to studying the path-dependent rewiring mechanism central to this research, since flood-prone areas are repeatedly exposed to the same hazard, allowing firms' memory of past shocks to influence future rewiring decisions. While other climate-related hazards, such as wildfires or hurricanes, fall outside the scope of this study, the generalizability of a model is important, and therefore the extent to which the model's shock mechanism and findings could extend to other climate-related hazards is discussed in Section 4.

Moreover, when referring to rewiring behavior, this study defines it as the behavior exhibited by a firm when it searches for a new supplier, rather than when a supplier searches for a new buyer. This

distinction arises from the way EMERGO models network dynamics: suppliers do not actively search for new buyers, but they can indirectly gain replacing buyers. This mechanism is further discussed in Chapter 2.3, in the section on the 'dynamic network'.

To define network resilience, this thesis draws on the framework proposed by Bruckler et al. (2024), in which resilience is conceptualized as the combined absorptive, adaptive, and restorative capacities of a network.

Following the knowledge gap, this study will focus on the main research question:

"How do firm-level rewiring behaviors, including those exhibiting path dependency through firms' memory of past shocks, reshape the inter-firm network structure and affect its resilience following a flood shock?"

To answer the main research question, the following sub-questions will be addressed.

- **SQ1:** How can the new sectoral interdependency structure be modeled into EMERGO to capture the different sector dependencies?
- **SQ2:** How can an inter-firm network be modeled into EMERGO to capture the inter-firm dependencies
- **SQ3:** How do different post-shock firm behaviors reshape the inter-firm network structure, and how do firms' memories of past shocks influence this restructuring?
- **SQ4:** How does the resulting network restructuring affect the absorb, adapt, and restore capacity (resilience) of the inter-firm network?

1.6. Methodology

The main method for this research is agent-based modeling (ABM), using the EMERGO model developed by (Akkerman et al., 2026). This model is implemented in the programming language Julia. ABM has been widely used to represent network structures and to study the impacts of climate change-related hazards (Gualdi & Mandel, 2016; Naqvi & Rehm, 2014), including the application to inter-firm networks (Otto et al., 2017). It is an effective method for studying complex systems, in which interactions at the micro-level give rise to emergent patterns at the macro-level, which can be systematically analyzed and understood (Antelmi et al., 2022; Medina et al., 2021; Page, 2012).

The main research question focuses on how different rewiring behaviors affect the network structure and resilience following a shock. Page (2012) discuss that in ABM the emergence of the patterns depends on the specifics of the model, including the network structure. The rewiring behaviors are assumed to have different effects on the network structure, thereby likely resulting in distinct emergent patterns and resilience outcomes. An important requirement is that the network needs to be dynamic, as this allows for the analysis of the evolution of the inter-firm network after the shock. ABM is therefore a suitable approach because it allows for the modeling of heterogeneous agents and their interactions over time, capturing how micro-level behaviors give rise to macro-level outcomes such as network resilience and structural adaptation.

Parts of EMERGO's architecture are adapted for this research to integrate the inter-firm network into the model, thereby addressing sub-questions 1 and 2. Furthermore, the rewiring behaviors discussed in the literature are incorporated into the model. These rewiring behaviors are subsequently used to run a series of experiments. The resulting network structures are analyzed by calculating relevant metrics, addressing sub-question 3. Sub-question 4 is then addressed by calculating resilience metrics for these experiments. Finally, the resilience outcomes are interpreted in relation to the network structure results, thereby providing an answer to the main research question.

1.7. Contribution

This study will contribute three elements. First, the inter-firm network will incorporate different firm-level rewiring strategies derived from the literature. This allows for the analysis of how alternative supplier selection and rewiring behaviors influence the evolution of the network structure following a disruption. By including firms' memory of past shocks and using this information to assess supplier risk,

the model introduces path dependency, whereby earlier states of the system influence its later stages (Setterfield, 2015). As a result, past shocks affect future supplier selection decisions and, consequently, the evolution of the network structure.

Second, a dynamic inter-firm network will be constructed within a macro-economic environment. Past studies have mostly focused on static networks. While the recently published paper of Reisch et al. (2026) also introduced a dynamic network, this statistical generative network and the inter-firm network within EMERGO will differ in their mechanisms that drive the network evolution.

Generative network models, reproduce the statistical structure of an observed network (degree distributions, clustering etc.) without modeling why individual firms form or break specific ties. As a result, they can describe what a network looks like, but not why firm-level decisions produce that structure, and how alternative firm-level behaviors would change it. An ABM such as EMERGO can simulate the decision rules firms follow (choosing suppliers based on competitiveness, risk, market share etc.) and lets network structure emerge from these rules. This makes it possible to link a specific resilience outcome to a specific behavioral assumption, which a statistical generative model cannot do by design.

Third, this study will examine how these changes in network structure affect the resilience of the network over time. In doing so, it contributes to the literature by linking firm-level rewiring behaviors to long-term recovery dynamics and network resilience in the aftermath of flood-induced shocks.

1.8. Report Structure

Following the introduction, Chapter 2 will provide a description of the research design. Figure 1.1 illustrates the four stages of the research design. First, the current sectoral interdependency structure of the EMERGO model is partially reconstructed to enable a fully connected network. After stabilizing the model with this new sectoral interdependency structure, an explicit network is incorporated. Subsequently, different rewiring behaviors are implemented, after which the resulting network structures are analyzed across the various experiments. Finally, the resilience of the network is assessed using a range of metrics for the various experiments. After this, the results are presented in Chapter 3, followed by a discussion and conclusion in Chapter 4 and 5.

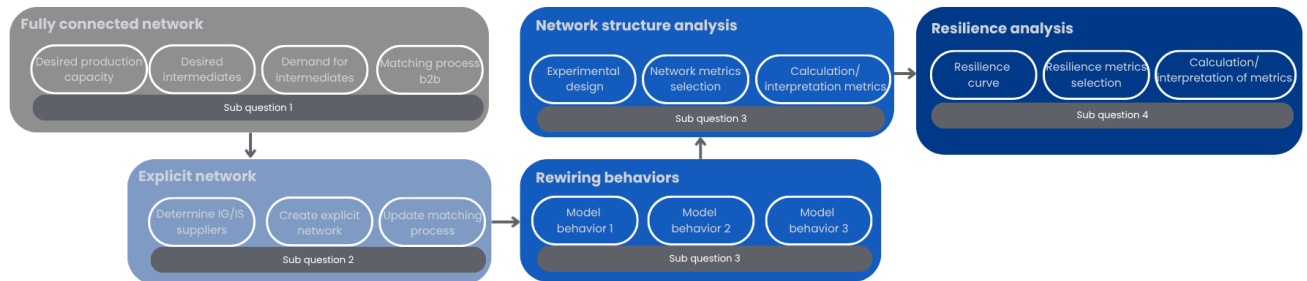


Figure 1.1: Research design

2

Research design

This chapter elaborates on the research design introduced in Chapter 1. The focus of this chapter lies on the methodological approach, as well as the conceptualization, the operationalization of the model, and experiments. Furthermore, Tables A.1-A.5 in Appendix A provide the formalization of the model, by outlining the model and agent variables as well as the parameter settings.

This chapter begins with the conceptualization of the EMERGO model, providing background on its development and functionality. In addition, the conceptual modifications made for this research are outlined. The model is used in the four main stages of the research design. Figure 1.1 illustrates these stages: Fully connected network, Explicit network, Modeling behaviors, Network structure analysis, and Resilience analysis. Each of these stages is discussed in detail, outlining how the model is adapted, extended, and analyzed to address the research questions.

This research follows a simulation-based methodological approach, in which the ABM EMERGO is developed and used to conduct computational experiments. The model is implemented in Julia and developed using Visual Studio Code. ABM is a widely used method for studying complex systems, as it enables the analysis of emergent patterns resulting from micro-level interactions (Antelmi et al., 2022; Medina et al., 2021; Page, 2012; Serdyuk, 2026). This approach, therefore, allows for the examination of how micro-level rewiring behaviors influence macro-level network structures and resilience outcomes. Moreover, ABM is particularly well-suited for this research because it allows for the analysis of path dependency (Serdyuk, 2026), which is a key element in this study, as firms' memory of past shocks is incorporated into a rewiring strategy.

There are three key elements in an ABM. First, it contains agents who together form the population of the model (Antelmi et al., 2022). Second, these agents are situated within an environment, which defines the context and setting of the model (Antelmi et al., 2022). Third, model rules specify how agents interact with one another and with their environment (Antelmi et al., 2022). The model evolves through discrete time steps, often referred to as model steps. Each model step represents a unit of time in which the model rules are executed in a predefined order. Through these interactions, the state of the model is updated after every step, allowing the system to evolve over time.

Akkerman et al. (2026) discuss that EMERGO's macroeconomic outcomes are driven by the dynamics of local states, agent behavior, and their microeconomic interactions. These dynamics ensure that when a shock hits the model, the economy moves out of equilibrium, agents recover, and the economy transitions into a new steady state. The emergent macro-economic dynamics allow for the analysis of how agent-level heterogeneities affect long-run post-shock outcomes (Akkerman et al., 2026). Given that the research question focuses on heterogeneous behavior in post-shock rewiring and its effect on network structure and resilience, the model is particularly well-suited for this analysis.

2.1. Conceptualization EMERGO

The EMERGO model represents a closed macroeconomy and consists of an exposed region, subjected to flood shocks, and a non-exposed region. It is a calibrated model that represents an archetypical industrialized economy, with representative studies and datasets from EU countries and the US used to set its parameters (Akkerman et al., 2026). EMERGO is populated by agents: firms, households, the government, and a mutual fund. The two regions are connected through trade and migration of firms and households. When the exposed region is subjected to a shock, it directly affects the firms and households in that region. The non-exposed region is impacted indirectly through the impact on trade and migration. Each step within EMERGO represents one month, during which agents update their decisions and interactions, allowing for the simulation of long-term economic dynamics.

Key agents

Agent behavior is affected by flows (goods, income, expenses) and stocks (inventories, cash holdings, capital goods), which endogenously cause constraints within the model (Akkerman et al., 2026). While households, the government, and the mutual fund are essential for the functionality of the model, this research focuses on firms. As modifications to the model's components involving households, the government, and the mutual fund are not required to answer the research questions, these agents are not further elaborated upon.

There are three aggregated sectors in EMERGO: capital goods (KG), consumer goods (CG), and consumer services (CS). All firms belong to one of these sectors and are therefore producers of the respective goods or services associated with that sector. Figure 2.1 illustrates the sectoral interdependency structure between the firms and households in the non-modified EMERGO model. Their production capacity uses a Leontief function with labor and capital as inputs. Because a Leontief function is used, there is no substitution possible between labor and capital. In reality, substitution is unlikely to occur in the short term. This is relevant because when a shock hits and capital is destroyed, firms cannot immediately hire more labor to compensate for the lost capital. As Figure 2.1 illustrates, firms obtain their capital from the KG sector and labor from households.

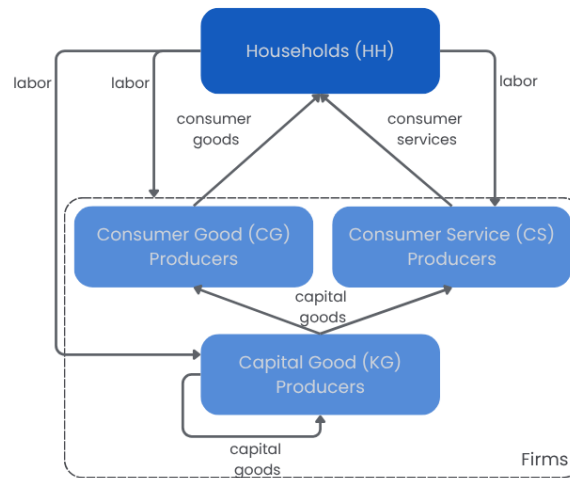


Figure 2.1: Schematic overview of sectoral interdependency structure in the non-modified model

For this research, it is important to consider the inter-firm network, as sectors continuously supply and demand from one another. To capture this, the feature is introduced that all firms also purchase from the CG and CS sectors, meaning the sectoral interdependency structure needs modification.¹ Figure 2.2 illustrates the sectoral interdependency structure in the modified model, and from this it can be derived that the production capacity is now not only constrained by labor and capital, but also intermediate goods and services (IG and IS). These are produced by the CG and CS sectors, making the units similar to the CG and CS units. However, when purchased by firms, the units are called

¹In reality, sectors are not aggregated and therefore have more inputs than only KG, IG, and IS. Moreover, there is heterogeneity in the extent to which these sectors, and therefore firms, depend on one another for inputs. However, this lies outside the scope of this research. This aspect could be explored in future research and will be further elaborated upon in the conclusion.

intermediates because firms use these units as intermediates in their production. This changes the production capacity function because there are more inputs needed for production besides capital and labor, as in the non-modified model. The operationalization of the production capacity function and the modifications made are further elaborated in Chapter 2.2.

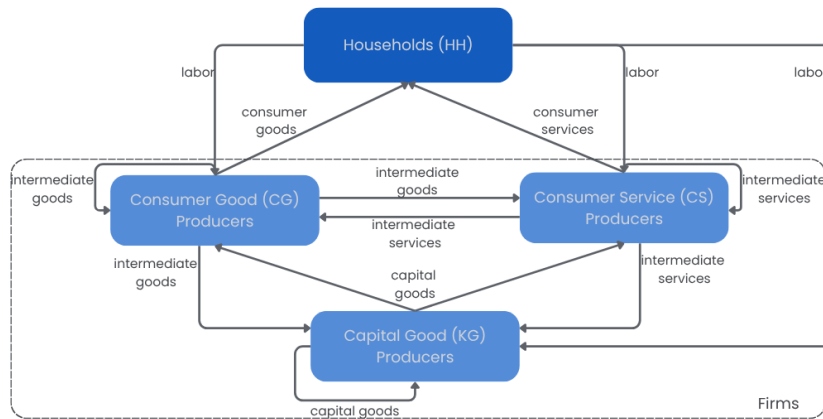


Figure 2.2: Schematic overview of sectoral interdependency structure in the modified model

Key outcomes

To explain the model's functionality, a few key outcomes of the non-modified model, discussed in the paper by Akkerman et al. (2026), are highlighted. At a certain step, a shock hits the model. The overall production capacity declines immediately due to the destruction of capital, leaving firms with reduced capital input for production. Moreover, some firms are so severely damaged that they enter bankruptcy. The sudden drop in production capacity directly translates to a sharp decline in output for the exposed region (E), shown as the green line in Figure 2.3a. A quick recovery follows because of the buffers in cash reserves, inventories, and machines that firms keep. In addition, firms have a machine utilization of 80% in the pre-shock phase. This means that they can uphold their pre-shock production capacity when their capital drops by 20%, which contributes to the recovery. When 40% of capital is destroyed, the effect on production would be 20% instead of 40%. These insights are relevant to this research because, in the modified model, there are more inputs besides capital and labor, making inventories important.

However, the quick recovery only occurs in the scenario where all firms are affected equally (the uniform and spread-out shock). In a more realistic scenario, where only 40% of firms are damaged, and firms are affected to different degrees, the results differ. Figure 2.3a shows the GDP for the uniform shock (green line) and the GDP for the heterogeneous and concentrated shock (orange line). Although the immediate impact is smaller for the heterogeneous shock, the recovery path has a longer duration. This is a result of more concentrated damage, because in this scenario, there are some firms that are not damaged and some firms that are severely impacted. In addition, keeping buffers is also less effective, as some firms experience losses that exceed their buffer capacity, leading to long-term effects for these firms and a greater impact on the GDP.

This describes the out-of-equilibrium state the model transitions into directly after the shock. To explain what dynamics transition the model to the steady state, Figure 2.3b presents a schematic overview of the different phases of shock transmission in the exposed region. In both scenarios, a decline in production capacity and a rise in bankruptcies lead to a reduction in labor demand, pushing the model into a new phase in which market adjustments occur. Units become more expensive because there is more demand than supply, while wages decline. As a result of these adjustments in price and wage, the expected profit rate rises. This, in turn, initiates the recovery phase, during which increased profitability stimulates investments in labor and production capacity. Consequently, prices decrease, and wages rise again as the model converges to a new steady state.

Shock

The decision was made to apply a heterogeneous and concentrated shock in this study. The memory of past shocks will be introduced later as a feature influencing firm-level rewiring decisions. For this

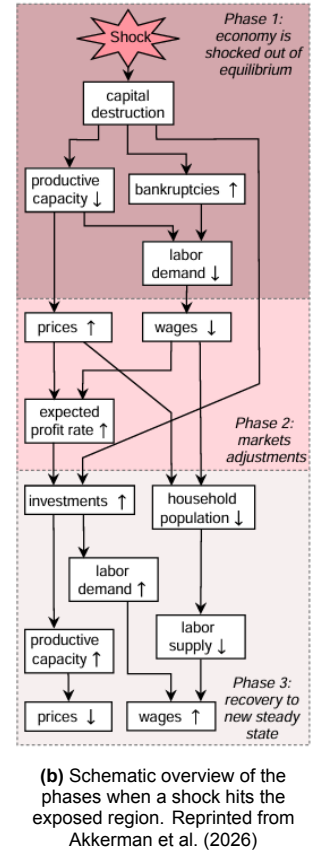
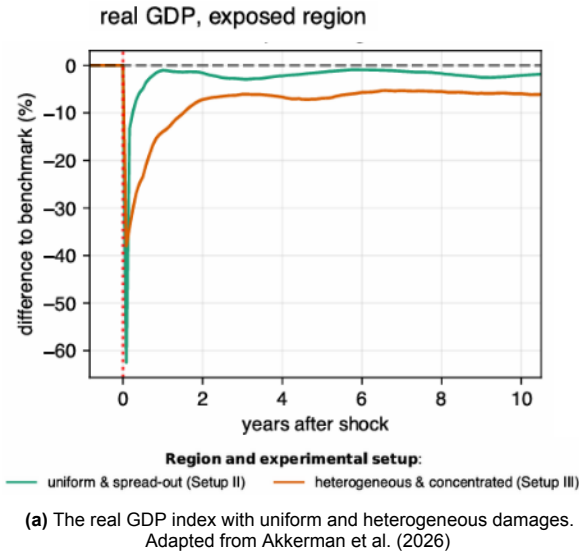


Figure 2.3: (a) GDP (b) schematic overview of phases shock transmission

purpose, it is important to only shock a subset of firms rather than all firms, since firms are more likely to connect with partners that have not been affected by previous shocks. The specifics of this firm-level behavior, as well as the rationale for the shock design, are elaborated in Chapter 2.4.

For now, it is important to understand that the model will undergo two shocks. During the first shock, the selection of affected firms is drawn randomly, with the severity of damage for each firm drawn from a Beta distribution. During the second shock, the same firms are targeted again, accounting for any firms that have gone bankrupt, in which case replacement firms are selected. The same firms are shocked during both events to represent firms located in a flood-prone area that is repeatedly exposed to flooding. This approach introduces path dependency, as firms' experience of previous shocks can influence future rewiring decisions and network evolution.

2.2. Fully connected network

As explained in Chapter 2.1, to incorporate the inter-firm network, the sectoral interdependency structure of EMERGO needs to be changed to Figure 2.2. First, it was decided to create an implicit fully connected network. This implies that, once firms are allowed to purchase intermediate goods and services, their demand is distributed across all IG and IS suppliers². Here, it should be noted that the CG and CS producers are the IG and IS suppliers, and that A, B, and C, used to denote three firms, carry no meaning in themselves and that there are more than three firms in the model. They are shown only to conceptually illustrate that each firm has a different supplier set compared to another firm.

As a result, all firms are linked with all IG and IS suppliers, forming a fully connected network, which is conceptualized in Figure 2.4. However, this network remains implicit, as buyers are not explicitly linked to sellers through edges within the model. Instead, it can be considered a network in the sense that all firms buy from all suppliers.

²The IG and IS suppliers are all the firms in the CG and CS sectors.

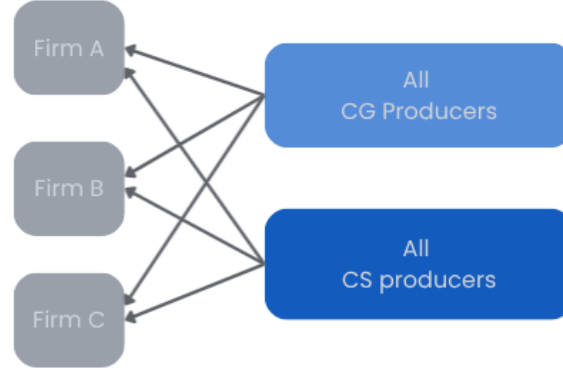


Figure 2.4: Conceptualization of the fully connected network

The reason for this transitional modeling step is that EMERGO is a highly complex model, in which even small modifications can cause the system to break almost immediately. By simplifying the matching process at the end of this phase, the model can first stabilize before increasing complexity in the subsequent phase, “Explicit Network”.

To best explain how to realize the phase “Fully connected network”, Figure 2.5 shows a state diagram of a firm buying intermediate goods and services. This flow shows in a simple way what states the firms go through within every model step to buy these units. While there are more steps happening before, after, and in parallel to this flow, these are the components relevant to explain for the reconstruction of the market. Each of the processes within this state diagram will be discussed in the next sections, as well as the equations used.

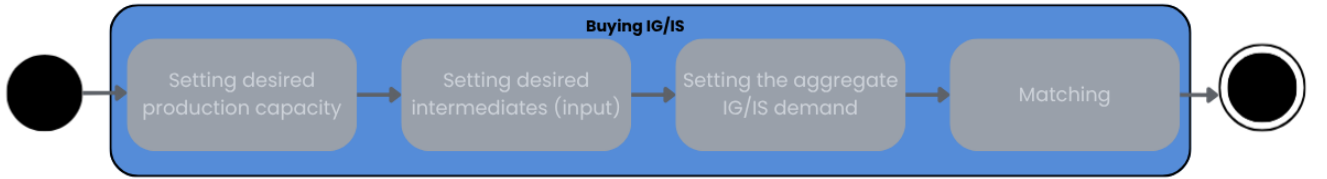


Figure 2.5: State diagram of a buying firm in a fully connected network

2.2.1. Setting desired production capacity

Production capacity calculation

First, firms decide on their desired production capacity, and therefore, a production capacity calculation is needed. In the non-modified model, the production capacity equation uses a full Leontief function. Here, the production is constrained by the minimum of the given inputs (Saito, 2011). Substitution is not possible because the elasticity of substitution is zero (Saito, 2011). The non-modified model only has labor and capital as inputs, which results in the production capacity function in equation 2.1, where $q_{i,t}$ is the production capacity, A_i the idiosyncratic productivity level, $L_{i,t}$ and $K_{i,t}$ labor and capital stock used by firm i at time t , and κ_s the capital intensity.

$$q_{i,t} = \min \left\{ A_i L_{i,t}, \frac{K_{i,t}}{\kappa_s} \right\} \quad (2.1)$$

However, in the modified model, the production is not only constrained by labor and capital, but also by consumer goods and consumer services. To include this in the model, the production capacity equation is changed to equation 2.2.³ In this equation, $I_{i,t}$ is the amount of intermediates used by firm i at time t , and is an aggregate of the inputs of intermediate goods and services. In addition, ν_s is the intermediate intensity.

³This equation is included in the model within the *production_capacity()* function.

$$q_{i,t} = \min \left\{ A_i L_{i,t}, \frac{K_{i,t}}{\kappa_s}, \frac{I_{i,t}}{\nu_s} \right\} \quad (2.2)$$

As explained before, the modeling choice of making labor and capital non-substitutable was needed to reflect reality. However, allowing for some degree of substitution is particularly important for this research, as the model is subject to shocks. With each additional constraint on production capacity, the impact of these shocks becomes more pronounced.

This study focuses on disruptions in the supply chain network, where the inability of suppliers to deliver inputs should have observable effects throughout the network. However, eliminating all possibilities for substitution would increase these effects excessively, causing the model to break down too quickly. This would make it difficult to analyze the transmission of shocks through the system in the long term.

Therefore, to calculate the $I_{i,t}$, a CES function (equation 2.3) and a special case of CES, a Cobb-Douglas function (equation 2.4), are considered. The difference with Leontief is that here substitution is possible, because the elasticity of substitution is greater than 0 (Saito, 2011). Eventually, the Cobb-Douglas production function is used, which is a CES function with an elasticity of substitution equal to 1 and a substitution parameter ρ of 0 (Saito, 2011). This means that inputs are substitutable to a moderate extent. This modeling choice was made because, when reconstructing the market, a CES function would create problems and increase the modeling complexity. While CES is still possible, it was not chosen because the research asks for some substitution, but it lies outside the research scope to fully explore different substitution levels.

The choice for Cobb-Douglas transforms equation 2.3 to equation 2.4, where the $ig_{i,t}$ and $is_{i,t}$ represent the intermediate goods and services used by firm i at time t . Together with α , which is the distribution parameter, $I_{i,t}$ is calculated and later used as input for equation 2.2.⁴

To include ig and is as inputs to firms' production capacity, an intermediate stock is added to the model. This addition is essential because the stock keeps track of how many ig and is units are available for the production of each firm, as well as how many ig and is units are desired.

$$I_{i,t} = [\alpha ig_{i,t}^\rho + (1 - \alpha) is_{i,t}^\rho]^\frac{1}{\rho} \quad (2.3)$$

$$I_{i,t} = ig_{i,t}^\alpha is_{i,t}^{1-\alpha} \quad (2.4)$$

2.2.2. Setting desired intermediates

To calculate the amount of intermediate goods desired for each firm, the model uses the desired production capacity to calculate the desired intermediates and eventually get to the desired ig and is .⁵

First, the model executes Equation 2.5 for each firm to calculate its desired level of intermediate inputs, which is the aggregate of desired ig and is . This equation can be derived from the production capacity equation (Equation 2.2), where it is rearranged such that, instead of dividing intermediates by ν , the desired intermediates are obtained by multiplying production capacity by ν . Additionally, the expression is divided by a factor ϕ_I^{desired} , which ensures that the desired level of intermediates slightly exceeds the amount strictly required for production. In this way, firms build up a small inventory buffer.

$$I_{i,t}^{\text{desired}} = \frac{q_{i,t}^{\text{desired}} \cdot \nu_s}{\phi_I^{\text{desired}}} \quad (2.5)$$

To eventually obtain the desired ig and is units, the model applies a Cobb–Douglas allocation of the desired intermediate inputs. Specifically, the total desired intermediates $I_{i,t}^{\text{desired}}$ are split between goods (ig) and services (is) according to their relative prices and the distribution parameter ρ_d . This allocation solves a cost-minimization problem, ensuring that the firm achieves the desired level of intermediates at minimal cost.

⁴In the model, this equation is implemented in the `input_intermediates()` function.

⁵In the model, this equation is implemented in function `set_desired_intermediates()`.

For this optimization problem, a Lagrange multiplier method is used 2.6, which is an optimization method, fit for Cobb–Douglas functions (Muhammad et al., 2023). Here, the first part of the equation represents what the firm wants to minimize, namely the costs, while the second part represents the constraint, which is the Cobb–Douglas aggregation.

$$\mathcal{L}(ig, is, \lambda) = \bar{p}_{r,g,t}ig + \bar{p}_{r,s,t}is + \lambda (I - ig^{\rho_d}is^{1-\rho_d}) \quad (2.6)$$

When this function is differentiated with respect to ig , is , and λ , and the resulting first-order conditions are set equal to zero, the equations can be combined to obtain the following expressions.

$$ig_{i,t}^{desired} = I_{i,t}^{desired} \left(\frac{\rho_d}{1 - \rho_d} \frac{\bar{p}_{r,s,t}}{\bar{p}_{r,g,t}} \right)^{1-\rho_d}, \quad is_{i,t}^{desired} = I_{i,t}^{desired} \left(\frac{\rho_d}{1 - \rho_d} \frac{\bar{p}_{r,s,t}}{\bar{p}_{r,g,t}} \right)^{-\rho_d} \quad (2.7)$$

Here, $\bar{p}_{r,g,t}$ and $\bar{p}_{r,s,t}$ represent the average prices of intermediate goods and services within region r where the firm is located, and at time t . The exponents $1 - \rho_d$ and $-\rho_d$ ensure that the firm substitutes between goods and services optimally: if one input becomes relatively more expensive, the firm will demand less of it and more of the cheaper input.

The purpose of this part of the model is to estimate the intermediates that each firm would want to buy. Because firms can hold inventory, it is important to subtract existing stock from the computed desired units. If a firm already has inventory, it will first draw down that stock and only place an order for the remaining shortfall. Firms may then rebuild inventory in a subsequent step.

2.2.3. Setting aggregate demand for IG and IS

The previous section described how firms calculate their desired ig and is units. Subsequently, the model calculates the aggregate demand of all firms per market type (IG or IS) and per region (N or NE).⁶ For this, the ig and is units desired (equations 2.7) are used as well as the average prices of ig and is within a region. Equation 2.8 shows the sum of the firms' demand for goods in market m (respectively ig or is), region r , and at step t .

$$D_{r,m,t}^{firms} = \sum_{i \in \mathcal{P}_r} m_{i,t}^{desired} \cdot \bar{p}_{r,m,t} \quad (2.8)$$

2.2.4. Matching process of firms to IG/IS producers (b2b market)

To model the matching process between producers of intermediates and firms that demand these inputs, the matching process is used that was already inside the model, the matching process of the households to CG and CS producers.⁷ The only modification made here is that when retrieving the demand, firm demand is used rather than household demand. Because the function is the same as the non-modified model, the functionality is explained briefly and illustrated in Figure 2.6.⁸

The model selects the relevant market and set of suppliers depending on whether ig or is are considered. Next, the aggregate demand of all firms in each region is taken as the starting point. This demand is expressed in monetary terms and is converted into total demand in units using the price average $\bar{p}_{r,m,t}$, which has been discussed before. This step ensures that price differences among producers are accounted for when translating budgets into quantities.

The total demand is then distributed across all producers according to their market shares. In this way, each firm's demand is not directed to a subset of suppliers, but instead allocated proportionally across all producers. This part of the matching process will be modified once the network structure is introduced, because here a specific set of suppliers per firm is essential. The purpose of this intermediate step is to first ensure that the model is stable before increasing its complexity.

⁶In the model this is implemented in the function `aggregate_demand()`

⁷When referring in Chapter 2.2.4 to producers, sellers of the units can be understood, and when referring to firms, buyers can be understood.

⁸In the model, this is implemented in the function `matching_cp_producers()` and the function `matching_hh_cp()` was used to structure the function.

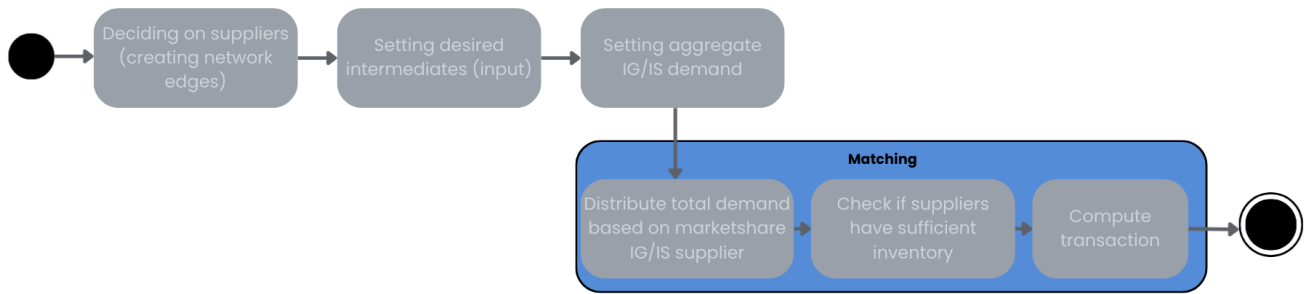


Figure 2.6: Process diagram of a firm in the 'buying' state within a fully connected network

After demand has been allocated, the model checks whether producers have sufficient inventory to meet this demand. If supply is limited, a service ratio is applied, meaning that only part of the demand can be fulfilled, while the remainder is recorded as unmet demand. This introduces capacity constraints into the system.

Finally, the model computes actual transactions: goods are sold, revenues are recorded, and trade flows between regions are tracked (including imports and exports). The goods are added to the stock of the buying firms, and the price is subtracted from their liquid assets. Moreover, the goods are subtracted from the stock of the selling firms, and the revenue is added to their liquid assets. To track the inventory value of intermediates, this inventory is added to the balance sheet of firms.

2.3. Explicit network

Once the fully connected network between IG and IS suppliers and their buyers is created and stable, the explicit network can be modeled, where all firms have a set of suppliers instead of distributing their demand over all suppliers. Figure 2.7 shows the conceptualization of this.⁹ Here, it should be noted that the CG and CS producers are the IG and IS suppliers, and that A, B, and C, used to denote three firms, carry no meaning in themselves and that there are more than three firms in the model. They are shown only to conceptually illustrate that each firm has a different supplier set compared to another firm.

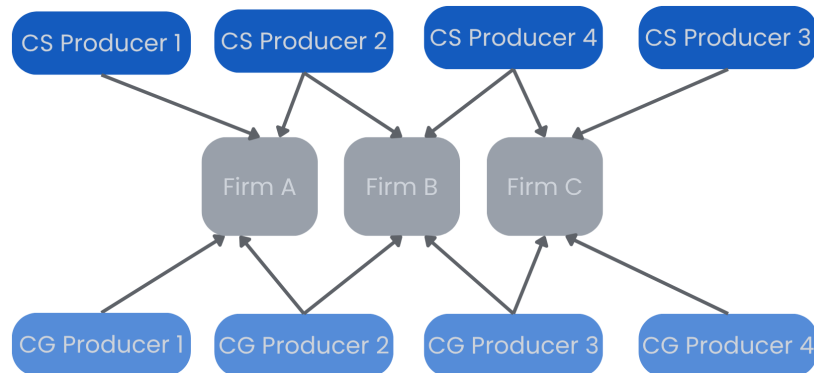


Figure 2.7: Conceptualization of the explicit network

2.3.1. Initializing IG and IS suppliers, nodes, and edges

The initialization of the IG and IS suppliers for each firm and the initialization of the explicit network are determined during the initialization of the model. The result is a randomly generated but constrained inter-firm network stored inside the model.¹⁰

⁹The packages `SimpleWeightedGraphs.jl` and `MetaGraphsNext.jl` are used within the code, which enable the creation of a directed weighted network consisting of nodes and edges. Here, the nodes represent the firms and the edges the supplier-buyer relationships. Using `MetaGraphsNext.jl`, in addition to `SimpleWeightedGraphs.jl`, enables the inclusion of firm-level metadata within the nodes.

¹⁰In the model, this is implemented in the function `initialize_intermediate_relations()`.

Number of suppliers considered

Before initializing the network, the model sets the number of KG, IG, and IS suppliers of all firms individually based on the mean production capacity of a firm.¹¹ This means that firms with a higher production capacity will obtain more suppliers, which allows for heterogeneity between firms.

The model takes a boolean to determine the type of market for which suppliers are being set, so it is executed three times, once for each supplier type (KG, IG, IS). First, the production capacities of all producers are collected and normalized relative to the minimum and maximum capacities in the economy (Equation 2.9). The normalized value of the mean production capacity of firm i is then used to calculate the number of suppliers considered for market type m within predefined minimum and maximum bounds 2.10. Finally, the calculated sample size is assigned to the corresponding firm attribute of the specific market type: $n_considered_kg$, $n_considered_cg$, or $n_considered_cs$, which tells how many suppliers a firm considers connecting with.

$$\bar{q}_i^{\text{norm}} = \frac{\bar{q}_i - \bar{q}_{\min}}{\bar{q}_{\max} - \bar{q}_{\min}} \quad (2.9)$$

$$n_considered_{i,m} = \text{round} (N_{\min,m} + (N_{\max,m} - N_{\min,m}) \cdot \bar{q}_i^{\text{norm}}) \quad (2.10)$$

Nodes

After determining the number of suppliers for each firm, the model retrieves the complete set of firms in the national economy and uses it to define the nodes that will populate the network.¹² A directed graph is created, and this network object is assigned to the model, making it available for later use in the simulation.¹³ Each firm is subsequently added as a node to the network, with the firm's ID used as the node label and the firm object itself stored as node data. As a result, the network nodes correspond one-to-one with the firms in EMERGO.

Edges

The edges in the network form the relationship between the buyer and seller. Creating these edges in the network, therefore, goes hand in hand with the initialization of the IG and IS suppliers of each firm. The method for determining these suppliers is based on the method used for initializing the KG suppliers, which was already present in EMERGO. For each firm in the economy, the set of all eligible IS suppliers is first constructed, which includes all firms in the CS sector. If the firm itself belongs to this sector, it is excluded from this set to prevent self-supply. From the remaining eligible firms, a random subset of IS suppliers is drawn using the model's internal random number generator, without replacement, ensuring that no firm is selected more than once. For this, a sample size is needed $n_considered_cs$ ¹⁴. Directed edges are then added from each selected supplier to the purchasing firm, representing intermediate service inputs flowing from the supplier to the buyer. These edges are initialized with a placeholder weight of 0, which can later be updated to reflect actual transaction volume during matching. This exact process is then repeated for the IG suppliers.

The edges between a firm and its KG suppliers are added differently in the current model. In the previous version of the EMERGO model, each firm was already assigned a set of KG suppliers at initialization, and the IDs of these suppliers were stored in a list attributed to the firm as *capital_supplier_ids*. This approach is preserved in the current model; however, at the end of *initialize_intermediate_relations()*, this list is read for each firm, and the KG suppliers contained in it are added as edges to the network.

Sub-networks

In addition to the full network, three sub-networks are required to support the network analysis performed in the later stages of the research. Each network includes all firm nodes but only contains edges corresponding to the KG, CG, or CS sector relationships. These sub-networks are required for subsequent network analysis. Two methods are considered to create them: slicing the full network or constructing three entirely new networks.

¹¹In the model, this is implemented in the function *set_supplier_sample_size()*.

¹²In the model, this is implemented in the function *initialize_intermediate_relations()*.

¹³The graph is wrapped in a MetaGraph structure, allowing firms to be stored as node metadata and numerical values to be associated with edges.

¹⁴This size is different for each firm and each supplier type. The calculation can be found in equation 2.10

For the slicing approach, the model takes as input the full network and a market type (KG, IG, or IS).¹⁵ It first copies all nodes from the full network into a new, empty network. Subsequently, it iterates over all edges in the full network, selecting only those with a source node belonging to the specified market type.¹⁶ Only edges that satisfy this criterion are added to the new network. Finally, the model returns the resulting sub-network.

The second method focused on building three additional networks. These sub-networks are built in the same way as the full network¹⁷, with the difference that only the edges from the corresponding sector are added. During initialization, the sub-networks are generated alongside the full network. They are then updated whenever the full network is modified, ensuring that they remain consistent with the overall network.

Both methods will be implemented separately within the model, and their performance will be evaluated. Particular attention will be paid to computational efficiency, as the use of networks and the switching of supplier relationships can be computationally expensive. Therefore, the method that results in the lowest runtime and memory allocation will be selected for further implementation.

2.3.2. Update matching process

To use the set of *ig* and *is* suppliers, the matching process between the firms and the intermediate producers is updated, because the former process divided the demand of firms over all suppliers instead of a selected set of suppliers.¹⁸ Figure 2.8 illustrates the adapted process diagram of a firm in the buying state within the explicit network.

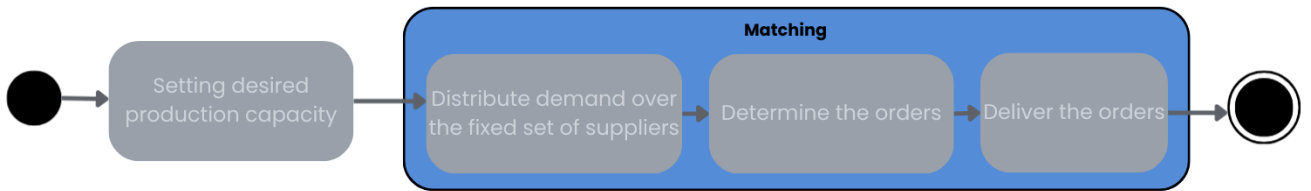


Figure 2.8: Process diagram of a firm in the 'buying' state within an explicit network

At the beginning, the model identifies the set of firms that actively demand intermediate inputs in the current period.¹⁹ It iterates over all firms in the economy and selects those firms whose desired intermediates, calculated in Chapter 2.2.2, are positive.

Determine orders

The matching takes place through a sequence of discrete rounds, up to the sample size of suppliers. In each round, every demanding producer considers a linked supplier from the network. For each considered supplier, the producer determines the quantity of intermediate input to order based on its total desired demand for that intermediate type and the supplier's relative competitiveness.

For each demanding firm, the model computes the competitiveness score for all its potential suppliers based on the edges in the network. The calculation for the competitiveness score for one supplier can be found in equation 2.11, where C_j is the competitiveness score for supplier j , p_j is the unit price of supplier j , ϑ_j is the trade markup for supplier j , and γ_f is the firm within-product elasticity of substitution.

¹⁵In the model, this is implemented in the function `slice_network()`.

¹⁶In the `Graphs.jl` package, the source node of an edge (the supplier) can be accessed using the built-in function `src(e)`, which takes an edge and returns the source node code. To convert this code into the corresponding node label, representing the firm ID in the network, the built-in function `label_for()` is used. This function takes a network and a node code as input and returns the associated node label. The functions `is_KG()`, `is_CG()`, and `is_CS()` are then used to determine whether a given firm ID belongs to the corresponding sector type.

¹⁷Not to be confused with the fully connected network from Chapter 2.2.

¹⁸For this, the function `matching_cp_producers()` is adapted.

¹⁹The function is parameterized by a Boolean indicator that determines whether the matching process applies to the IG or IS producers. This design allows the same matching logic to be used consistently across different intermediate input markets. True means goods and false means services.

$$C_j = (p_j \cdot \vartheta_j)^{-\gamma_f} \quad (2.11)$$

For every supplier j of the demanding firm i , the relative competitiveness (equation 2.12) is calculated by dividing the competitiveness score of supplier j by the sum of the competitiveness scores of all the suppliers of firm i .

$$RC_{j,i} = \frac{C_j}{\sum_{j \in S_i} C_j} \quad (2.12)$$

As a result, each supplier holds an order object specifying the quantity of units requested by a particular firm. These orders need to be processed by delivering them to the respective firms.²⁰

Deliver orders

The model identifies all orders in the economy and, for each, the receiving firm and requested quantity. The delivered amount is then determined by taking the minimum of the ordered quantity and the producer's available inventory. Subsequently, it updates the producer's inventory by subtracting the delivered amount from it and logs the sale by updating the balance sheet. In addition, the units are added to the intermediate stock of the buyer, and it logs the payment in the balance sheet.

However, when the quantity that can be delivered is lower than the quantity ordered, the model records the shortfall as unmet demand. This unmet demand is calculated as the difference between the ordered amount and the delivered amount and is accumulated at the level of the supplying firm. To assess the severity of the shortage, the unmet demand is expressed as a ratio relative to the original order size. This ratio is then used as an input for a switching decision, where the receiving firm evaluates whether to remain with the current supplier or to switch to an alternative supplier within that market. In this way, supply constraints not only affect current transactions but also influence the evolution of supplier relationships over time.

A dynamic network

The network is dynamic through three mechanisms: firms switch suppliers based on unmet demand, seek the lowest costs, and enter and exit the economy and therefore the network. These mechanisms were already inside the model for KG suppliers, but have been updated because firms now also have IG and IS suppliers and are therefore important to explain.

The mechanism by which firms switch from suppliers based on unmet demand determines whether a firm replaces its current IG or IS supplier based on the extent to which demand has not been met²¹, and is based on the same mechanism for the KG suppliers already present in the model. First, a switching probability is calculated as an increasing function of the unmet demand ratio, using an exponential form. This ensures that higher levels of unmet demand lead to a higher likelihood of switching, while small shortages only result in a limited probability. This probability is then compared to a random draw, introducing stochasticity into the decision-making process. If the switching condition is higher than the random draw, a new supplier is selected from the set of eligible alternatives in the same way as the initialization of suppliers was done, after which the existing supplier is replaced by the newly selected one in the firm's supplier network. In this way, the model captures adaptive behavior, where firms respond to supply shortages.

When new firms enter the economy, the network also needs to be updated. The firms are added as new nodes and create new edges by determining their *ig* and *is* suppliers. It therefore samples suppliers, as in the initialization of the network, and it adds the edges to the network. These firms can also become suppliers if other firms decide to switch suppliers based on lower costs.

First, the firm evaluates potential improvements by randomly selecting one of its current suppliers and comparing it to a newly sampled alternative supplier from the market.²² To ensure diversity, the model attempts to find an alternative that is not already in the firm's supplier set. If a valid alternative is

²⁰In the model, this is implemented in the functions *deliver_cg_units()* and *deliver_cs_units()*. Both functions perform the same operation but are applied specifically to orders for goods from *ig* suppliers and services from *is* suppliers.

²¹In the model, this is implemented in the function *decide_switch_cp_unmet_demand()*

²²In the model, this is implemented in the function *check_better_cp()*.

found, the model checks whether this supplier offers a lower effective price per unit than the currently connected supplier. Equation 2.13 shows the calculation of the effective price for supplier j relative to its buyer i , which is obtained by multiplying the unit price of firm j by the trade markup of buyer i and supplier j . If the alternative supplier has a lower effective price, the firm cuts the edge with the current supplier and creates a new edge with the alternative supplier ²³.

$$p_{i,j}^{effective} = p_j \cdot \vartheta_{i,j} \quad (2.13)$$

Finally, when a firm goes bankrupt, its corresponding node is removed from the network, which automatically eliminates all associated edges. For each supplier that exits the market, the model identifies the firms it previously supplied. These firms subsequently search for alternative suppliers, and the corresponding edges are added to the network.

These mechanisms are focused on finding new suppliers. Implementing a dynamic network could also be approached through suppliers finding new buyers when they lose one. However, in this version of EMERGO, when a supplier loses a buyer, the supplier does not actively seek a new buyer. This is because the supplier can indirectly regain new buyers through the mechanisms explained above. When this does not happen, it may mean that the supplier is unable to compete sufficiently with its competitors, and it will eventually go bankrupt if it cannot sell enough. Changing this mechanism of the current buyer-supplier relationship to a more proactive role of the supplier and what this means for the model and the results will be further reflected upon in the future research discussion in Chapter 5.

In the current implementation, each time a firm finds an alternative supplier (bankrupt supplier, check better supplier, etc.), it is done through random selection. This serves as the baseline scenario against which other approaches are compared. The following chapter provides a more detailed discussion of alternative supplier selection mechanisms, referred to as rewiring behaviors.

2.3.3. Results interpretation SQ1 and 2

To conclude, Chapters 2.2 and 2.3 focused on the implementation of the new sectoral interdependency structure in which sectoral and firm interdependencies are explicitly represented. Chapter 2.2 outlined the steps required to transform the current sectoral interdependency structure into the new one, while Chapter 2.3 described the transition from a fully connected network to an explicit network in which firms maintain a dynamic set of suppliers.

Furthermore, Chapter 3 evaluates the two methods for constructing sub-networks to support the subsequent network structure and resilience analyses. In addition, several macro-level variables are plotted to illustrate the basic behavior of the modified model. Finally, model verification and validation are presented to assess whether the model behaves as intended and adequately represents the system that is being studied, and a sensitivity analysis will test the robustness of the model.

2.4. Rewiring behaviors & network structure analysis

The previous section described both the structure of the inter-firm network within EMERGO and the mechanisms through which the network evolves over time. Through firm bankruptcies, the entry of new firms, and supplier switching based on unmet demand or competitiveness, the network acquires a dynamic character. Firms currently select alternative suppliers through a probabilistic choice, where the probability of selecting a supplier is influenced by its competitiveness. However, as discussed in the introduction, firms may exhibit different behaviors when searching for new suppliers.

The following section discusses the different alternative supplier selection mechanisms, referred to as rewiring behaviors, and how these are modeled within the network. Subsequently, this section outlines the methodology used to analyze the evolution of the network structure over time.

2.4.1. Modeling rewiring behaviors

Chapter 1.3 described three behaviors: firms connecting with industry leaders, highly connected suppliers, and suppliers with disruption risk. It is expected that the first two behaviors will produce similar

²³In this model, this is implemented in `decide_switch_cp_comp()`.

outcomes, as industry leaders are also likely to be highly connected. In EMERGO, connectivity is determined by production capacity, meaning that firms with higher production capacity (Chapter 2.3) will naturally have more buyers and suppliers. Therefore, for the purposes of the experiments, the first two behaviors have been merged, and the focus is placed on industry leaders and suppliers with low disruption risk.

Probabilistic competitiveness-based rewiring

This behavior represents the default rewiring behavior already present in EMERGO. Alternative suppliers are chosen probabilistically, while still taking their competitiveness into account.²⁴

When a producer searches for an alternative supplier, the model first determines the set of all potential suppliers based on the market it searches in. If no alternative suppliers are available, the model returns no supplier. Otherwise, a weight is assigned to each candidate supplier based on its relative competitiveness.

The competitiveness weight of supplier i is calculated according to Equation 2.14, where p_i denotes the supplier's unit price and $\vartheta_{i,j}$ represents the trade markup between the firm's region i and the supplier's region j . Suppliers with lower prices and lower trade markups receive larger weights and therefore have a higher probability of being selected.

$$w_i = \frac{1}{p_i \cdot \vartheta_{i,j}} \quad (2.14)$$

Subsequently, a weighted random draw is performed over all candidate suppliers using these weights. As a result, more competitive suppliers are more likely to be selected, while less competitive suppliers still retain a chance of being chosen. This introduces stochasticity into the supplier selection process while preserving a preference for suppliers offering a more attractive price-quality combination.

Market leader-based rewiring

As discussed in the literature review, firms prefer industry leaders as new suppliers (Ersahin et al., 2024; Khanna et al., 2022). To find industry leaders within EMERGO, the national market share of firms is used. The firms' market share is updated every step.²⁵ This feature was already within EMERGO, but will be discussed briefly.

The model executes the following two equations to calculate the market share of firm i in market m . Equation 2.15 calculates the total sales of all producers in market m . Equation 2.16 then takes the sales of firm i and divides this by the total sales of all producers in market m to calculate the market share of firm i .

$$S_m^{\text{national}} = \sum_{i \in \mathcal{M}} s_i \quad (2.15)$$

$$\text{Marketshare}_{i,m}^{\text{national}} = \frac{s_i}{S_m^{\text{national}}} \quad (2.16)$$

Subsequently, the model takes these market shares to find an alternative supplier.²⁶ The model first determines the corresponding pool of all producers based on the market (KG, IG, IS). It then excludes suppliers that are already current suppliers, leaving only potential new suppliers.

From this remaining set, it identifies the producers with the highest national market share. If multiple producers share this maximum value, one is randomly selected. The model includes checks to ensure no current suppliers are considered and that all selected candidates indeed have the maximum market share. Finally, it returns the ID of the selected alternative supplier.

²⁴The functions `sample_new_capital_supplier()` and `sample_new_cp_supplier()` execute this process. The functions use the same method, where the first is specifically for KG suppliers and the second for IG and IS suppliers.

²⁵In the model, this is implemented in the function `update_cp_marketshares()` for IG and IS suppliers, and `update_kg_marketsharest()` for KG producers.

²⁶In the model, this is implemented in the functions `sample_new_capital_supplier_marketshare()` and `sample_new_cp_supplier_marketshare()`.

Risk-averse rewiring

To include risk-averse rewiring behavior, the flood shock mechanism within EMERGO was modified. Two consecutive flood shocks are applied instead of one to ensure that firms remember the exposure of other firms. The first shock, at step 300, identifies the affected firms and assigns each a *fraction_destroyed*, representing the share of capital destroyed. This fraction is sampled from a Beta distribution. Hsu et al. (2020) discuss that damage on a scale of 0 to 1 is a good proxy for vulnerability as a consequence of natural hazards. Therefore, the initial rewire risk is calculated as the square of this fraction, as shown in Equation 2.17.

$$\text{rewire_risk}_i = (\text{fraction_destroyed}_i)^2 \quad (2.17)$$

This formulation ensures that firms with higher capital destruction have proportionally higher risk, amplifying the effect in the model. When the second flood shock occurs at step 500, the same firms are targeted again, simulating persistent vulnerability due to their location in flood-prone areas. Because some firms may have exited the economy due to bankruptcy, it is necessary to ensure that the same number of firms is targeted. Therefore, additional firms are randomly added to the shock list to compensate for the firms that have left the system.

The new rewire risk after the second shock is calculated in Equation 2.18. This approach ensures that risk accumulates for repeatedly affected firms, while remaining bounded by 1. Trojand et al. (2025) discuss that greater damage in past events can lead to lower vulnerability in the future. The paper explains that this effect arises because firms implement adaptation measures after experiencing damage. Currently, adaptation mechanisms are not included in the model. To compensate for this, the following equation is designed to reduce the impact of additional damage for firms that have already experienced serious damage in the previous period. In other words, it assumes that these firms have partially implemented adaptation measures, which decrease their vulnerability. As a result, other firms perceive the impact as less severe, leading to a smaller increase in rewire risk after subsequent shocks.

$$\text{rewire_risk}_i^{\text{new}} = \text{rewire_risk}_i^{\text{old}} + (1 - \text{rewire_risk}_i^{\text{old}}) \cdot (\text{fraction_destroyed}_i)^2 \quad (2.18)$$

The *rewire_risk* is subsequently used by the model to first identify all potential suppliers for a producer, excluding current suppliers.²⁷ Among the remaining candidates, the firm selects those with the minimum rewire risk. Finally, one supplier is randomly sampled from this set of best candidates. This procedure ensures that firms preferentially reconnect to suppliers with lower accumulated risk, reflecting risk-averse behavior in response to repeated flood shocks.

2.4.2. Experimental design

To evaluate the impact of different rewiring behaviors on the network structure, 7 experimental scenarios were designed, shown in Table 2.1. These experiments will each be executed with 30 runs to reduce uncertainty. The Baseline competitiveness scenario represents the original EMERGO implementation and applies competitiveness-based rewiring, in which alternative suppliers are selected through weighted random sampling based on relative competitiveness. The Market leader scenario activates market leader-based rewiring, where firms preferentially select industry leaders based on national market share. The Risk-averse scenario activates risk-averse rewiring, where firms select suppliers based on their disruption risk.

In addition to the individual behaviors, four combination scenarios were included. The Performance-Oriented scenario combines competitiveness-based and market leader-based rewiring, the Strategic Selection scenario combines market leader-based and risk-averse rewiring, and the Competitiveness-Risk trade-off scenario combines competitiveness-based and risk-averse rewiring. In these combination scenarios, the method alternates randomly between the active behaviors with equal probability (50/50) whenever a firm rewires a disrupted supplier relationship. Finally, the combination behavior scenario combines all three rewiring behaviors, with each behavior having an equal probability of being selected by firms.

²⁷In the model, this is implemented in functions *sample_new_cp_supplier_risk()* and *sample_new_capital_supplier_risk()*.

To enable this experimental setup in which firms alternate between different rewiring behaviors, a dedicated rewiring procedure is structured.²⁸ This procedure is called every time a firm seeks an alternative supplier, which can occur due to supplier bankruptcy, unmet demand, or competitiveness considerations, as discussed before. Depending on the experimental scenario specified by the model attribute *scenario*, *rewire()* selects the supplier according to the active behavior(s), and, in combination scenarios, the selection mechanism alternates randomly among the active behaviors with equal probability. This approach reduces the risk of implementation errors, as supplier rewiring occurs at multiple points within the model. This centralization ensures that all rewiring decisions are handled consistently in one location.

Table 2.1: Experimental design of scenarios, with rewiring behaviors in the rows and scenarios in the columns.

Scenario	Competitiveness-based rewiring	Market leader-based rewiring	Risk-averse rewiring
Baseline competitiveness	1	0	0
Market leader	0	1	0
Risk-averse	0	0	1
Performance-oriented	1	1	0
Strategic selection	0	1	1
Performance-risk trade-off	1	0	1
Combined behavior	1	1	1

2.4.3. Network structure metrics

For each experiment, the evolution of the network structure over time is analyzed. This is done by calculating network metrics for every experiment over time. The final set of network metrics needs to be selected such that it provides a representative characterization of the network structure while maintaining computational efficiency.

Ledwoch et al. (2018) employ, among others, closeness centrality and betweenness centrality to assess disruption propagation, making these metrics relevant for this study. Furthermore, the built-in network metrics available in the `Graphs.jl` package were reviewed and added to the list of candidate metrics.

The following network metrics are calculated for the full network and the three sub-networks:

- **Network density** D : measures the proportion of possible connections that actually exist in the network (T. Chakraborty et al., 2017). For a network with N nodes and E edges, the density is calculated as follows.

$$D = \frac{2|E|}{|N|(|N| - 1)} \quad (2.19)$$

- **Maximum eigenvector centrality** $C_{\text{eig}}^{\text{max}}$: a high (Meghanathan, 2015) eigenvector centrality indicates a node with many connections to other important nodes. The maximum eigenvector centrality over time reflects how dominant the most influential node becomes. If v_i is the eigenvector centrality of firm i the equation is as follows.

$$C_{\text{eig}}^{\text{max}} = \max_{i \in N} v_i \quad (2.20)$$

- **Maximum degree centrality** $\tilde{C}_{\text{deg}}$: the mean degree centrality is the average number of connections per node in the network (Meghanathan, 2015), showing how connected a typical supplier is. However, because firms only replace connections and do not make additional connections, the mean degree centrality is expected to remain stable over time. Therefore, the choice was made to review the maximum degree centrality, which is the number of edges of the most connected node in the network. If k_i is the degree of node i the normalized maximum degree centrality can be calculated by the following equation.

$$C_{\text{deg}}^{\text{max}} = \max_{i \in N} (k_i) \quad (2.21)$$

²⁸In the model, this is implemented in the function *rewire()*.

- **Network modularity Q** : measures the strength of division of the network into communities (T. Chakraborty et al., 2017). For a network divided into communities, modularity is calculated by the following equation.

$$Q = \frac{1}{2|E|} \sum_{i,j \in N} \left[A_{ij} - \frac{k_i k_j}{2|E|} \right] \delta(c_i, c_j) \quad (2.22)$$

Here A_{ij} is the adjacency matrix, k_i the degree of node i , and $\delta(c_i, c_j)$ is 1 if nodes i and j belong to the same community, and 0 otherwise.

- **Maximum betweenness centrality $C_B^{\max}$** : measures the importance of the most central node in terms of the number of shortest paths passing through it (Ledwoch et al., 2018). For each node i , betweenness centrality is calculated by the following equation.

$$C_B(i) = \sum \frac{\sigma_{st}(i)}{\sigma_{st}} \quad (2.23)$$

Here σ_{st} is the total number of shortest paths between nodes s and t , and $\sigma_{st}(i)$ is the number of those paths that pass through node i . When a node has the largest betweenness centrality, it can mean it acts as a bridge between parts of the network. The max betweenness centrality is calculated by taking the maximum of the betweenness centralities of all firms

$$C_B^{\max} = \max_{i \in N} C_B(i) \quad (2.24)$$

- **Maximum closeness centrality C_{clo}** : measures how close a node is to all other nodes in the network, reflecting its potential to quickly interact with or influence others (Ledwoch et al., 2018). For node i the closeness centrality is calculated by the following equation.

$$C_{\text{clo}}(i) = \frac{|N| - 1}{\sum_{j \in N \setminus \{i\}} d(i, j)} \quad (2.25)$$

Here $d(i, j)$ is the length of the shortest path between nodes i and j , and $|N|$ is the total number of nodes. The maximum closeness centrality in the network is calculated by taking the maximum of the closeness centralities of all firms.

$$C_{\text{clo}}^{\max} = \max_{i \in N} C_{\text{clo}}(i) \quad (2.26)$$

- **Average clustering coefficient $\bar{C}$** : measures the average local cohesion of nodes, meaning the tendency of a node's neighbors to be connected (Hearnshaw & Wilson, 2013). For each node i with degree k_i and E_i edges between its neighbors, the equation is as follows.

$$C_i = \frac{2E_i}{k_i(k_i - 1)} \quad (2.27)$$

The average clustering coefficient over all nodes in the network is calculated by taking the average of the average clustering coefficients of all firms.

$$\bar{C} = \frac{1}{|N|} \sum_{i \in N} C_i \quad (2.28)$$

For the base scenario, one metric is added to the data collection at a time, and the simulation is executed for a single run. Subsequently, it is assessed whether the inclusion of the metric has a significant impact on runtime and memory allocation. If this is the case, the respective metric is excluded from the final set used for the analysis.²⁹

²⁹The metrics are computed using the built-in functions of `Graphs.jl`, as this reduces runtime.

2.4.4. Results interpretation SQ3

The previous section has explained the modeling of the rewiring behaviors, the experimental design, and several network metrics considered. The results shall focus on the final set of network metrics chosen for this research, based on computational efficiency. Moreover, to answer the sub-questions, these network metrics will be plotted over time for each network type and experiment, allowing for interpretation of the network structure and comparison across the different experiments.

2.5. Resilience analysis

The past section described the experimental setup and the methodology to analyze the network structure. This section uses the same experimental setup to examine the resilience of the network. For this, the paper of Bruckler et al. (2024) is used. The paper describes that a resilient supply chain network depends on the capacity to absorb, adapt, and restore disruptions.

Figure 2.9 shows that Bruckler et al. (2024) uses the resilience curve as a framework to identify key time points during the shock phase, such as the moment of impact, the minimum performance level, the start of recovery, and the return to equilibrium. These time markers serve as reference points for the calculation of the resilience metrics. This means that the metrics are not directly observed but derived from the dynamics of the resilience curve by measuring performance changes between these critical time points.

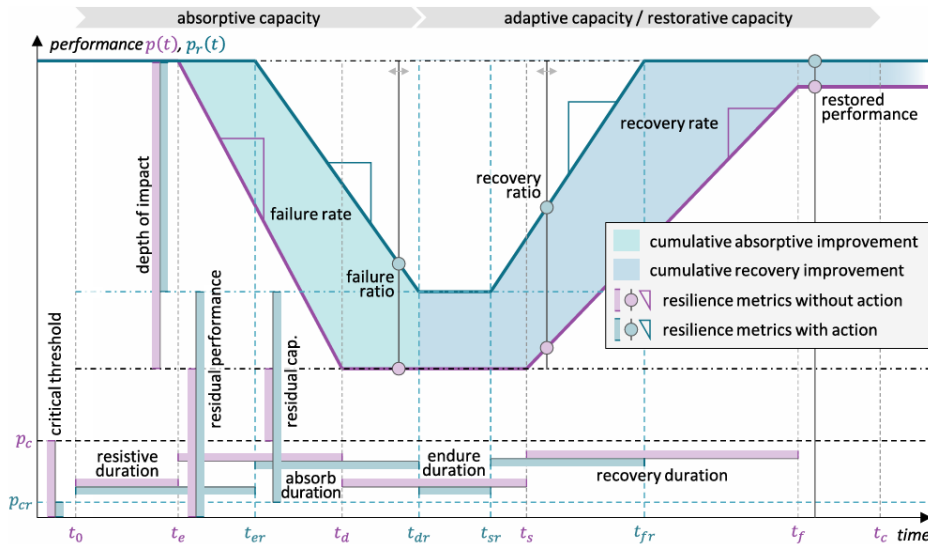


Figure 2.9: Application of resilience metrics to determine the resilience of a network. Reprinted from (Bruckler et al., 2024)

Figure 2.10 presents these 17 metrics to assess the resilience of a supply chain network. These metrics are all linked to a resilience capacity type: absorb, adapt, or restore. To use these metrics in this research, two decisions need to be made: which performance outcome is appropriate to use as a resilience curve, and which subset of metrics should be selected.

2.5.1. Resilience curve

In selecting an appropriate performance outcome to construct the resilience curve, two criteria are important. First, the chosen variable must exhibit a clear drop in response to a shock, ensuring that the impact of the disruption is reflected in the variable's performance. Second, the performance measure should not immediately return to its equilibrium level at the same time step. Without these criteria, it would be difficult to observe and quantify the recovery dynamics.

After analyzing the results of sub-questions 1 and 2 and generating the corresponding plots, it is possible to determine which performance outcome is most suitable for constructing the resilience curve.

Resilience metric	Articles	Capacity	Type	(a) Quantification	(b) Positive effect of resilience decisions
(1) resistive duration	1	absorptive	time-based	$t_e - t_0$	$(t_{er} - t_0) - (t_e - t_0) = t_{er} - t_e$
(2) absorb duration	8	absorptive	time-based	$t_d - t_e$	$(t_{dr} - t_{er}) - (t_d - t_e)$
(3) depth of impact	10	absorptive	performance-based	$p(t_d) - p(t_0)$	$(p_r(t_{dr}) - p_r(t_0)) - (p(t_d) - p(t_0))$
(4) critical threshold	1	absorptive	performance-based	p_c	$-(p_{cr} - p_c)$
(5) residual capacity	1	absorptive	performance-based	$p(t_d) - p_c$	$(p_r(t_{dr}) - p_{cr}) - (p(t_d) - p_c)$
(6) residual performance	11	absorptive	performance-based	$p(t_d)$	$p_r(t_{dr}) - p(t_d)$
(7) failure ratio	5	absorptive	performance-based	$\frac{p(t) - p(t_d)}{p(t_0) - p(t_d)}$	$\frac{p_r(t) - p_r(t_{dr})}{p_r(t_0) - p_r(t_{dr})} \cdot \frac{p(t) - p(t_d)}{p(t_0) - p(t_d)}$
(8) failure rate	2	absorptive	rate	$\frac{p(t_d) - p(t_e)}{t_d - t_e}$	$\frac{p_r(t_{dr}) - p_r(t_{er})}{t_{dr} - t_{er}} \cdot \frac{p(t_d) - p(t_e)}{t_d - t_e}$
(9) cumulative absorptive performance	20	absorptive	time integral	$\int_{t_0}^{t_d} p(t) dt$	$\int_{t_0}^{\max(t_d, t_{dr})} (p_r(t) - p(t)) dt$
(10) cumulative absorptive impact	14	absorptive	time integral	$\int_{t_0}^{t_d} (p(t) - p(t_0)) dt$	$\int_{t_0}^{\max(t_d, t_{dr})} ((p_r(t) - p_r(t_0)) - (p(t) - p(t_0))) dt$
(11) endure duration	14	adapt. / restor.	time-based	$t_e - t_d$	$-((t_{er} - t_{dr}) - (t_e - t_d))$
(12) recovery duration	22	adapt. / restor.	time-based	$t_r - t_e$	$-((t_{rp} - t_{er}) - (t_r - t_e))$ s.
(13) restored performance	13	adapt. / restor.	performance-based	$\frac{p(t_r)}{p(t_0)}$	$\frac{p_r(t_{rp})}{p_r(t_0)} \cdot \frac{p(t_r)}{p(t_0)}$
(14) recovery ratio	7	adapt. / restor.	performance-based	$\frac{p(t) - p(t_e)}{p(t_0) - p(t_e)}$	$\frac{p_r(t) - p_r(t_{er})}{p_r(t_0) - p_r(t_{er})} \cdot \frac{p(t) - p(t_e)}{p(t_0) - p(t_e)}$
(15) recovery rate	5	adapt. / restor.	rate	$\frac{p(t_r) - p(t_e)}{t_r - t_e}$	$\frac{p_r(t_{rp}) - p_r(t_{er})}{t_{rp} - t_{er}} \cdot \frac{p(t_r) - p(t_e)}{t_r - t_e}$
(16) cumulative recovery performance	32	adapt. / restor.	time integral	$\int_{t_e}^{t_r} p(t) dt$	$\int_{t_e}^{\max(t_r, t_{rp})} (p_r(t) - p(t)) dt$
(17) cumulative recovery impact	22	adapt. / restor.	time integral	$\int_{t_e}^{t_r} (p(t) - p(t_0)) dt$	$\int_{t_e}^{\max(t_r, t_{rp})} ((p_r(t) - p_r(t_0)) - (p(t) - p(t_0))) dt$

Figure 2.10: Overview of resilience metrics to determine the resilience of a network. Reprinted from (Bruckler et al., 2024)

2.5.2. Resilience metric selection

Due to time constraints and the overall scope of this study, it is not feasible to include and analyze all 17 resilience metrics presented in the literature. Therefore, a selection of metrics is made while ensuring comprehensiveness. The selected metrics aim to capture the most relevant aspects of system resilience while maintaining interpretability within the context of the EMERGO model.

The chosen metrics are *depth of impact*, *endure duration*, and *restored performance*. Together, these metrics provide a broad representation of the system's response to shocks, covering the initial severity of the impact, the duration over which the performance remains low, and the level at which performance stabilizes after the shock. These metrics also cover all three capacities mentioned in the paper: absorptive, adaptive, and restorative.

2.5.3. Resilience metric calculation

In this study, a procedure is developed to calculate the resilience metrics on the chosen resilience curve.³⁰ For every scenario, a DataFrame is constructed containing the performance metric for the total network, as well as the disaggregated performance metric for the KG, CG, and CS sectors. Since each scenario is simulated using 30 different seeds, the results are first aggregated by taking the mean value across all seeds for each time step.

The shock time defines the exact moment at which the system is disrupted. To analyze the system's response, a window is defined as a fixed number of time steps following the shock. This window determines the time horizon over which the post-shock dynamics are evaluated. Within this period, the minimum value of the performance metric is identified, which is used to compute the depth of impact and to determine the recovery trajectory of the system. The bandwidth of the window shall be chosen based on the trend of the performance metric and will be discussed in E.2.

In addition, a tolerance parameter is introduced to identify the duration of the shock's effect. This tolerance defines a band around the minimum value, within which the system is considered to still be disturbed. The choice was made to accept a tolerance of 1%. The endure duration is then calculated as the number of time steps for which the system remains within this tolerance band before recovering towards a new equilibrium.

This code will be executed for all combinations of scenarios, shocks, and network types. The resulting outputs are then stored in a DataFrame. This DataFrame is subsequently used to generate bar plots, enabling comparison of the different scenarios in terms of the resilience metrics.

2.5.4. Results interpretation SQ4

The results of sub-question 4 are interpreted by analyzing the resilience of the network. In addition to examining the performance of the full network, the performance of the individual sub-networks (KG,

³⁰The code for this function is shown in Listing E.1 in Appendix E.2.

CG, CS) is also considered. This allows for a comparison between different parts of the system and provides insight into how resilience is distributed across the network structure.

Furthermore, resilience metrics are computed for each experimental setting. This makes it possible to assess how variations in rewiring behaviors influence system performance over time. In this way, the analysis provides insights into how different rewiring strategies affect the overall resilience of the network and its underlying sub-networks.

3

Results

This chapter presents the results following the research design shown in Figure 1.1. First, the functioning of the EMERGO model with the newly introduced mechanisms, including the inter-firm network, is examined through an analysis of its macro-level dynamics. Next, the rewiring behaviors and the effects of the experiments on the network structure are discussed. Finally, the results of the resilience analysis for every experiment are presented by discussing the resilience metrics.

3.1. Fully connected network & Explicit network

This section presents the EMERGO model after the implementation of the inter-firm network. It explains the decision to construct separate sub-networks. Subsequently, the basic functioning of the modified model is examined through its macro-level dynamics. In addition, the verification and validation results of the modified model are discussed, demonstrating whether the model behaves as intended and produces plausible outcomes.

3.1.1. Sub-networks

During the research design, two methods to create sub-networks were introduced: slicing the full network or constructing three new networks. Both methods were implemented, and their runtime and memory allocation were analyzed. The results showed that constructing three separate networks significantly reduced both runtime and memory allocation compared to slicing the full network.

A likely explanation for this is that, when slicing the network, the algorithm must iterate over all edges at each step to determine whether an edge belongs to a particular supplier type. Given that each firm has around 10 to 15 suppliers, this results in a large number of edges that need to be checked repeatedly. In contrast, when constructing separate networks, filtering is no longer required. Instead, the only requirement is that the sub-networks are updated whenever the full network is updated. These findings suggest that constructing separate sub-networks is a more computationally efficient approach for calculating network metrics while maintaining consistency with the full network structure.

3.1.2. Macro-level dynamics in modified EMERGO model

GDP real

Figure 3.1 illustrates the evolution of real GDP over time in the base scenario for the exposed and non-exposed regions, as well as for the total economy. Two flood shocks are introduced at simulation steps 300 and 500, which are clearly visible as sharp declines in GDP. The shaded areas of the plot represent the variation across simulation runs. The relatively narrow confidence bands suggest that the overall response of the economy to the flood shocks is consistent across the 30 runs. However, some variability exists in the magnitude of the recovery after the shocks.

Before the first shock, GDP increases for both regions, indicating that the economy is growing similarly under normal conditions. At step 300, the first flood shock causes a decline in GDP, particularly for the exposed region. Its GDP drops sharply from approximately 580,000 to less than 400,000, reflecting the

direct destruction of capital. There is a slight bend in the curve of the non-exposed region, which may indicate that indirect effects propagate through the supply network, although these remain relatively small.

Following the first shock, all groups quickly recover. However, the recovery is incomplete before the second shock occurs at step 500. The second flood event produces a similar pattern: the exposed region experiences the largest decline, and the non-exposed region is only moderately affected. Notably, the decline in GDP after the second shock is smaller in magnitude than after the first shock, despite the incomplete recovery beforehand. This pattern is examined further in Chapter 4.1.1.

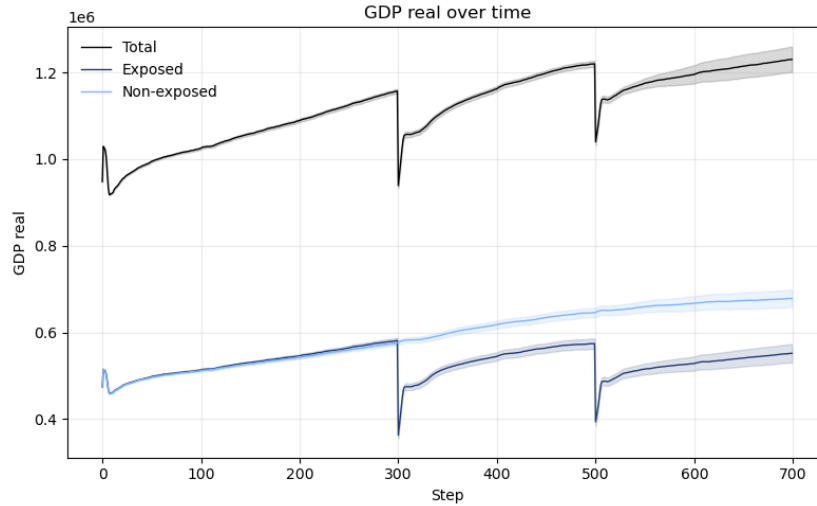


Figure 3.1: The real GDP for the exposed and non-exposed region, as well as for the total economy

Average production

Figure 3.2 shows the average production over time for KG, CG, and CS firms. At the beginning of the simulation, production levels fluctuate as the model transitions from its initial conditions toward a stable state. Once this stabilization phase is completed, clear differences between the firm types emerge.

The average production of both CG and CS firms follows the trend observed in real GDP. In particular, both firm types experience a large decline following the first flood shock and a somewhat smaller decline after the second shock, after which production gradually recovers. The reason for following the trend of the real GDP is that these sectors also sell to households. The GDP grows, and therefore, households receive more income, which increases the demand for units from the CG and CS sectors. Moreover, the average production of a CG firm is consistently higher than that of a CS firm. This can be explained by the model's production structure: equal amounts of ig and is are required for the production process, making the demand of firms for ig and is units somewhat the same. There are more CS firms in the model than CG firms. As a result, the required output is distributed across a larger number of CS firms, leading to a lower average production per firm.

In contrast, KG firms exhibit the lowest average production levels throughout the simulation and display a different response to the shocks. The reason for their lowest average production level is that the KG sector only sells to firms, and the CG and CS sectors also sell to households. Following the first flood event, the kg production drops sharply as capital is destroyed. This is immediately followed by a strong increase in production because of the heightened demand for capital required to replace damaged assets. Production temporarily exceeds its pre-shock level before experiencing another sharp decline as replacement demand diminishes. Thereafter, production gradually stabilizes around its long-term level.

Inventory

Figure 3.3 presents the total inventory available for sale in each sector. The CG and CS sectors show a broadly similar trend. At the beginning of the simulation, both sectors experience a substantial increase in inventory as the model adjusts from its initial conditions toward a stable equilibrium. However, the

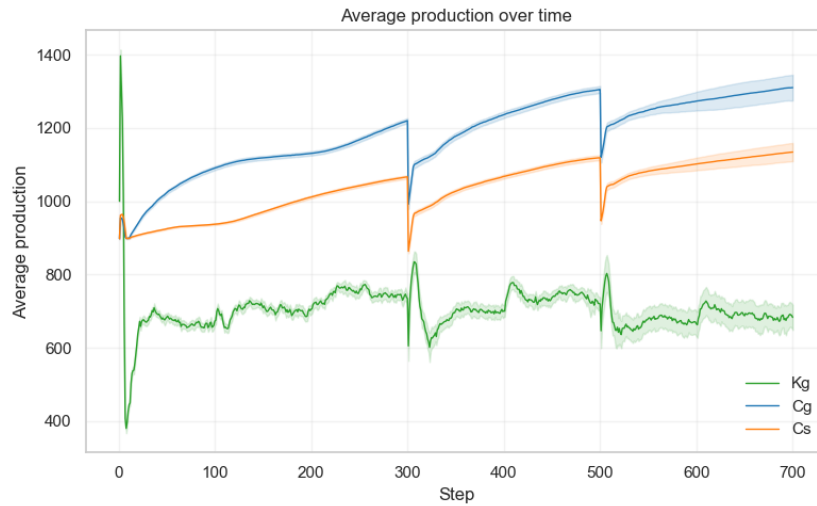


Figure 3.2: The average production over time for each sector (KG, CG, CS)

increase is more pronounced in the CS sector, which reaches its equilibrium inventory level more rapidly. In contrast, the CG sector displays a more gradual increase followed by a slower decline, resulting in elevated inventory levels for a longer period of time.

Once the system has stabilized, the total inventory held by the CG sector is lower than that of the CS sector. This can be attributed to the fact that the model contains fewer CG firms than CS firms, resulting in fewer firms holding inventories and therefore a lower aggregate inventory level. Following both flood shocks, the inventories of the CG and CS sectors decline. As some firms experience reduced or even stopped production after the shock, they satisfy demand by using their inventories. Consequently, the sectors' inventories decrease before gradually recovering and stabilizing again over the following months.

The KG sector maintains lower inventory levels throughout the model run. This is likely related to the higher capital utilization rate of KG firms compared to firms in the CG and CS sectors, leaving less output available to accumulate as inventory. After both flood shocks, the KG inventory exhibits a small drop where the total inventory falls to zero. This indicates that inventory accumulation is disrupted in response to the increased post-shock demand and the fall in production. As production recovers, inventory levels gradually return to their equilibrium state.

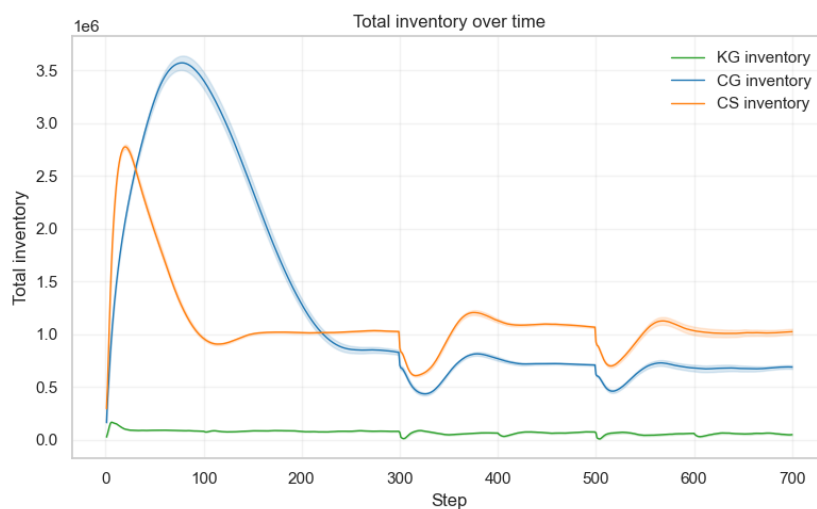


Figure 3.3: The total inventory over time for each sector (KG, CG, CS)

Ratio received to ordered units

The ratio between received and ordered units over time shows de verhouding tussen wat een sector received aan units en wat het eigenlijk had besteld. Figure 3.4 shows this ratio for the kg units.

The received-to-ordered ratio over time indicates the extent to which firms can obtain the units they order. A ratio of 1 implies that all ordered units are successfully received, whereas lower values indicate shortages. Figure 3.4 presents this ratio for kg units, while Figures 3.5 and 3.6 show the ratios for ig and is units.

Figure 3.4 shows a sharp decline in the ratio of received to ordered kg units for all three sectors following both flood shocks. This indicates that firms continue to demand capital goods, but suppliers are unable to satisfy all incoming orders. The effect is particularly pronounced because the KG sector is directly affected by the destruction of capital, increasing the demand for replacement capital, but it also disrupts the production process of KG firms themselves. Moreover, as explained before, the KG sector holds less inventory than the other sectors. Consequently, demand for capital goods rises when the ability to produce and supply them is reduced. Similar dynamics can be observed for the CG and CS sectors, which also experience difficulties obtaining the capital goods they require after the shocks. However, the KG sector shows more volatility in its trend.

In contrast, Figures 3.5 and 3.6 exhibit a different pattern. The ratios for ig and is units show only a small decline following the shocks and recover immediately to their pre-shock levels. This suggests that the supply of consumption goods and services is considerably more resilient to the disruption. One possible explanation is that the CG and CS sectors maintain larger inventories than the KG sector. These inventories can temporarily absorb supply disruptions, allowing firms to continue fulfilling orders despite reduced production capacity. As a result, shortages remain limited, and the received-to-ordered ratio quickly returns to equilibrium.

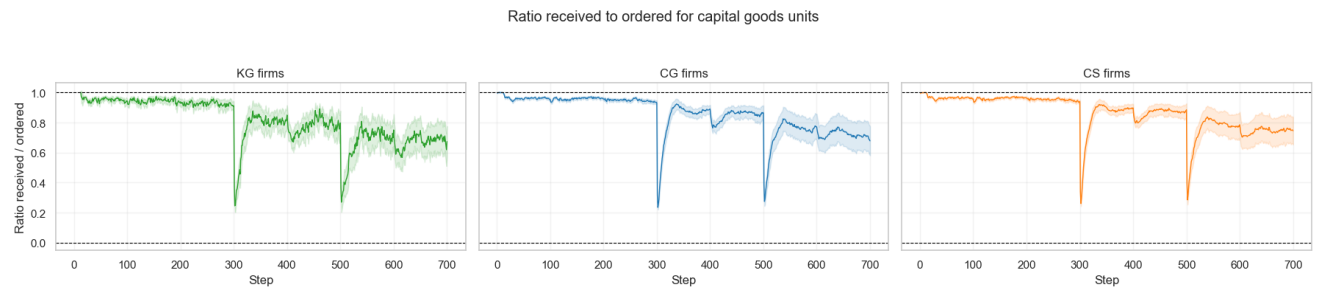


Figure 3.4: The ratio between received and ordered capital goods for each sector (KG, CG, CS)



Figure 3.5: The ratio between received and ordered intermediate goods for each sector (KG, CG, CS)



Figure 3.6: The ratio between received and ordered intermediate services for each sector (KG, CG, CS)

3.1.3. Verification

Verification of the model is essential to ensure that the implemented logic within the code aligns with the model's intended conceptualization. For the verification, four steps can be executed: recording and tracking agent behavior, single-agent testing, interaction testing in a minimal model, and multi-agent testing. It was decided to only execute the steps: recording and tracking agent behavior, and multi-agent testing. The remaining steps require reducing the model to a single firm agent or reducing the model to a simplified version, which is not suitable for EMERGO. The model relies on interactions between multiple firms because firms buy goods from one another, and not buying goods would mean no production and the collapse of the model. Moreover, other elements in the model, like the government and households, are also essential for its functioning. In addition to these steps, the results used to verify the consistency of the networks are also presented.

Recording and tracking agent behavior

The first step in the verification process is to record agent behavior, with a focus on firm agents. This is achieved through a log attribute that tracks the actions and state of a firm during each simulation step. Since the newly implemented features primarily concern the sectoral interdependency structure and network formation, the log records four key attributes: the number of suppliers, the number of goods ordered, the number of goods received, and whether the firm switched to a different supplier. These attributes are tracked separately for each market type: KG, IG, and IS. Consequently, the log records, for example, the number of KG suppliers, IG suppliers, and IS suppliers of a firm over time.

Based on the model design, firms are expected to order and receive goods from each market type throughout the simulation. If this does not occur, a firm's inventory will eventually reduce to zero, preventing it from producing its own goods and potentially leading to bankruptcy. Therefore, a stable flow of orders and deliveries across all market types is expected over time. If a firm consistently orders large quantities of goods but receives substantially fewer, this may indicate a problem in the implementation of the ordering or delivery mechanisms. Conversely, receiving significantly more goods than were ordered would also suggest an inconsistency in the model.

Furthermore, the number of suppliers for each market type is expected to remain relatively stable. When a firm loses a supplier, it should replace it by establishing a relationship with a new one. Consequently, a strong decline in the number of suppliers over time would indicate unexpected behavior and may point to an issue in the implementation of the supplier selection mechanism. Moreover, a stable number of suppliers would also mean that the explicit network with edges and nodes works, because the suppliers are directly taken from this network.

Finally, supplier switching is not expected to occur at every step or for every market type. Particularly during the early stages of the simulation, when firms are still establishing their networks. Observing some switching events in the log provides evidence that the switching mechanism functions as intended, while the absence of switching or switching every step for every market type may indicate implementation errors.

Figure 3.7 shows the log of a randomly selected agent between steps 20 and 30, with the values rounded for readability purposes. As the figure illustrates, the number of suppliers remains consistent over time. It also means the explicit network contains the right edges, because the suppliers are retrieved directly from the network. Moreover, the ordering shows normal behavior where the firm orders

consistently over time and receives goods for all market types. Finally, the switching events occur occasionally, as expected, indicating that the mechanism for replacing lost suppliers functions correctly without causing unrealistic switching occurrences. This behavior is also tracked for the different scenarios, where switching happens through different rewiring behaviors. For the different scenarios, it shows similar switching behavior, indicating that the switching also works with different rewiring behaviors.

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```

Figure 3.7: Recording agent behavior - Firm's log

Multi-agent testing

The second step in the verification process focuses on multi-agent behavior, where the model is evaluated at the system level rather than at the level of individual firm agents. In contrast to the previous analysis, which tracked the behavior of a single representative firm, this step aggregates behavior across all firms in the economy to examine whether the newly implemented mechanisms function correctly in a fully interacting system.

Figure 3.3 presents three plots showing the aggregated inventories of *kg*, *ig*, and *is* across all firms in the economy. The results indicate that all three inventories remain positive throughout the simulation period. This implies that firms are successfully receiving goods from all market types. Consequently, this provides evidence that the new sectoral interdependency structure, where sectors are dependent on the CG and CS sectors and firms also need intermediates for their production, works as expected. Firms can both order and receive goods across all implemented markets. If this mechanism did not work correctly, inventories would be expected to gradually reduce to zero, since a lack of incoming goods would prevent production, which in turn would eliminate the ability of firms to place orders.

Furthermore, all three inventories show similar dynamic patterns. In each case, there is a large initial increase during the early simulation steps, followed by a stabilization phase where inventories fluctuate around a stable level. This behavior is consistent with a system in which firms are still building up their supply chains at the beginning of the simulation before reaching a steady-state flow of production and consumption.

In addition, there are two downward shifts in inventories for all three plots. These declines occur around the times the two flood shocks hit the model. This is expected because capital is destroyed, making firms not able to keep up with their production capacity. After each shock, inventories recover and

return to a stable range again, suggesting that the system is resilient and that the underlying market and network mechanisms are capable of re-establishing an equilibrium.

However, the *kg* inventory exhibits a higher level of volatility compared to the intermediates. This variability increases after the shocks. The inventory levels stay positive, but the *kg* dynamics show more pronounced short-term oscillations around the steady state. Since capital is required in larger quantities for the production of goods compared to intermediates, it functions as a more critical input within the production process (κ_s is bigger than ν_s). This higher dependency increases the sensitivity of the *kg* inventory dynamics, leading to larger fluctuations in response to shocks and network adjustments.

Moreover, Figure 3.4 shows the ratio between received and ordered capital for KG, IG, and IS firms. Prior to the shocks, this ratio fluctuates around 1, indicating that firms generally received approximately what they ordered. Following the first shock, however, the ratio declines and only partially recovers, implying that firms receive less capital than they order. After the second shock, this downward trend becomes even more pronounced, further increasing the gap between ordered and received quantities.

This pattern may be explained by increased centrality effects within the network. In the base scenario, firms tend to rewire toward more competitive suppliers. As a result, even though sufficient aggregate inventory is available in the system, the matching process becomes more selective. Consequently, firms may concentrate their connections with highly competitive suppliers, while other firms, despite having sufficient inventory, are less frequently chosen as trading partners. This leads to a mismatch between available inventory and realized transactions, which is reflected in the declining ratio.

For *kg* firms, this effect is even more visible, with higher volatility observed throughout the steps. This further supports the idea that *kg* functions as a more central and sensitive input within the production network, making it more susceptible to disruptions and network restructuring effects.

In contrast to the capital market, the ratio in the intermediate goods and services market remains relatively stable around 1 (Figures 3.5 and 3.6). Although there is a decline during the shocks, it quickly recovers to this stable level. This indicates that this market mechanism works as it was intended. However, it must be noted that when ν_s is increased, making production more dependent on intermediates, the model breaks down almost immediately. The underlying mechanism behind this behavior is not yet fully understood and requires further research. This forms a limitation of the current model, which will be discussed in more depth during the conclusion.

Overall, the results provide evidence that the new market mechanism behaves as expected under both normal conditions and shocks. However, some volatility is observed, particularly for the KG firms, indicating that not all market dynamics are fully smooth. Moreover, the model becomes unstable when production becomes more dependent on intermediates, suggesting that certain aspects of the newly implemented market mechanism may not yet be fully robustly integrated into the model.

Verification of the full network & sub-networks in the initialization

To ensure that the full network was implemented correctly and that the sub-networks consistently represented the full network, several verification tests were incorporated into the model code. Appendix B presents the code fragments that are executed during the initialization of the networks. First, Listing B.1 shows how the number of nodes and edges in the network are verified. Subsequently, the incoming and outgoing edges of a randomly selected firm are inspected to confirm that supplier relationships are correctly represented within the network structure. In addition, the test checks whether any firms exist without incoming or outgoing connections. Since all firms are expected to have relationships within the model from the beginning, no isolated firms should be present in the network.

Moreover, Listing B.2 verifies that a firm's supplier relationships are correctly assigned. The code prints the KG, CG, and CS suppliers of a selected firm. For each supplier type, a minimum and maximum number of suppliers is specified within the model properties. Therefore, if the number of suppliers falls outside this range, it may indicate an error in the network initialization process.

Furthermore, these supplier lists are compared with the supplier relationships represented in the sub-networks. Listing B.3 presents this code. This step makes it possible to determine whether the suppliers represented in the KG, CG, and CS sub-networks correspond to the correct supplier types in the full network.

Listing B.4 shows the output of the code fragments. A reasonable number of nodes and edges based on the number of firms in the model are found. Moreover, there are no nodes without edges, and there is consistency between the KG supplier list and the KG suppliers within the network. There is also consistency between the full network and the sub-networks, which provides evidence that the network structure has been initialized correctly and that supplier relationships are assigned to the appropriate sub-networks.

Verification of the full network & sub-networks throughout the model run

Because the inter-firm network is dynamic, it is also important to ensure consistency of network types throughout the simulation. To support this, a verification code fragment (Listing B.5) is implemented within the model. This check is implemented at the location in the model after the firm has switched KG suppliers.¹ This location is chosen because, at every simulation step, at least one firm updates its KG suppliers, ensuring that the consistency check is executed regularly.

The check is deliberately placed after a firm has switched KG suppliers, because any inconsistency in the resulting network structure indicates that the switching mechanism has not been implemented correctly. Although the check could also have been implemented when switching IG or IS suppliers, any inconsistencies arising there would still be detected by the verification in switching KG suppliers. This avoids duplication of checks.

The code fragment first retrieves the suppliers of each type for a firm based on the full network structure. It then verifies whether the list of KG suppliers in the model is consistent with the KG suppliers derived from the network. If inconsistencies are detected, the code outputs both lists and raises an error that stops the model execution.

In addition, the code extracts supplier sets from the respective sub-networks. For each supplier type (KG, CG, and CS), it checks whether the suppliers identified in the sub-network correspond to those derived from the full network for that same type. If inconsistencies occur, the code again returns both lists and triggers an error to ensure consistency across networks.

During the modeling phase, these errors occurred multiple times. However, they were also used to identify and resolve bugs within the model, which ultimately resulted in a model without any errors related to these checks.

3.1.4. Validation

Validation of the model is essential to ensure the model results represent real-world dynamics. This research uses two types of validation: micro validation, which assesses whether individual agent behaviors align with expectations, and macro validation, which evaluates whether the model's aggregate properties reflect real-world patterns.

Micro validation

Micro validation focuses on aligning the individual firm behaviors to real-world expectations. Table 3.1 shows an overview of assumptions of firm behavior and the observed behavior in the model.

Table 3.1: Micro: comparison between assumed real-world behavior and observed model behavior

Assumptions of real-world behavior	Observed behavior in model
A firm purchases different types of inputs from different sectors for its own production, reflecting interdependency between sectors.	Within EMERGO, firms purchase intermediate goods, services, and capital, which they use as inputs in their production process. This reflects interdependencies between sectors, as firms rely on inputs produced elsewhere in the economy. However, it should be noted that this represents a simplified version of reality, in which sectors are aggregated. In practice, the economy consists of a much larger number of disaggregated sectors.

¹In the model, this is implemented in the function `switch_kg()`.

Assumptions of real-world behavior	Observed behavior in model
To spread uncertainty, a firm needs to distribute its orders across multiple suppliers (Agrawal & Nahmias, 1997).	In the model, a firm spreads its orders across several suppliers. This is necessary because, within EMERGO, a firm faces supply uncertainty due to shocks.
Based on the size of a firm's production capacity, order quantities are determined. Firms with higher production capacities, therefore, place larger orders (Li et al., 2013). However, relying on too many suppliers can create coordination costs (Agrawal & Nahmias, 1997).	A firm bases its ordered quantities on its production capacity. It relies on multiple suppliers, with the number of suppliers depending on the size of its production capacity. However, this number is capped at a fixed maximum to prevent excessive coordination complexity.
The cost of units and the reliability of a supplier are both factors in the choice of a firm to connect (Li et al., 2013).	In the baseline scenario, cost is a key factor that firms consider when connecting with a supplier. Additionally, reliability becomes relevant in other scenarios.

Macro validation

Instead of focusing on the individual firm behaviors, macro validation examines whether the overall model properties and trends align to real-world expectations. Table 3.2 shows an overview of assumptions of firm behavior and the observed behavior in the model.

Table 3.2: Macro: comparison between assumed real-world behavior and observed model behavior

Assumptions of real-world behavior	Observed behavior in model
When a shock hits the model, production within the economy drops through both the destruction of capital and the interruption within the supply chain (Di Noia et al., 2025).	The model shows this effect. When a shock hits the model, the GDP immediately drops due to the destruction of capital and therefore the interruption of business activity.
Within a real supply chain, there is constant rewiring, which enhances the adaptive capacity (Reisch et al., 2026).	Within EMERGO firms rewire throughout the model steps, where they switch suppliers when demand is unmet, when they lose a supplier, or based on competitiveness.
There is sectoral heterogeneity in the reaction to shocks. This depends on different factors like the sector's exposure and the importance of a sector (Gosselin, 2025).	The model shows that the sectors react differently to the shocks. Capital goods are more important for production than intermediate goods and services. The KG sector therefore also exhibits a sharper decline (Figure 3.4).
When a sector is important for the production process of other sectors, and the units are not substitutable, the effects of a shock become larger for that first sector (Gosselin, 2025).	Within EMERGO, capital goods are not substitutable, whereas intermediate goods and services are substitutable with each other. When examining the effects across the three sectors, it becomes apparent that the capital goods (KG) sector is more strongly affected. For instance, the ratio between received and ordered quantities in the KG market exhibits greater volatility and experiences a larger decline after a shock compared to the other markets.

3.2. Rewiring behaviors & network structure analysis

This section presents the results of the phase in the research design focused on rewiring behaviors and network structure analysis. To facilitate this analysis, different rewiring behaviors were integrated into the model, resulting in a set of experiments. In addition, several network metrics were defined and applied to assess the resulting network structures and evaluate the effects of the different rewiring behaviors.

3.2.1. Final set of network metrics

As explained in the research design, a selection of network metrics was made. These metrics were included in the data collection of the model and computed over time. The final set of metrics was chosen to provide a representative overview of the network structure while taking computational efficiency into account.

The results show that using the built-in functions *betweenness centrality()* and *closeness centrality()* caused the runtime to increase significantly, approximately twice as long compared to when these were not included. One possible explanation is that both functions require going over all (shortest) paths in the network, which involves substantial computational effort.

This leads to the final set of metrics: network density, maximum eigenvector centrality, maximum degree centrality, network modularity, and average clustering coefficient.

3.2.2. Network structure analysis

This section will present the results obtained from the experiments. The network structure will be analyzed by discussing the evolution of the network metrics over time. First, the findings of the market leader scenario will be explained separately. Subsequently, the network metrics will be presented to analyze and explain the results of the remaining scenarios. Appendix D presents the plots of the network metrics.

Market leader scenario

During the execution of this scenario, it quickly became apparent that this rewiring strategy was not sustainable for the network. After approximately 200 time steps, the first firms started to go bankrupt, followed shortly by a wave of additional bankruptcies that ultimately caused the model to break down.

The breakdown of the model is likely related to increasing centralization. As more buyer-supplier relationships become concentrated around a few dominant firms, other firms receive fewer or no customers at all. These firms eventually go bankrupt due to insufficient demand. When bankruptcies become widespread, production capacity in the economy declines, leading to disruptions that propagate throughout the network and ultimately cause the model to fail. The results therefore suggest that relying exclusively on market leader-based rewiring makes the network excessively centralized, fragile, and ultimately unsustainable.

To substantiate the claim of excessive centralization, agent-level data would be required, in which the degree of each firm is recorded at every simulation step. This would make it possible to analyze the degree distribution of firms over time and assess whether a small group of firms accumulates a disproportionately large number of connections. Such an analysis could provide direct evidence of increasing concentration within the network. However, storing the degree of every firm at each time step proved to be computationally too expensive, substantially increasing the model's runtime. As a result, this approach was ultimately not feasible within the scope of this study.

To further investigate this issue, an additional print statement check is added to the model at the location where firms execute the behavior market leader-based rewiring² As explained in the research design, the model generates a list of firms with the highest market share. To assess potential excessive centralization, the length of this list is recorded and printed.

The results show that each time this rewiring behavior is called, the list contains only a single firm, implying a high likelihood that the same firm is repeatedly selected for rewiring. Although this may change over time as firms' market shares evolve and another firm may eventually attain the highest share, the observed model breakdown suggests that the system is already too centralized and therefore destabilized before such adjustments can occur.

Network density

Network density measures the proportion of realized connections in a network relative to the maximum number of connections that could exist in that network. A higher network density indicates that firms have a high number of connections, whereas a lower density reflects a more sparsely connected network.

²In the model, this is implemented in the rewiring functions *sample_new_cp_supplier_marketshare* and *sample_new_kg_supplier_marketshare*.

As illustrated by the network density plots (Figures D.1-D.6) in Appendix D, network density remains relatively stable throughout all experiments for the full network as well as the sub-networks. This suggests that the overall level of connectivity in the network is unaffected by the flood shocks and the different rewiring scenarios. An explanation is that firms immediately seek new suppliers whenever an existing connection is lost. Moreover, bankrupt firms are replaced by new firms in the network. Consequently, although individual connections may be removed and replaced over time, the total number of links in the network remains relatively constant. This shows that the rewiring process changes the composition of supplier relationships rather than the overall density of the network.

Maximum degree centrality

The maximum degree centrality indicates how connected the most connected node in the network is. An increase in maximum degree centrality over time implies that at least one firm becomes more central within the network. In this model, it also means that other firms lose connections, since new supplier relationships are formed only when existing ones are cut.

Figures D.7-D.12 show the evolution of the maximum degree centrality. Among the scenarios, two groups can be observed. The first group, scenarios, includes the Baseline competitiveness scenario, the Risk-averse scenario, and the Performance-risk trade-off scenario. This group has in common that they include the competitiveness-based rewiring behavior. This behavior entails that the probability of gaining buyers becomes greater when a firm is more competitive. In these scenarios, the maximum degree centrality gradually increases over time, meaning that the most connected node gains more connections. This likely shows a self-reinforcing mechanism within competitiveness-based rewiring: firms that already attract more buyers can produce and sell more, which improves their relative competitiveness in the model's matching process, making them increasingly likely to attract still more buyers in subsequent rewiring events. As a result, even without market-leader rewiring, competitiveness-based rewiring alone generates a gradual centralized dynamic.

Moreover, a small decrease in the maximum degree centrality occurs after the two shocks at steps 300 and 500, indicating that the node loses some connections following a shock. This decrease likely reflects the direct impact of capital destruction on the central firm's production capacity: when a highly connected firm is vulnerable to the shock, the shock reduces the firm's output and therefore its competitiveness, causing some of its buyers to rewire toward alternative suppliers. However, this decrease stabilizes quickly, after which the metric resumes its upward trend. When comparing the responses to the shocks across the scenarios within this group, no notable differences can be observed. The magnitude of the shock effects appears similar across scenarios, as well as the speed with which the metric returns to its pre-shock growth trend.

These results indicate that, within the scenarios of the first group, at least one firm becomes increasingly central within the network over time. As this firm gains additional buyers, other firms necessarily lose buyers, resulting in a more centralized network structure. The same trend is visible within the sub-networks. Since within each sub-network, only firms of the corresponding market type have outgoing edges, the increasing trend implies that for each market type, at least one firm becomes more connected over time.

The effect of the shocks on this metric appears to be primarily attributable to the KG relationships in the network, as the decrease following the shock is only observed in the KG sub-network. This suggests that the temporary reduction in maximum degree centrality at the network level is driven mainly by changes in the connectivity structure including KG firms.

The second group includes the Combined behavior scenario, the Performance-oriented scenario, and the Strategic selection scenario. These groups have in common that they include the market leader-based rewiring. Here, firms tend to search for market leaders to connect with. These scenarios show a rapid increase in the maximum degree centrality of the full network and the CG and CS sub-networks in the early stages of the model run. This rapid early increase reflects the market leader rewiring mechanism: because the candidate pool for market-leader-based rewiring is restricted to the single firm holding the maximum market share, every rewiring event in this period directs new connections toward the same firm, producing a much faster concentration than the gradual concentration seen with competitiveness-based rewiring. After that, the trend shows a gradual increase, which stabilizes between steps 200 and 300.

It is noteworthy that the shocks have little to no effect on the trends of the full network and the CG and CS sub-networks. In contrast, the KG sub-network shows a clear decrease in maximum degree centrality following both shocks. Moreover, when compared to the corresponding trends in group 1, the KG sub-network exhibits greater volatility throughout the simulation. Despite this increased volatility, the magnitude of the shock effects appears to be slightly smaller than that observed in group 1.

As for risk-averse rewiring, comparing the scenarios that include this behavior with those that do not, reveals no notable differences in the evolution of maximum degree centrality. This suggests that risk-averse rewiring has less impact on the evolution of this metric compared to the behaviors.

Maximum eigen vector centrality

Figures D.13-D.18 present the evolution of the maximum eigenvector centrality for the full network and its sub-networks under the different scenarios. Eigenvector centrality measures not only the number of connections of a firm, but also the importance of the firms to which it is connected. A rising maximum eigenvector centrality of a node within the network indicates the emergence of a group of highly influential firms because the node with the maximum eigenvector centrality is connected to other nodes that are also highly connected. Therefore, it exceeds the maximum degree centrality, as that metric only provides information about a single node, whereas eigenvector centrality also captures the importance of the nodes connected to that particular node. Moreover, for this network, an increase in maximum eigenvector centrality could imply greater network centralization, because new connections are only formed at the expense of existing ones. As a result, when a group of nodes gains edges and becomes more important, other nodes must lose edges, which makes the overall network more centralized.

A first observation is that three scenarios show a gradual increase in the maximum eigenvector centrality over time. These are: the Baseline competitiveness scenario, the Risk-averse scenario, and the Performance-risk trade-off scenario. All of these scenarios have the behavior competitiveness-based rewiring in common. The increase suggests that when firms concentrate their supplier relationships around highly competitive firms, the network becomes more centralized around a group of suppliers. The behavior entails that competitive suppliers are more likely to be selected during the rewiring process. Therefore, these firms attract additional buyers over time, reinforcing their importance within the network, which creates an advantage effect in which already well-connected firms become even more central. This mechanism is reinforced specifically through eigenvector centrality because the buyers a competitive firm attracts are themselves gradually becoming better-connected under the same rewiring logic: as competitiveness-based rewiring operates network-wide, a firm's own centrality score rises not only because it gains buyers, but because those buyers are increasingly well-connected firms themselves. Therefore, this reinforces the initial firm's importance beyond what its degree alone would suggest. This trend implies for both the full network and the sub-networks.

In contrast, when market leader-based rewiring is included in the Combined behavior scenario, the initially increasing trend changes: the maximum eigenvector centrality first increases more strongly at the beginning of the simulation and subsequently decreases gradually over time until it reaches a steady state. This pattern also holds for the remaining scenarios: the Performance-oriented scenario and the Strategic selection scenario. These scenarios have the market leader-based rewiring behavior in common. This trend is visible in both the full network and the sub-networks. The sharp rise reflects the same mechanism of the Market leader scenario collapse: because the candidate pool for market leader-based rewiring is restricted to the single firm with maximum market share, early rewiring events disproportionately route new connections toward that one firm, producing a much faster concentration than competitiveness-based rewiring alone. Although firms rewire, among others, towards market leaders, the resulting concentration is strong at the beginning, but appears to weaken over time. This weakening is consistent with the fact that market leader-based rewiring, alternates with competitiveness-based or risk-averse rewiring, preventing the initial peak from continuing and instead stabilizing the metric down toward a more steady state. As firms continuously adjust their supplier relationships, the dominance of individual firms becomes less pronounced than at the beginning of the simulation, and the network structure becomes more balanced.

To explain a contrast between the scenarios, we will refer to the scenarios as follows: group 1 consists of the Baseline competitiveness scenario, the Risk-averse scenario, and the Performance-risk trade-off scenario. group 2 consists of the Combined behavior scenario, the Performance-oriented scenario, and the Strategic selection scenario. This distinction between scenarios is the same as was made

before in the results for the maximum degree centrality. The maximum eigenvector centrality in the steady state of group 2 is approximately equal to the maximum eigenvector centrality observed in the final stages of the simulations in group 1. The key difference between the two groups is therefore the path toward this outcome: in group 1, the maximum eigenvector centrality increases gradually over time, whereas in group 2 it exhibits a strong initial increase that subsequently weakens and stabilizes at a level comparable to the final phase of group 1.

Moreover, it can also be observed that for the scenarios in group 1, there is a small decrease in the trend when a shock occurs at steps 300 and 500, which stabilizes immediately. In contrast, for the scenarios in group 2, there is a small increase in the trend at the shock moments, which also stabilizes. At the shock moments, a small set of firms goes bankrupt, causing some firms to search for new suppliers. In group 1, competitiveness-based rewiring can direct firms toward any sufficiently competitive supplier rather than exclusively the most central node, temporarily spreading connections away from it and producing the small dip. In group 2, roughly half of these rewiring events are still governed by market leader-based rewiring, which instead directs firms toward the single dominant, already highly-connected supplier, pushing its eigenvector centrality up further and producing the small increase instead. These results therefore indicate that including market leader-based rewiring leads the model to initially respond with increased centralization, whereas including competitive-based rewiring results in a more gradual response, with less immediate centralization.

As for risk-averse rewiring, comparing the scenarios that include this behavior with those that do not reveals no notable differences in the evolution of maximum eigenvector centrality. This suggests that risk-averse rewiring has less impact on the evolution of this metric compared to the others.

Regarding the difference between the full network and the sub-networks, the sub-networks show a higher overall trend than the full network. However, this can be explained by the structure of the sub-networks, in which only the edges of a specific supplier type are included. As a result, each sub-network already consists of a more selective set of nodes with higher connectivity, since, for example, in the sub-network CS, only CS nodes have outgoing edges. In the full network, all nodes have outgoing edges, which leads to a more dispersed connectivity structure and therefore a lower maximum eigenvector centrality.

Network modularity

Network modularity refers to the extent to which the network is divided into communities. A high network modularity means the network has a strong division into communities, meaning that nodes are densely connected within communities but only sparsely connected between communities. Figures D.19-D.24 show the evolution of this metric under the different scenarios.

The full networks under the different scenarios show an increase at the beginning, which gradually decreases over time and stabilizes around a value of zero. This indicates that during the initialization, the network starts with a relatively high network modularity, but throughout the model the network rewires over and over again and therefore loses its communities. This initial modularity likely reflects the way suppliers are assigned at initialization. Each firm is randomly assigned its own distinct subset of KG, CG, and CS suppliers, meaning connections are initially spread across many different firm-specific groupings rather than concentrated around a small set of dominant nodes. As competitiveness-based and market leader-based rewiring progressively concentrate buyer-supplier relationships around a decreasing set of increasingly central firms, these initially distinct groupings merge into overlapping ties around the same dominant suppliers. This removes the separation between communities and driving modularity to around zero. The full network shows similar behaviors under the different scenarios, with small differences. The baseline competitiveness scenario, the Risk-averse scenario, and the Performance-risk trade-off show a small decrease in modularity following the first shock at step 300, whereas the remaining scenarios show a small increase during both shock events. However, these increases and decreases are negligible in magnitude, indicating that the shocks have only a limited impact on the overall community structure of the network.

Moreover, the CG and CS sub-networks also show a higher network modularity at the beginning of the simulation, which gradually decreases over time to around zero. The CS sub-networks have a slightly lower network modularity at the beginning than the CG sub-networks. This difference is consistent with the larger number of CS firms relative to CG firms: a larger, more homogeneous population of suppliers

at initialization produces a more spread out set of buyer-supplier connections, resulting in weaker initial community separation compared to the smaller CG sub-network. The different scenarios for each of the sub-networks all show a similar trend. During both shocks, there is a small but negligible peak, which stabilizes immediately. These results indicate that the rewiring process gradually removes the communities that initially exist within the CG relationships. Furthermore, the different rewiring behaviors do not appear to have a significant effect on this process, as all scenarios exhibit similar trends.

The KG sub-network shows similar behavior throughout all scenarios, where the network modularity remains slightly higher than zero at all times, also at the beginning of the simulation. This indicates that the KG relationships show little to no community structure. This is consistent with the small number of KG firms (compared to CG and CS): with relatively few firms and connections to redistribute, there is limited room for community structure to emerge or dissolve, regardless of which rewiring behavior is active. Furthermore, the different rewiring behaviors appear not to influence the formation of communities within this sub-network, as the modularity remains unchanged across scenarios.

Average clustering coefficient

Figures D.25-D.30 show how the average clustering coefficient evolves for the different scenarios. The metric measures to what extent the network includes local clusters. It assesses whether a node's neighbors also share connections. If there are more of these 'triangles' within the network, the average clustering coefficient increases.

For all network types in all scenarios, the average clustering coefficient remains under 0.1, with trends that are similar to those observed for network modularity. This low overall level is consistent with the way suppliers are assigned in this network. Firms are randomly assigned to their own individual subsets of suppliers at initialization, rather than being grouped into pre-existing, densely interconnected clusters, which limits the number of triangles that can form even before any rewiring takes place. At the beginning of the simulation, there is a short peak, after which the coefficient gradually decreases over time and eventually reaches zero for the CG and CS sub-networks as well as for the full network. This decline is consistent with the centralization dynamics discussed in the previous sections. As competitiveness-based and market leader-based rewiring progressively concentrate buyer-supplier relationships around a shrinking set of dominant firms, the network increasingly approaches a structure around these hubs. In such a structure, the many buyers connected to a dominant supplier not directly connected to one another, which drives the clustering coefficient toward zero as centralization increases. However, this initial peak is relatively small, starting at approximately 0.03 for the full network and around 0.02 and 0.01 for the CS and CG sub-networks. The higher initial value for the full network is likely because it combines all three supplier types, giving firms that simultaneously buy KG, CG, and CS inputs from overlapping sets of counterparts more opportunities to form triangles than within any single sub-network alone. Also, the shocks at steps 300 and 500 do not affect this pattern. This is likely because the clustering coefficient has already declined to near zero when shocks occur, therefore there is little remaining local cluster structure left for the shocks or subsequent rewiring to further reduce.

The KG network exhibits a similar trend across all scenarios, with the metric remaining close to zero throughout the entire simulation period. This is consistent with the small number of KG firms, which limits the number of alternative supplier combinations available to form triangles in the first place.

For all network types, there are minimal to no differences when comparing the scenarios, which indicates that the different rewiring strategies do not have a significant effect on local cluster formation within the network.

3.3. Resilience analysis

This section presents the results of the resilience analysis, in which the resilience curve and resilience metrics are discussed for each network type across all scenarios. This allows for a comparison of the scenarios in terms of their resilience. First, the selection of the performance metric used as the resilience curve is presented. Subsequently, the results for the resilience metrics are discussed.

3.3.1. Resilience curve

Identifying an appropriate performance metric to be used as a resilience curve proved to be quite challenging. As outlined in the research design, the chosen metric should exhibit a decline following

a shock, while not showing an immediate, sharp recovery. A fast recovery would make it difficult to compute resilience metrics, as the time of impact would be the same as the time of recovery and therefore limit the ability to compare scenarios.

Several performance metrics were considered for this purpose, including the ratio of received to ordered goods, real GDP, and firm entry and exit within the economy. However, these metrics proved to be not usable, as they consistently exhibited sharp recoveries immediately after the shock. In these cases, the system appeared to bounce back almost instantly to its pre-shock level. If this behavior is consistent across all scenarios, it becomes impossible to meaningfully distinguish between them, and therefore the calculation of resilience metrics would not provide informative comparative insights.

Ultimately, one performance metric was found to be suitable for use as a resilience curve: total inventory within the network. Figures E.1-E.6 in Appendix E.1 present the aggregate inventory, both at the total network level and disaggregated by unit type, across all scenarios. This metric was selected because it exhibits a clear decline following a shock, followed by a gradual recovery towards a new equilibrium rather than an immediate rebound.

However, for the KG units, the inventory plot is less suitable as a resilience metric. As explained earlier, the KG market holds relatively little inventory compared to the CG and CS markets. Therefore, the decline after a shock is smaller compared to CG and CS scenarios. Moreover, as Figures E.1-E.6 show, the plot for the KG market is very volatile, making the resilience metrics hard to interpret. Nevertheless, the inventory metric was still selected as the resilience curve. This is because, compared to the other considered metrics, it provides the most consistent and interpretable behavior across all scenarios and market types.

Moreover, using a different performance metric specifically for KG is not appropriate, as the purpose of this resilience analysis is not to focus on absolute values but rather on comparing behavior across scenarios. If a different metric were used for KG, the results would no longer be comparable to the other markets and scenarios, thereby undermining the purpose of the analysis.

3.3.2. Resilience metrics

Table E.1 in Appendix E.3 shows the results of the calculated resilience metrics for each scenario, network type, and shock moment. These results are presented and discussed in the bar plots below.

Depth of impact

Figure 3.8 shows the depth of impact across the different scenarios and network types for both shock 1 (dark blue) and shock 2 (light blue). A first observation is that the depth of impact is consistently lower in all scenarios for the second shock compared to the first shock. This may suggest that the rewiring process improves the system's ability to absorb shocks over time, leading to a reduced immediate impact in later disturbances.

When focusing on the full network, it can be observed that the Baseline competitiveness, Risk-averse, and Performance-risk trade-off scenarios exhibit relatively similar levels of depth of impact. Likewise, the Performance-oriented, Strategic selection, and Combined behavior scenarios also form a second group with comparable values, which are higher in absolute terms than those of the first group. This grouping structure was previously identified in the network analysis for the maximum eigenvector centrality and maximum degree centrality. This suggests a potential relationship between network structure and the impact of shocks. This is consistent with the centralization mechanisms, because market leader-based rewiring concentrates buyer-supplier relationships around a small number of dominant firms, the disruption of one of these firms during a shock propagates to a disproportionately large share of the network, producing a deeper impact than under the more gradual, distributed centralization of competitiveness-based rewiring.

However, the overlap between scenarios is more visible for shock 1 than for shock 2. In shock 2, there is more variation within both groups. Both the Risk-averse scenario, within group 1, and the Performance-oriented scenario, within group 2, appear to experience a lower depth of impact compared to the other scenarios in their groups, indicating that their resilience response differs more strongly under second shocks. This is consistent with the mechanism of risk-averse rewiring because this rewiring behavior relies on firms' memory of previously shocked suppliers, it can only influence supplier selection after

the first shock has occurred. This explains why its effect on depth of impact only becomes visible in the second shock rather than the first, where no such shock history yet exists.

When the resilience curve is disaggregated to CG, similar patterns are observed. The Baseline competitiveness, Risk-averse, and Performance-risk trade-off scenarios show lower absolute levels of depth of impact compared to the Performance-oriented, Strategic selection, and Combined behavior scenarios. This grouping into two groups is therefore also visible at the level of the CG sub-network.

This distinction is less pronounced in the CS sub-network. In this case, the differences in depth of impact for the first shock between the two scenario groups are smaller, as the absolute values in the second group are relatively lower in CS compared to CG. However, when comparing CS and CG directly for the second shock, it becomes apparent that the absolute depth of impact values in CS are higher than those in CG. This suggests that the rewiring mechanisms may be less effective in mitigating shock impacts in the intermediate services sector, indicating that this part of the network is more vulnerable to disruptions across scenarios. As discussed in Chapter 4.3, this asymmetry may partly reflect differences between the sectors (not only the network structure), such as capital intensity or the larger number and smaller average size of CS firms, rather than a weaker rewiring effect specific to the CS market; disentangling these explanations would require the controlled comparison proposed there.

When the curve is disaggregated to KG, the results are harder to interpret. As explained before, the KG market holds less inventory than the other sectors. As a result, the depth of impact is also lower in absolute terms. In addition, no clear distinction between the different scenarios can be observed, as the variation in outcomes is limited across all scenarios. This is consistent with that shock effects on the KG sub-network are heavily affected by the direct destruction of capital rather than by network-level rewiring dynamics, since KG firms cannot substitute capital inputs and hold a large inventory buffer, it leaves little room for differences in rewiring strategy to produce interpretable outcomes.

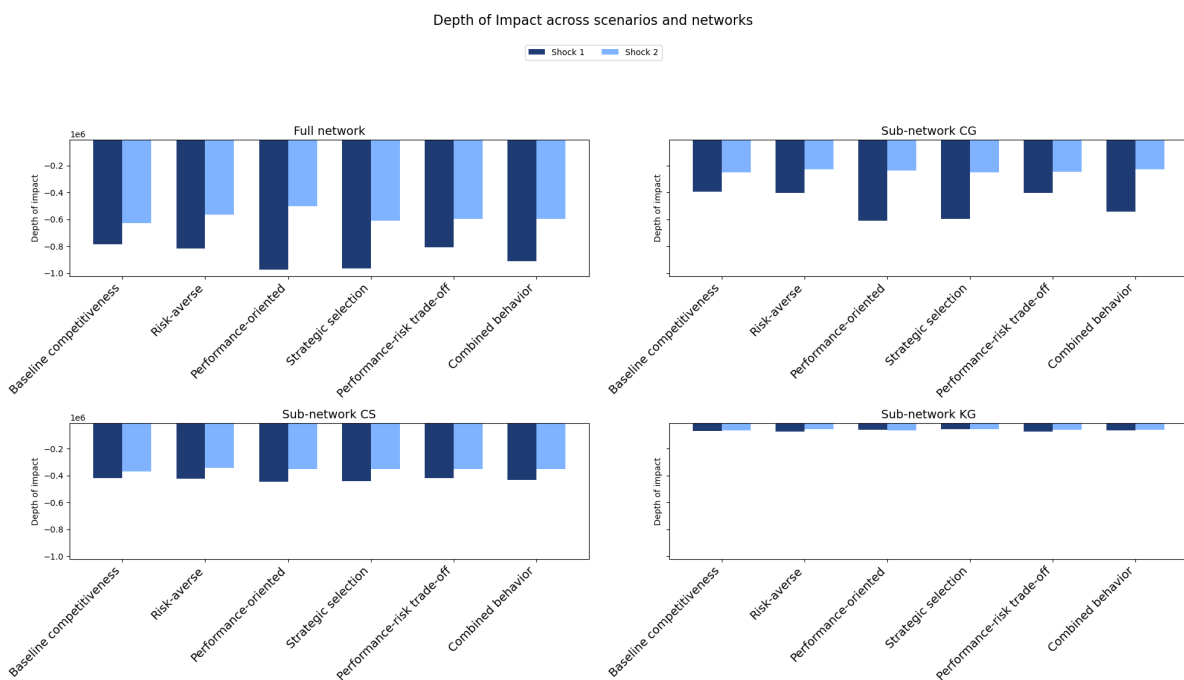


Figure 3.8: The depth of impact for each scenario, network type, and shock moment

Endure duration

Figure 3.9 shows the endure duration across the different scenarios and network types for both shock 1 (dark blue) and shock 2 (light blue). Here, it is also observed that the endure duration metric performs equally as or better after the second shock than the first shock, indicating that rewiring behavior contributes to increasing the adaptive and restorative capacity of the network. This is consistent with the mechanism of competitiveness-based rewiring that gradually redirects buyer-supplier relationships

away from firms that are vulnerable from the floods between the first and second shock. Because under competitiveness-based behavior, firms with the lowest prices are preferred, and these are not the firms affected by the shock. Therefore, fewer firms remain dependent on the exposed region by the time the second shock occurs, allowing the network to return to a steady state more quickly.

When focusing on the full network, the distinction in groups made for the depth of impact is different for the endure duration. The Baseline competitiveness scenario, the Performance-oriented scenario, the Strategic selection scenario, and the Combined behavior scenario all show similar results in their endure duration for the first shock. The Risk-averse and the Performance-risk trade-off scenarios show a lower endure duration. However, again, the second shock shows more variability.

Moreover, when disaggregating to the CG and CS market, the endure duration is the same or higher for CG across the scenarios than for CS. As discussed in Section 4.3, this may partly reflect structural differences between the sectors, such as capital intensity or the smaller number and larger average size of CG firms, rather than a mechanism specific to network restructuring. In particular, the Performance-oriented, the Strategic selection, the Performance-risk trade-off, and the Combined behavior scenarios show a greater endure duration for shock 1 than in CS. However, the difference between shock 1 and shock 2 is mostly greater in CG than in CS, which could indicate that the constant rewiring has more impact in the CG market than in the CS market. This is consistent with the possibility, raised in Section 4.3, that the smaller number and larger average size of CG firms make network-level rewiring effects more visible in aggregate metrics than in the higher number, smaller CS firms, rather than reflecting a genuinely stronger rewiring effect within the CG market itself. The same was found in the results of the depth of impact.

Also similar to the results for the depth of impact, when the curve is disaggregated to KG, no clear distinction between the different scenarios can be observed, as the variation in outcomes is limited across all scenarios. The endure duration is equal to one in all cases, as the resilience curve quickly returns to a new steady state after reaching its minimum following the shock. Because the KG sector's response to a shock is dominated by the immediate destruction of capital rather than by supplier-switching behavior, there is little room for differences in rewiring strategy to affect how quickly the network returns to a steady state.

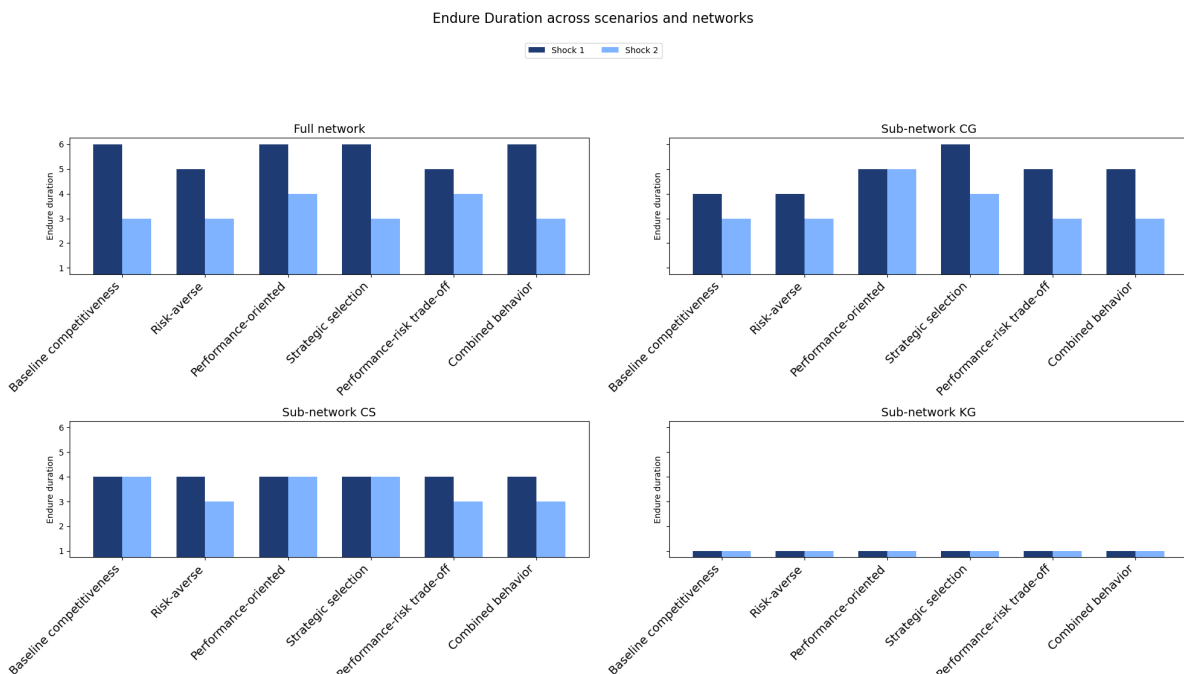


Figure 3.9: The endure duration for each scenario, network type, and shock moment

Restored performance

Figure 3.10 shows the restored performance across the different scenarios and network types for both shock 1 (dark blue) and shock 2 (light blue). The restored performance is the ratio between the level of the performance metric after the system has stabilized following a shock and the level of the performance metric before the shock. A value above one therefore indicates that performance has improved relative to the pre-shock baseline after the system has reached a new steady state.

For the full network, the two distinct groups can again be observed for the first shock. The first group, consisting of the Baseline competitiveness, Risk-averse, and Performance-risk trade-off scenarios, performs better, exhibiting a higher restored performance ratio than the other scenarios. This is consistent with the difference in the centralization mechanism between the two groups. The competitiveness-based rewiring produces a more gradual, distributed concentration of buyer-supplier relationships than market leader-based rewiring, firms in this group (group 1) have more alternative suppliers available to rewire toward after a disruption, supporting a stronger recovery. However, this grouping is no longer visible for the second shock. In this case, all scenarios converge to values between 0.9 and 1.0, with some scenarios showing a slight increase and others a slight decrease relative to the first shock. This convergence is consistent with the timing argument made earlier. By step 500, the network structures of both groups have centralized toward a similar steady state, reducing the structural differences between groups that drove the divergence in restored performance observed under the first shock.

When a disaggregation is made to CG and CS, a clear distinction can be made. In CG the ratio is clearly higher in the second shock compared to the first shock across all scenarios. Here, the ratio in the first shock is mostly low across the scenarios. The higher ratio for the second shock across the scenarios could indicate the positive effect of the rewiring. In contrast, for CS, the ratio is higher for the first shock than for the second across all scenarios. It could be argued that the rewiring process has a less pronounced positive effect in this case. However, the ratio of restored performance was already relatively high for the first shock across all scenarios, at approximately 1.1. As a result, a further increase in this ratio for the second shock is less likely, which may explain the limited additional improvement.

Moreover, when the KG sub-network is analyzed, a high variability can be observed. The resilience curve underlying this metric exhibits fluctuations (Appendix E.1), which increases the uncertainty in the interpretation of the results. Nevertheless, the Strategic selection scenario shows a particularly high restored performance ratio for shock 1. However, for shock 2, this value decreases and converges to a level comparable to the other scenarios in the KG sub-network. This suggests that no conclusion can be drawn regarding a particularly strong positive effect of the rewiring strategy in this scenario on the restorative capacity of the network.

In addition, scenarios that include risk-averse rewiring behavior (Risk-averse, Strategic selection, and Performance-risk trade-off) perform relatively the best in the second shock compared to the other scenarios. This may indicate that risk-averse behavior contributes to a more stable recovery performance under repeated shocks for the KG market, although this effect remains less pronounced in the KG sub-network due to the overall low levels of inventory and high variability in the resilience curve. This is consistent with the mechanism underlying risk-averse rewiring. This behavior relies on firms' memory of previously shocked suppliers, its effect can only emerge after the first shock has occurred, which explains why it is visible in the second shock but not the first.

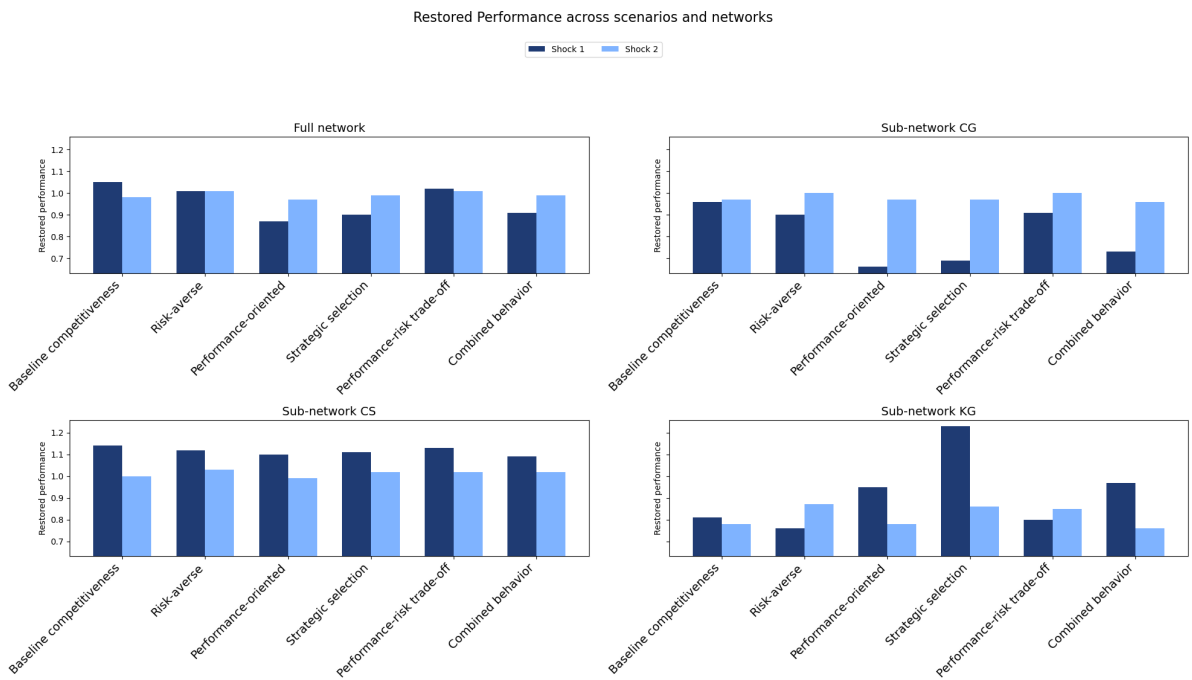


Figure 3.10: The restored performance for each scenario, network type, and shock moment

4

Discussion

In this chapter, the results presented in Chapter 3 are interpreted and discussed. It will cover the different phases of the research, which, for convenience, are presented again in Figure 4.1. Here, all sub-questions are addressed, followed by the main research question. Finally, the limitations of the study as well as the policy implications will be discussed.

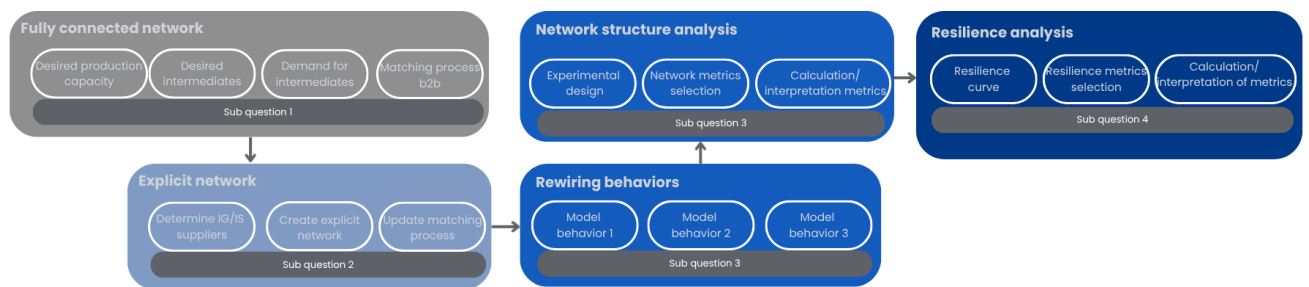


Figure 4.1: Research design

4.1. Implications for science

4.1.1. Interpretation of the EMERGO model modifications (SQ1 & SQ2)

This section will focus on the interpretation of the results from phases one and two: the fully connected network and the explicit network. This will cover sub-questions 1 and 2. These are addressed together because the results of these phases are interlinked.

The new sectoral interdependency structure

To implement the inter-firm network, sector interdependencies needed to be added to the model. For simplicity, the choice was made to stick with the already present aggregated sectors within EMERGO: the capital goods sector (KG), the consumer goods sector (CG), and the consumer services sector (CS). In the non-modified model (Figure 2.1), the firms in all three sectors were only dependent on the KG sector. However, the feature was added that all firms also buy from the CG and the CS sector, which made all sectors dependent on each other (Figure 2.2). The micro validation in Table 3.1 explained that, in reality, sectors are disaggregated and that the economy consists of a larger number of sectors where the strength of the dependency is heterogeneous among sector relationships.

The simplicity adopted in this study is motivated by the complexity of implementing sectoral interdependencies in macroeconomic supply chain agent-based models (ABMs), where firms in one sector depend on outputs from firms in other sectors, and vice versa. Most ABM supply chain models avoid such sectoral interdependency structures due to the volatility they can introduce. Chudziak (2025) discuss that studying supply chain networks in a macroeconomic model usually features only two sectors where cross-sectoral buying is not included. For example, a well-known macroeconomic ABM is the

model developed by Caiani et al. (2016). The model distinguishes two sectors: capital goods and consumer goods. Firms in both sectors depend on capital goods, but not on consumer goods, thereby excluding interdependence between the two sectors.

However, when sectors are interdependent, the production function extends beyond the classical formulation of capital and labor, as each additional sector introduces a new input. Consequently, as more sectors are added, the production function becomes increasingly high-dimensional. In such a setting, a shortage of goods from sector A to sector B can trigger a spiraling effect: sector B is unable to produce sufficient output due to shortages from sector A, which in turn affects all sectors that depend on B, including sector A, which already experiences shortages. This leads to reduced production across multiple sectors, eventually leading to the collapse of the system.

Therefore, restricting the model to the aggregated sectors already present provides sufficient complexity for this study. Introducing the dependency on the CG and CS sectors adds intermediate goods and services as additional inputs in the production function. To enable this new mechanism, a substitution for intermediate goods and services is implemented using a Cobb-Douglas function. Relying solely on a Leontief specification would be too rigid and could lead to the spiraling effects described above, because substitution is not allowed by Leontief.

Choosing a CES function instead of a Cobb-Douglas specification could enhance empirical realism, as it allows substitution and elasticity parameters to be chosen, whereas in Cobb-Douglas, these are defined. Heterogeneity in elasticity values across sectors has been observed (Agrawal & Nahmias, 1997), which supports the potential empirical advantages of a CES approach. However, such heterogeneity is highly context-specific, and assessing the sensitivity of the model for substitution and elasticity parameters is beyond the scope of this study.

For the scope of this study, the use of aggregated sectors means that the findings reflect dynamics at a high level of sectoral abstraction. The inter-firm dependencies in this model represent general cross-sectoral flows between the KG, CG, and CS sectors, rather than the specific relationships that exist between disaggregated industries in reality. As a result, the model cannot capture sector-specific vulnerabilities, such as the distinct role of logistics, energy, or financial services in post-flood recovery, which may play an important role in real-world network resilience. However, the chosen approach to the sectoral interdependency structure should be sufficiently suited to the scope of this study. Since interdependencies are introduced, an inter-firm network can be constructed, enabling the analysis of the evolving network structure over time.

The model behavior

A first observation in the model behavior is that the decline in real GDP after the second shock is smaller than after the first shock. An expectation would be the opposite given the explanation of Chapter 4.1.2: since suppliers gradually concentrate around a smaller set of firms over time, the network is expected to become more vulnerable to a repeated shock, not less. Therefore, this requires distinguishing where concentration occurs from and how much concentration occurs.

Because the same firms are targeted in both shocks, any firm that lost a supplier due to damage or bankruptcy in the first shock has had the opportunity to rewire away from the exposed region before the second shock hits. Given that competitiveness-based rewiring prefers better-performing (fit) firms, and exposed firms are disproportionately represented among the weaker performers post-shock, the rewiring process likely shifts relationships away from the exposed firms and towards the non exposed firms. This means that even though the network as a whole becomes more concentrated, the concentration is now centered around firms that are better protected and therefore perform better. The result is that fewer firms in the network still depend on the exposed region as a supplier by the time the second shock occurs, which would reduce the indirect propagation of the second shock even if its direct severity is unchanged. This is consistent with the findings from Reisch et al. (2026): high rewiring rates reflect adaptive capacity, but this adds a more specific mechanism: it is not rewiring only that produces resilience, but the direction of the rewiring away from repeatedly damaged firms.

It is important to note, however, that this observation is made at the level of the base scenario, where rewiring is purely competitiveness-based. The extent to which rewiring drives this effect, as opposed to other model dynamics such as inventory buffering, cannot be fully disentangled from these results alone. A more controlled analysis would be needed to isolate this effect.

Second, the KG sector shows volatile behavior in both the average production plot and the received-to-ordered ratio. Two mechanisms likely contribute to this. On one hand, capital goods are not substitutable within the production function, whereas intermediate goods and services can be substituted for one another. When a firm cannot obtain sufficient intermediate goods, it can partially compensate with intermediate services. No such fallback exists for capital goods, making production more sensitive to shortages. On the other hand, the capital intensity is larger than the intermediate intensity, meaning production is more dependent on capital goods than on intermediates. This combination of non-substitutability and higher input dependency could be the reason for more volatility in the KG sector. Moreover, the sharp post-shock decline in KG production, followed by an increase shown in the average production plot, is consistent with real-world patterns of capital replacement demand following disasters. Poledna et al. (2018) describes this as a cyclical economic response to a disaster. When capital is destroyed, firms must replace capital to restore their production capacity. This generates an overshoot in production in the reconstruction phase, which is followed by a decrease after all the capital is replaced. Also, the initial decline before the overshoot is due to destroyed capital and losses in income, demand, and supply (Poledna et al., 2018).

Third, the inventory levels of the CG and CS sectors are higher than those of the KG. This reflects the difference in capital utilization rates across sectors: KG firms operate at a higher utilization rate, leaving less output to accumulate as inventory. In this model with cross-sectoral buying, inventory buffers are essential to prevent the spiraling production collapse that arises when one sector cannot fulfill orders from another (Chudziak, 2025). Without sufficient inventory in the CG and CS sectors, a temporary supply shortage could propagate through the network and destabilize the entire system. This also explains why the CG and CS sectors show only a small decline in the received-to-ordered ratio after shocks compared to the KG sector. However, this sensitivity is explained in more detail in the model robustness below.

Finally, the received-to-ordered ratio for capital goods shows a downward trend, after the two sharp declines at the shock moments. This means that even in periods without shocks, firms are receiving fewer capital goods than they order. The reason for this could be that in the model, firms rewire towards more competitive suppliers. Therefore, some less competitive KG producers have fewer buyers, but do have available inventory for more buyers. This creates a mismatch between aggregate supply and realized transactions. This is a model-internal dynamic that may not fully reflect real-world behavior. In reality, unmet demand would be expected to trigger price adjustments, which would restore competitiveness. However, the model includes price adjustments, which also affect competitiveness. In the base scenario, rewiring is based on competitiveness, so the self-correcting mechanism should be working properly. However, the downward trend suggests a limitation in the current market implementation and requires further investigation into the model structure.

Model robustness

The attempts at Morris's sensitivity analysis revealed that the model is highly sensitive to capital and intermediate utilization rates, which are the inventory target parameters for capital goods and intermediate goods. Small changes led to firm bankruptcies and ultimately complete model collapse. This sensitivity implies that the model dynamics are driven by the level of inventory that firms aim to hold. Since inventory buffers determine how well firms can absorb supply disruptions, the network structure results and resilience outcomes may rely heavily on these specific parameter choices.

The baseline value for the intermediates utilization is set at 0.3. This value was not derived from empirical data but was chosen based on that sufficient inventory must be maintained for the model to function stably. If firms in reality hold more or less inventory than assumed, the absorptive capacity of the network, and therefore the resilience outcomes, could differ substantially from what is observed in this study. The results should therefore be interpreted as conditional on this parameterization, and the directional patterns in network restructuring and resilience are more reliable than the precise values.

A related sensitivity issue concerns the intermediate intensity, which governs how dependent production is on intermediate goods and services. The current model uses a low value of (0.1) to ensure model stability. When this parameter is slightly increased, the model breaks down almost immediately. This indicates that the inter-sectoral market mechanism, while functioning correctly at the current parameterization, is not fully robust to increases in intermediate dependency.

The PAWN sensitivity analysis indicates that the model's outcomes are largely insensitive to the switching weight parameters. The supplier range parameters, by contrast, show a moderate degree of sensitivity, with the maximum number of suppliers for CG and CS most strongly influencing network structure outcomes, and the minimum number of KG suppliers most strongly influencing economic outcomes. This sensitivity remains within a reasonable range. Taken together, this suggests that the rewiring-related conclusions of this study are relatively robust to the chosen switching parameter values, while the supplier range parameters show a slight sensitivity but remain robust overall.

The robustness of the model should therefore be understood as conditional rather than absolute. Provided that the utilization parameters and intermediate coefficient remain within their narrow range, the PAWN results suggest that the conclusions regarding network restructuring and resilience are relatively stable under variation of the remaining, rewiring-related parameters: number of supplier ranges and switching weights. From this, conditional robustness, the findings reported in this thesis are reasonably certain, while also emphasizing that the model's overall stability remains reliant on a small set of parameter choices that were not empirically grounded.

4.1.2. Rewiring and network restructuring (SQ3)

This section interprets the results from phase three of the research: the rewiring behaviors and the network structure analysis. This will cover sub-question 3.

The market leader rewiring collapse

The Market leader scenario resulted in model collapse after approximately 200 simulation steps, caused by a wave of cascading firm bankruptcies. As a result, this scenario was excluded from the network structure and resilience analysis. However, the collapse itself is worth interpreting, as it reveals important insights about the consequences of extreme centralization in inter-firm networks.

The market leader-based rewiring behavior was based on empirical literature, which suggests that firms tend to prefer connecting with industry leaders (Ersahin et al., 2024; Khanna et al., 2022). However, when this behavior is exclusively applied within EMERGO, it probably leads to a concentration of buyer-supplier relationships around a very small number of firms. This can be seen as a preferential attachment that follows the rich-get-richer mechanism, where the more connected a node is, the more likely it is to receive new connections (A. Chakraborty & Ikeda, 2020). Bigger firms in EMERGO have more connections, with the market leader behavior; these firms are more likely to receive new connections because buyers move towards market leaders. Therefore, other firms lose buyers, ultimately pushing them into bankruptcy. These bankruptcies then propagate through the network, as firms that depended on the now-bankrupt firms rewire as well, triggering further bankruptcies and eventually causing the model to collapse entirely.

It is important to note that this outcome is likely driven more by the modeling choices made rather than by the market leader rewiring behavior being useless for analysis. The implementation of the rewiring behavior defined the set of potential alternative suppliers as only those firms holding the maximum market share in the model. A check confirmed that in practice, this resulted in a single firm being identified as the new supplier at each rewiring step. As a result, all rewiring decisions pointed to the same firm, making excessive centralization unavoidable under this implementation. A less radical modeling approach could have been implemented, for instance, by defining the candidate pool as the top percentile of firms by market share rather than strictly the maximum, allowing for some diversity in supplier selection while still capturing the preference for market leaders.

This suggests that the collapse observed in this scenario should not be interpreted as evidence that market leader preferences are inherently destabilizing in real supply chains. Rather, it reflects the sensitivity of the model to excessive centralization around a small group of suppliers. Future research could explore a more graduated market leader preference implementation within the model that allows for partial concentration without triggering excessive centralization. This ability to link resilience outcomes to specific behavioral rules illustrates the explanatory value of the behavior-driven approach outlined in Section 1.7: the collapse of the Market leader scenario, for instance, is not only an observed structural pattern, but is directly attributable to the implementation choice of restricting the candidate supplier pool to the single firm with maximum market share, which enforced total convergence on one firm. A generative network model calibrated to reproduce a similarly centralized structure could not have identified

this specific mechanism as its cause, because it only reproduces the statistical shape of the network rather than the firm-level decision rules that generated it.

The two-group pattern in network metrics

A two-group pattern emerges from the network analysis results, where the scenarios can be divided into two groups based on showing similar behavior across network metrics. The behavior that seems to determine these groups is the presence or absence of the market leader-based rewiring behavior, where we concluded before that this behavior causes concentration within the network. Group 1 consists of the Baseline competitiveness, Risk-averse, and Performance-risk trade-off scenarios, all of which share competitiveness-based rewiring as their common feature. Group 2 consists of the Combined behavior, Performance-oriented, and Strategic selection scenarios, which all include market leader-based rewiring.

The consistent emergence of the same two groups across both maximum degree centrality and maximum eigenvector centrality suggests that the presence of market leader-based rewiring is a decisive factor in shaping this inter-firm network structure. Competitiveness-based rewiring alone produces a gradual, distributed form of centralization, whereas adding market leader-based rewiring fundamentally accelerates the speed of that process. This aligns with the rich-get-richer principle, where nodes that are already dominant attract more new connections (A. Chakraborty & Ikeda, 2020).

The finding that both groups eventually evolve to a similar steady-state level of maximum eigenvector centrality, despite following entirely different trends, has an important implication: what matters is the path taken to reach that structure. Group 2 passes through a phase of strong early centralization that makes the network potentially more vulnerable during the period when the first shock hits, because increased centralization can trigger cascading failures (Zeng et al., 2025). In contrast, Group 1 reaches a comparable structure only gradually and never experiences that early concentration peak. This can be seen as a form of path dependency, where the history of the network structure shapes risk exposure even when endpoints appear similar. However, this will be discussed in more detail when linking network structure to resilience.

The two groups also show opposite shock responses. In Group 2, which includes market leader based rewiring shocks, accelerate centralization precisely at the moment the network is most vulnerable, where group 1 shows a gradual decrease. When firms lose suppliers due to a shock, market leader-based rewiring directs them immediately toward the same dominant suppliers, further concentrating the network at a critical moment. This creates a self-reinforcing dynamic: disruption triggers rewiring, and rewiring deepens the concentration that could make the network more susceptible to future disruptions.

Although the pure Market leader scenario collapsed entirely due to rewiring with a single supplier, the scenarios that include market leader-based rewiring (Group 2) do not exhibit the same total collapse, despite showing signs of greater centralization and vulnerability across several metrics. This is likely because market leader-based rewiring is only active in 50% of rewiring decisions in these scenarios, alternating with competitiveness-based or risk-averse rewiring. This means that not all disrupted supplier relationships are directed toward the same firm, which prevents the extreme concentration that caused the Market leader scenario to collapse. Group 2 therefore experiences a milder version of the same underlying mechanism: elevated centralization and reduced resilience, but not the cascade of bankruptcies that happens when market leader-based rewiring is applied exclusively. Since centralization continues to increase gradually throughout the simulation, it is possible that running the model beyond 700 steps would allow concentration to increase to a point where it eventually destabilizes the network, even with only partial market leader-based rewiring. Whether and after how many steps this destabilization would occur could not be established within the current simulation length and could be a focus for future research.

Little effect of including memory from past shocks

The absence of any visible pattern of risk-averse rewiring on network structure metrics across the scenarios is also important. It indicates that avoiding previously shocked suppliers does not produce a significantly different network structure. This could mean that the number of firms affected by the shock is too small relative to the total network for the rewiring to leave a visible pattern. However, this could also mean that the network metrics used for this analysis did not cover this effect. Whether risk-averse rewiring has any meaningful effect on the network structure, therefore, needs to be researched in more

depth.

Little modularity and clustering

Both network modularity and average clustering coefficient show a decreasing trend across all scenarios and network types, indicating that continuous rewiring removes any community structure and clustering that initially exists in the network. This counts for all scenarios across all network types. This covers real-world expectations as A. Chakraborty and Ikeda (2020) discuss that for most real-world networks, the average clustering coefficient shows a downward trend over time.

This outcome could be a consequence of the model's constant rewiring. Because firms continuously replace suppliers throughout the simulation, existing clusters are disrupted as edges are redistributed. Over time, this produces a network that centralizes around a smaller number of firms. However, the fact that the community structure and clustering evolve to zero could also be a result of the fixed number of edges in the model. Firms only rewire when they lose a supplier, meaning that no additional edges emerge, and that formed clusters and communities are continuously disrupted.

4.1.3. Rewiring behaviors and resilience (SQ4)

This section focuses on interpreting the results of the last phase in the research design, which covers the last sub-question: the resilience analysis.

The two-group pattern in resilience metrics

The two-group pattern identified in the network structure analysis reappears in the resilience analysis, specifically in the depth of impact metric and the restored performance for the first shock. Group 2 scenarios, which include market leader-based rewiring, show a larger depth of impact and a lower restored performance than group 1 scenarios, meaning that the absorptive, adaptive, and restorative capacity is lower here. It is likely that the rapid centralization of group 2 at the beginning of the simulation, due to market leader-based rewiring, makes the network more vulnerable to the first shock, as suggested in section 4.1.2. The literature also confirms this, as A. Chakraborty and Ikeda (2020) assess that the fit-gets-richer mechanism, firms that perform better receive more links, is the drive behind an efficiently working network and not the rich-get-richer mechanism. The market leader-based rewiring behavior is mostly focused on the rich-get-richer mechanism, and the competitiveness-based rewiring behavior present in group 1 is mostly based on the fit-get-richer mechanism. The scenarios in group 1 show a better absorptive capacity of the first shock than the scenarios in group 2, therefore confirming what is said by A. Chakraborty and Ikeda (2020).

However, the fact that this effect is only observed for the first shock suggests that continuous rewiring may allow a network with initially low absorptive capacity to improve over time. As shown in 4.1.2, the network structures of the scenarios in both groups become more similar at this stage, thereby reducing the variation in outcomes for the second shock.

Differences in the first and second shock

Across all scenarios and network types, the depth of impact and endure duration metrics consistently produce better results for the second shock than for the first. The network absorbs the second shock better and recovers more quickly, regardless of which rewiring behavior is active. This pattern suggests that the continuous rewiring that occurs between the two shocks has a positive effect on the network's absorptive, adaptive, and restorative capacity. As firms repeatedly adjust their supplier relationships following the first shock, the network gradually builds up a more adapted structure better equipped to handle disruptions. This is consistent with Reisch et al. (2026), who find that high rewiring rates within a supply chain network reflect its adaptive capacity and contribute positively to post-shock resilience.

The restored performance metric shows a more nuanced pattern. Unlike depth of impact and endure duration, it does not consistently improve after the second shock across all scenarios and network types. However, overall, this metric does not perform substantially worse in the second shock, given that restored performance was already relatively high after the first shock. Therefore, the lack of further improvement in the second shock may reflect a ceiling effect rather than a limitation of the rewiring mechanism. This stability can suggest that continuous rewiring maintains the restored performance at a comparable level under repeated shocks.

The effect of memory of past shocks

The resilience results show that scenarios including risk-averse rewiring behavior, the Risk-averse, Strategic selection, and Performance-risk trade-off scenarios perform relatively best on restored performance under the second shock compared to the other scenarios. Because no significant effect could be found on the network structure for this behavior, these results suggest that the memory of past shocks does influence resilience, but not through reshaping the overall network structure, but rather that risk-averse rewiring selectively improves the quality of individual supplier relationships by directing firms away from previously shocked suppliers.

However, the effect is limited in scope. It is only visible in the restored performance metric and primarily in the second shock, meaning that risk-averse rewiring does not appear to improve the absorptive capacity of the network, because firms still experience a comparable depth of impact, nor does it clearly reduce the endure duration. This suggests that the memory of past shocks helps the network recover to a better steady state after repeated disruptions, but does not make it more resistant to the initial impact of those disruptions. The resilience in the network for the first and second shocks seems to be driven by different mechanisms: network centralization shapes resilience in the first shock, while behavioral memory shapes only the restorative capacity in the second shock.

This finding extends, rather than confirms, existing literature on risk in supplier relationships. Zsidisin et al. (2004), Banerjee et al. (2014), and Lo et al. (2024) establish that buyers prefer to avoid risky suppliers, but do not claim that this avoidance actually improves network resilience. This study tests that link directly and finds a narrow effect: risk-averse rewiring improves restored performance after the second shock, but not the depth of impact or endure duration, and produces no observable change in network structure. This suggests avoiding previously shocked suppliers helps a network settle into a better steady state after repeated disruption, but does not make it more resistant to the initial impact of a shock, a distinction the existing literature does not address.

Comparing sub-networks

The KG sub-network resilience results cannot be meaningfully interpreted. As discussed in Section 4.1, the KG market is highly volatile throughout the simulation, as explained before. This volatility is directly shown in the resilience metrics: while the metrics can be computed for the KG sub-network, the underlying resilience curve is too unstable to produce reliable values. The endure duration equals one in all scenarios, reflecting the fact that the KG inventory returns to its equilibrium immediately after the shock rather than showing a gradual recovery. This means that the resilience metrics for KG do not reflect real absorptive, adaptive, and restorative dynamics but rather the volatility of the inventory trend. As a result, no certain conclusions can be drawn from the KG resilience results about how rewiring behaviors affect capital goods market resilience.

For the CG and CS sub-networks, more can be concluded, though the two markets behave differently in important ways. The CG sub-network shows the clearest effects of rewiring on resilience compared to the CS sub-network. The two-group pattern is clearly visible in depth of impact: the improvement between shock 1 and shock 2 is the most visible of all network types, and the restored performance ratio shows the largest increase in the second shock across all scenarios. Taken together, this could suggest that rewiring dynamics have a stronger and more consistent positive effect on resilience in the CG market than in the CS market.

It is important to note, however, that CG and CS producers not only differ in number and average size, but also structurally in their capital intensity, with CG producers having a higher capital intensity than CS producers (elaborate explanation in Chapter A.1). Because production capacity is bound by the minimum of capital, labor, and intermediate inputs (Equation 2.2), CG production is more sensitive to capital losses per unit of output than CS production. It would be expected that the larger dependency on capital would result in weaker resilience results for CG compared to CS. However, the opposite is true. This suggests that firm count and average size, or rewiring dynamics operating differently across the two markets, may play a larger role than capital intensity in explaining this asymmetry. Disentangling the effect of capital intensity and size of the sectors would require a controlled comparison, for example re-running the model with equal capital intensities and equal firm counts across CG and CS, which falls outside the scope of this study.

This sub-network comparison reveals that the resilience effects of rewiring are unevenly distributed across markets. The study can draw its strongest conclusions about rewiring and resilience for the

CG market, more limited conclusions for CS, and no meaningful conclusions for KG. This uneven distribution is important as it suggests that the resilience benefits of different rewiring strategies are market-specific, and that a single rewiring policy applied uniformly across all supplier types may not produce uniform resilience outcomes across the different parts of the inter-firm network.

Reconciling rewiring and stability

These findings both confirm and extend the existing literature on rewiring and network resilience. The finding that gradual, competitiveness-based rewiring improves resilience is consistent with Reisch et al. (2026), who link high rewiring rates to adaptive capacity. However, the collapse of the pure Market leader scenario also supports Reisch et al. (2026) alternative observation that rewiring can signal instability, suggesting that the resilience effect of rewiring depends on which rewiring logic is applied rather than rewiring intensity, which is a distinction that has not been made explicit in earlier work.

This also nuances Reggiani (2022), who argues that hubs, nodes with a high degree of interconnectedness, enable networks to adapt by redistributing flows, thereby allowing resilience to emerge. While the gradual centralization produced by competitiveness-based rewiring is consistent with this view, the collapse of the Market leader scenario shows that the same underlying mechanism, concentration around a small number of highly connected hub firms, can also destabilize the network entirely once centralization becomes excessive. This suggests that connectivity and hub formation support resilience only up to a certain degree of centralization, beyond which reliance on a small number of central firms becomes a systemic vulnerability rather than a source of adaptive capacity.

4.1.4. The link between network structure and resilience (Main RQ)

This section synthesizes the findings from the sub-questions, in particular, from the network structure analysis and the resilience analysis to address the main research question: How do firm-level rewiring behaviors, including those exhibiting path dependency through firms' memory of past shocks, reshape the inter-firm network structure and affect its resilience following a flood shock?

The most important finding that links network structure to resilience is that the same two-group pattern appears in both analyses. The scenarios that produce higher centralization through market leader-based rewiring (Group 2) also show a larger depth of impact and lower restored performance under the first shock. The scenarios that centralize more gradually through competitiveness-based rewiring (Group 1) show better absorptive capacity. This suggests that the rewiring behavior shapes the network structure, and the network structure in turn shapes how the system responds to a shock. The rewiring behavior, therefore, influences resilience indirectly, through the network structure it generates before the shock.

This insight suggests that a network that has centralized rapidly in the past is more vulnerable when the shock arrives, because the disruption of a small number of central suppliers affects a large share of the network. This is consistent with the concept of path dependency described by Setterfield (2015), in which earlier states of the system shape its later path. Here, how quickly and how strongly the network is centralized before the shock, determines its exposure to vulnerability at the moment of disruption. However, the insights also suggest that this depends on the interaction between the rewiring strategy used and the timing of the shock relative to the network's trend. This timing argument explains why the two-group distinction in resilience outcomes is most pronounced for the first shock and less visible for the second: by step 500, the network structures of both groups have converged toward a more similar steady state, reducing the structural differences that drove the first-shock differences. This means that a vulnerable network can also recover itself through continuous rewiring and supports the argument of Reggiani (2022) that network connectivity enables resilience by allowing flows to be redistributed after disruption, and extends Reisch et al. (2026) finding on rewiring and adaptive capacity by showing that this self-correcting effect can patch even a structurally vulnerable starting point.

However, this link between network structure and resilience is not similar across all three resilience dimensions. Network centralization, shaped by rewiring behavior, primarily drives absorptive, adaptive, and restorative capacity as captured by the depth of impact and restored performance metric in the first shock. In contrast, risk-averse rewiring leaves no visible impact on the network metrics, yet it improves restorative capacity in the second shock compared to the scenarios without this behavior by improving the quality of individual supplier relationships. This means network structure alone is not adequate in

determining resilience. The recovery to a new steady state is additionally shaped by the memory of previous shocks operating below the level of observable structural change.

Taken together, the results suggest that firm-level rewiring behaviors reshape the inter-firm network primarily through the speed and degree of centralization they produce. Market leader-based rewiring drives rapid early centralization that increases network vulnerability at the moment of a shock, reducing absorptive capacity. Competitiveness-based rewiring produces a more gradual centralization that leaves the network in a less concentrated and more resilient state when a shock arrives. Risk-averse rewiring, which focuses on firms' memory of past shocks, does not observably reshape the network structure but does contribute to restorative capacity, and therefore the adaptive and restorative capacity of the network, under repeated shocks. The resilience of the inter-firm network is therefore shaped in two ways: the structural dimension, through which rewiring behavior determines the network structure and absorptive, adaptive, and restorative capacity, and the behavioral dimension, through which firms' memory of past shocks influences adaptive and restorative capacity without producing visible structural change.

4.2. Implications for policy

Several policy implications follow from the findings of this study. First, the collapse of the pure Market leader scenario shows that supplier relationships concentrating excessively around a small number of dominant firms can make a network vulnerable to cascading failures. Connecting with well-performing suppliers can be beneficial, as shown by the gradual centralization under competitiveness-based rewiring. However, when this preference is applied without any constraint, as in the pure Market leader scenario, rewiring funnels nearly all buyers toward a single dominant supplier, driving the remaining suppliers out of business. This removes the redundancy a network needs to survive the loss of any one supplier.

Second, competitiveness-based rewiring behavior was found to gradually improve the network's resilience over repeated shocks. This suggests that continuous, performance-based supplier diversification could help a network recover from a disruption more effectively than static, long-term supplier contracts.

Third, risk-averse rewiring was found to improve restorative capacity without producing a visible change in network structure. This suggests that firm-level practices, such as keeping track of previously disrupted suppliers and factoring this into future switching decisions, can improve recovery outcomes even without changing the broader network structure. However, this effect was limited to restorative capacity and did not reduce the initial impact of a shock. This suggests that policies relying solely on firms' own risk-averse switching behavior are unlikely to be sufficient on their own, and that other measures, may still be needed to reduce the initial impact of a disruption.

Fourth, the resilience benefits of rewiring were found to differ between sectors, with the clearest effects observed in the CG market and more diverse and limited effects in the CS and KG markets. This suggests that supply chain resilience policy should be sector-specific rather than uniform, as a single diversification or monitoring requirement is unlikely to be equally effective across capital goods, consumer goods, and consumer services markets.

Fifth, the model's sensitivity to parameters linked to inventories, together with the more volatile behavior observed in the KG sector, suggests that maintaining sufficient inventory buffers is an important mechanism for absorbing supply disruptions, particularly for capital-intensive sectors, because these sectors rely heavily on capital.

These recommendations should be interpreted with caution. The sensitivity analysis was not fully completed, and several outcomes are conditional on specific model parameterizations. The recommendations should therefore be read as directional insights from an exploratory model, rather than as specific policy prescriptions.

4.3. Limitations

Several limitations of this study should be acknowledged, spanning from model implementation choices to methodological constraints in the analysis.

The attempts to execute the Morris method revealed extreme sensitivity to the capital goods and intermediates utilization parameters. As a result, it cannot be ruled out that some of the observed differences between scenarios are partly driven by these parameter choices rather than the rewiring behaviors themselves.

Despite this limitation, the inventory level was used for the resilience curve. The inventory plot was the only performance metric that showed a relatively slow decline and stabilization following the shocks, making it the only performance metric usable for this method. However, its use means that the resilience analysis in this study is effectively measuring inventory resilience rather than broader economic resilience. The inventory levels in the model are directly determined by the inventory target parameters, capital goods, and intermediates utilization, which, as discussed before, are the most sensitive parameters in the model. The conclusions drawn about the absorptive, adaptive, and restorative capacity of the network in this study, therefore, rely on the performance of the accumulated inventory. Moreover, this limits the confidence with which quantitative differences between scenarios can be attributed to the rewiring strategies themselves.

A related limitation is that the inter-firm network in this study captures cross-sectoral buying, but the strength of these dependencies is relatively low for intermediates and is also constrained. When the intermediate input coefficient is increased beyond its current value of 0.1, the model becomes unstable almost immediately. This means the network dynamics and resilience outcomes observed here represent a setting where inter-sectoral dependencies are weaker than they may be in practice, and that sensitivity to this parameter cannot be examined in this study. This could mean that the shock propagation and resilience outcomes could differ significantly from what is observed in this study. Furthermore, for the KG sub-network, the inventory plot was too volatile to serve as a reliable resilience curve, meaning no meaningful conclusions can be drawn about capital goods market resilience, which is a relevant market for post-flood recovery, as capital is affected the most in this model.

Additionally, the results presented in this study are based on 30 simulation runs per scenario. While this provides a reasonable basis for comparison, a higher number of runs would reduce the uncertainty in the results by better capturing the stochastic variation in the model. The current number of runs, therefore, limits the confidence of the results. The number of runs will be increased to 100 in the final version of this thesis, which will reduce this uncertainty and provide a more robust base for the conclusions.

Another limitation of the model is the absence of firm-level adaptation mechanisms. The risk-averse rewiring implementation calculates accumulated risk based on capital destruction, but the model does not include adaptation mechanisms for the shocked firms themselves. Trojand et al. (2025) explain that over time, firms that are repeatedly damaged implement mitigation measures to reduce their vulnerability. This is not taken into account because firms deviate from suppliers that have been shocked previously and do not consider these suppliers to have taken the relevant measures for the future. The absence of this could mean the effect of memory of past shocks on resilience may be overestimated in this study.

Finally, the research depends on network metrics and resilience metrics. However, the network analysis relied on aggregate metrics such as maximum degree centrality and maximum eigenvector centrality. While these capture system-level trends, they do not show how the degree distribution evolves at the agent level over time. Tracking individual firm connectivity would allow for a more precise characterization of centralization dynamics and would provide stronger evidence for the centralization mechanisms hypothesized in this study. Because of this, the mechanism found in the results, that centralization increases vulnerability by concentrating dependency on fewer suppliers, is grounded in the literature (Zeng et al., 2025), but it cannot be directly observed from the metrics used in this study. Moreover, only three resilience metrics were selected: depth of impact, endure duration, and restored performance, due to the scope of this thesis. While these cover the absorptive, adaptive, and restorative capacities, the full framework proposed by Bruckler et al. (2024) includes 17 metrics that together provide a more comprehensive picture of network resilience. Other metrics may show differences between scenarios that the selected metrics did not capture.

5

Conclusion

Floods are one of the climate change effects most likely to intensify, and with their disproportionate contribution to the climate-related economic burden, it is important to protect business activity from flood shocks. Economic production is structured around complex supply chains. Because shocks propagate through the network, non-resilient firms can disrupt the supply chain and indirectly affect initially unaffected firms. Therefore, ignoring sectoral interdependencies and, with that, firm interdependencies, underestimates the economic impacts of floods. Therefore, this research uses the EMERGO model introduced by Akkerman et al. (2026) and extends this to incorporate an inter-firm network. The following research questions have been addressed in this study.

This study extended the EMERGO model by introducing cross-sectoral buying between the KG, CG, and CS sectors and constructing an explicit dynamic inter-firm network in which supplier relationships evolve through firm-level rewiring behaviors (SQ1, SQ2). The model was verified and validated. The model proved to be sensitive to some parameters, meaning results are conditional on the chosen parameterization. The rewiring behaviors produced two distinct groups of network evolution: scenarios with competitiveness-based rewiring centralized gradually, while scenarios including market leader-based rewiring centralized rapidly in the early stages. Firms' memory of past shocks did not produce an observable difference in network structure, and across all scenarios, modularity and clustering converged toward zero (SQ3). These structural differences translated directly into resilience outcomes: the gradually centralizing group showed better absorptive, adaptive, and restorative capacity in the first shock, while continuous rewiring improved all three capacities for all scenarios under the second shock. Memory of past shocks does not reshape the network structure in an observable way in this study, but does contribute positively to resilience under repeated shocks (SQ4). This reveals that resilience in the inter-firm network is shaped through two dimensions: a clear structural dimension, through which rewiring behavior determines network centralization and absorptive, adaptive, and restorative capacity, and a behavioral dimension, through which firms' memory of past shocks improves recovery without producing observable structural change. This could indicate path dependency where the experience of a past shock influences future supplier selection decisions, and through these decisions, the ability of the network to recover from subsequent disruptions (Main RQ).

These findings contribute to the literature in two ways. First, this study introduces the first dynamic inter-firm network within EMERGO, a macroeconomic agent-based model that includes cross-sectoral buying between multiple sectors. Most macroeconomic ABMs feature only two sectors and restrict inter-firm buying to the capital goods sector, excluding intermediate goods and services (Caiani et al., 2016; Chudziak, 2025). By introducing mutual dependencies between the KG, CG, and CS sectors within a macroeconomic environment, this study extends the modeling frontier for inter-firm network analysis. While Reisch et al. (2026) also introduced a dynamic supply chain network, that model is data-driven and descriptive. The inter-firm network within EMERGO is behavior-driven and explanatory, making it particularly suited to examining how individual firm-level rewiring behaviors give rise to resilience outcomes.

Second, this study directly builds upon the research gap identified by Son et al. (2021), who examined how network structure changes following a shock and highlighted the need for further research into how such restructuring affects the long-term resilience of supply chain networks. This study addresses that gap by linking firm-level rewiring behaviors to network structural evolution and resilience outcomes under repeated flood shocks. The finding that the speed of centralization, not just the final network structure, determines resilience under a shock is a specific contribution to understanding how network restructuring shapes long-term resilience.

Future work

Several recommendations for future work emerge from the limitations mentioned in Chapter 4.3. First, this study applied two flood shocks to the model. The finding that the second shock produces a smaller GDP decline and better resilience metrics than the first suggests that continuous rewiring may strengthen the network over time. Future research should examine what happens under a longer sequence of repeated shocks, to determine what level of resilience emerges.

Second, the memory of past shocks did not produce an observable difference in network structure metrics in this study, though this may partly reflect the limitations of the aggregate metrics used. Future work should investigate more deeply how risk-averse rewiring influences network structure at the agent level, by tracking individual firm-level connectivity. Complementing aggregate network metrics with agent-level analysis would also strengthen the causal interpretation made between network structure and resilience in this study.

Moreover, future work could further explore market leader preferences, as the model implementation used in this study appeared to be too radical, leading to rapid and excessive market concentration.

Fourth, future work should combine risk-averse rewiring with explicit firm-level adaptation actions, such as firms reducing their own vulnerability after repeated damage. This would provide a more realistic representation of how path dependency operates in real supply chains. Additionally, applying the full set of 17 resilience metrics proposed by Bruckler et al. (2024) would provide a more comprehensive overview of how rewiring behaviors affect all dimensions of network resilience beyond the three metrics used here.

Fifth, the current model focuses mainly on switching behavior from the buyer's perspective, but not from the supplier's perspective. As explained in Chapter 2.3, in the current version of the model, suppliers can indirectly obtain new buyers when they lose one, but suppliers do not actively seek new buyers. The results in this study were therefore analyzed while keeping in mind that the switching behavior modeled is that of the buying firms, rather than the supplying firms. Future work could therefore focus on what happens on the supplier side when a supplier loses buyers, and how the model could be enriched with such behavior. If future work shows that this behavior is relevant to include, adding it could provide a more complete picture of how both sides of a supplier relationship contribute to network restructuring and resilience.

Finally, future work could also study whether the model's shock mechanism generalizes to other climate-related hazards, such as wildfires, hurricanes, or earthquakes. Since EMERGO represents a shock through the destruction of physical capital rather than through a flood-specific mechanism, the underlying shock dynamics may be transferable to other capital-destroying hazards. However, for this it is necessary to reconsider several of the shock design choices made in this study. The repeated targeting of the same firms reflects the recurrent, spatially concentrated nature of flood exposure, and may not reflect hazards that are less spatially predictable. Future work could therefore explore how adjusting the spatial concentration of the shock affects the applicability of the model's rewiring and resilience findings to hazards beyond floods.

Policy recommendations

As for policy recommendations, these should be interpreted with caution, given the limitations of this study. The results are conditional on some of the chosen parameters. The recommendations therefore reflect directional insights from an exploratory model rather than specific policy prescriptions.

A key finding is that rewiring toward market leaders, the rich-gets-richer mechanism, results in rapid centralization that increases network vulnerability under flood shocks, whereas rewiring based on competitiveness, the fit-gets-richer mechanism, produces a more distributed structure that better absorbs

disruptions. Policymakers could therefore discourage excessive and particularly rapid supplier concentration. Encouraging performance-based supplier selection over market dominance could help maintain a more resilient network structure during recovery.

Furthermore, the positive effect of risk-averse rewiring on restorative capacity, though limited to recovery rather than the initial impact of a shock, suggests value in improving the availability of flood risk information at the industry level. If firms have better access to information about which suppliers have been damaged in past flood events, they can make more informed rewiring decisions. Databases documenting firm exposure to flood risks, coordinated by regional water authorities and national disaster management organizations, could facilitate this. However, such measures would need to be extended by structural steps to address the initial impact of a disruption.

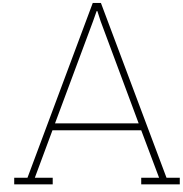
Finally, the finding that resilience benefits differ across sectors, and that inventory buffers play an important role in absorbing disruptions, particularly for capital-intensive sectors, suggests that a uniform, one-size-fits-all resilience policy is unlikely to be effective. Policymakers should therefore tailor resilience requirements to sector-specific characteristics. However, since this study could not conclude with certainty what drives the observed differences between sectors, such as capital intensity, firm count and size, or rewiring dynamics, further research into these sector-specific mechanisms is needed before concrete policy recommendations can be formulated.

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Variables & Functions

This Appendix provides an overview of the important model properties, the model and firm state variables and functions. While there are more functions and variables used in EMERGO, the most important properties and functions for this study are presented here.

A.1. Properties

Table A.1 presents the most relevant model properties. The parameter settings are also explained in this section. A subset of the model properties was already included in the EMERGO model, therefore, the parameter settings from Akkerman et al. (2026) were used. The specific properties concerned are listed in Table A.1. To further explain the parameterization of these properties, the supplementary materials of Akkerman et al. (2026) are consulted. Section 3 of these materials describes how empirical literature and available data are used to inform parameter values. It also discusses the calibration of certain parameters using a combination of datasets and empirical findings from the European Union and the United States. However, this calibration approach is not applied to the parameters listed in Table A.1.

The remainder of the parameter settings are discussed in order of Table A.1. First, the number of steps and the timing of the shocks were chosen with computational efficiency in mind. After running simulations with different numbers of steps, it was decided to use 700 steps, as this provides sufficient time for two shocks while keeping the computational heaviness manageable.

Moreover, as outlined in the research design, two shocks are required for this study. The first shock occurs at step 300 to allow the model to reach a steady state pre-shock. At step 300, sufficient time has passed for the system to stabilize. The second shock is introduced at step 500, leaving 200 steps to analyze the system's behavior following the second shock.

Moreover, the values for the substitution parameter and the elasticity of substitution were already explained in the research design. This chapter described the use of a Cobb-Douglas function for the intermediate input equation. In a Cobb-Douglas function, the substitution parameter is equal to 0, and the elasticity of substitution is equal to 1 (Saito, 2011), which explains these parameter settings.

The distribution parameter determines how the two inputs—in this case, intermediate goods and services—contribute to the overall production. It is specified based on the relative share of consumer goods producers compared to consumer goods and services producers. This approach ensures that the contribution of both inputs is weighted according to the number of firms in each sector, with the weight allocated proportionally to the sector size.

There is uncertainty regarding the values of several intermediate input parameters, namely the intermediate input coefficients for CG, CS, and KG firms, as well as the desired intermediate inputs per unit of production. For the desired intermediate inputs per unit of production, a lower value was chosen during model debugging compared to the capital utilization rate, which was set at 0.8. This adjustment leads to a higher accumulation of intermediate stock within the system, which in turn reduces overall

model volatility. As a result, the system exhibits more stable dynamics over time. However, because there remains uncertainty this value will be included in the sensitivity analysis of the model to examine what variations in this parameter does for the model.

For the intermediate input coefficients, a simplifying assumption is made by keeping these parameters equal for the three sectors. However, their level is set lower than the capital intensity. This ensures that production is less dependent on intermediate inputs than on capital inputs. The capital intensity differs between sector types: 1 for CG/IG producers, 0.75 for CS/IS producers, and 1 for KG producers, following the calibration used by Akkerman et al. (2026). If these coefficients were set at a magnitude similar to that of the capital input coefficient, the model would exhibit excessive fluctuations and instability. Although these parameter choices are subject to uncertainty and would ideally be included in a sensitivity analysis, this is not feasible in practice. Even small increases of 0.1 lead to model breakdown within a few time steps. This indicates that the model is highly sensitive to the intermediate input coefficients. However, such extreme sensitivity likely reflects underlying structural limitations in the model rather than meaningful economic behavior. This issue is therefore further discussed as a limitation in the conclusion. Moreover, these parameter settings result in that CG, CS and KG firms differ by construction in their capital dependency but not in their intermediate dependency, which should be kept in mind when interpreting differences in their behavior and resilience outcomes.

Moreover, the model specifies a minimum and maximum number of considered suppliers. In the original EMERGO model, firms were assigned a fixed number of KG suppliers (set at 6), while no distinction was made for CG and CS suppliers. In the current model, however, firms are allowed to consider a varying number of suppliers, depending on their production capacity. To enable this, minimum and maximum bounds are introduced for both KG suppliers and CG/CS suppliers. These bounds are based on the original KG value of 6. For KG suppliers, a relatively narrower range is chosen (with a bandwidth of 4 and 2), slightly below the original fixed value. This introduces variability while preventing the number of considered suppliers from dropping too low, as a minimum of 1 supplier would lead to excessive instability in the model.

For CG and CS suppliers, the minimum and maximum values are set slightly higher, reflecting the larger number of suppliers in these sectors. At the same time, the upper bound is constrained to avoid excessive computational burden, as a higher number of potential suppliers would increase switching complexity and slow down the model. There remains some uncertainty regarding the exact parameter values of the amount of suppliers. Therefore, these choices are included in the model's sensitivity analysis to assess how variations in supplier ranges affect the results.

Lastly, for the weights governing switching decisions based on price and unmet demand were already set for KG, the choice was made to set the same values for switching to CG and CS suppliers. This assumption is made to maintain consistency across sectors.

Table A.1: Relevant model properties

Property	Description	Type and parameter setting	Source
T	The number of steps for each run	Integer: 700	Explained in text above
$t_{floodshocks}$	The time steps and intensity of the floodshocks. There is only one intensity in this model.	List: [(300, 1), (500,1)]	Explained in text above
$N_{households}$	Number of households	Integer: 10,000	(Akkerman et al., 2026)
N_{kg}^{total}	Total number of KG firms	Integer: 50	(Akkerman et al., 2026)
N_{cg}^{total}	Total number of CG firms	Integer: 350	(Akkerman et al., 2026)
N_{cs}^{total}	Total number of CS firms	Integer: 650	(Akkerman et al., 2026)
κ_{cg}	The capital intensity of a CG firm. How much capital is needed for one unit of CG production	Float: 1	(Akkerman et al., 2026)
κ_{cs}	The capital intensity of a CS firm. How much capital is needed for one unit of CS production	Float: $0.75 * \kappa_{cg}$	(Akkerman et al., 2026)

Property	Description	Type and parameter setting	Source
κ_{kg}	The capital intensity of a KG firm. How much capital is needed for one unit of KG production	Float: $1.5 * \kappa_{cg}$	(Akkerman et al., 2026)
$\phi_K^{desired}$	The desired capital utilization rate. As a result, firms tend to request more capital than they actually need for production	Float: 0.8	(Akkerman et al., 2026)
$K_{per\ machine}$	The capital goods required for one machine	Integer: 5	(Akkerman et al., 2026)
$\rho_{substitution}$	Substitution parameter for intermediates in the production function	Float: 0	in a Cobb-Douglas function (Saito, 2011)
$\sigma_{elasticity}$	Elasticity of substitution for intermediates in the production function	Float: $1/(1 - \rho_{substitution})$	in a Cobb-Douglas function (Saito, 2011)
$\rho_{distribution}$	Distribution parameter for consumer goods and services in the Cobb-Douglas consumption function	Float: $N_{cg}^{total} / (N_{cg}^{total} + N_{cs}^{total})$	Explained in text above
ν_{cg}	Intermediate input coefficient for CG firms. How many intermediates are needed for one unit of CG production	Float: 0.1	Explained in text above
ν_{cs}	Intermediate input coefficient for CS firms. How many intermediates are needed for one unit of CS production	Float: 0.1	Explained in text above
ν_{kg}	Intermediate input coefficient for KG firms. How many intermediates are needed for one unit of KG production	Float: 0.1	Explained in text above
$\phi_I^{desired}$	Desired intermediate inputs per unit of production capacity. As a result, firms tend to request more intermediates than they actually need for production	Float: 0.3	Explained in the text above
γ_f^{inv}	Within-product elasticity of substitution between firms	Float: 3.5	(Akkerman et al., 2026)
$max_{cp}^{considered}$	Maximum number of CG or CS suppliers considered	Integer: 6	Explained in text above
$min_{cp}^{considered}$	Minimum number of CG or CS suppliers considered	Integer: 4	Explained in text above
$max_{kg}^{considered}$	Maximum number of KG suppliers considered	Integer: 4	Explained in text above
$min_{kg}^{considered}$	Minimum number of KG suppliers considered	Integer: 2	Explained in text above
$scenario$	Scenario identifier used for parameter changes	Integer: [0,5] (initial: 0)	Based on what scenario is run this parameter is set
$\gamma_{switch,p}^{price}$	Weight assigned to price when switching suppliers	Float: 0.5	(Akkerman et al., 2026)
$\gamma_{switch,p}^{unmet}$	Weight assigned to unmet demand when switching suppliers	Float: 0.5	(Akkerman et al., 2026)
$\vartheta_{in,exposed}$	Trade markup within the exposed region	Float: 1.0	(Akkerman et al., 2026)
$\vartheta_{in,nonexposed}$	Trade markup within the non-exposed region	Float: 1.0	(Akkerman et al., 2026)
$\vartheta_{inter,regions}$	Trade markup between regions	Float: 1.1	(Akkerman et al., 2026)

A.2. State variables

This section presents the relevant model and firm-agent variables that evolve during the simulation and are initialized at the start of the model run.

Table A.2: Model state variables

Variable	Description	Type
$firms_{shocked}^{memory}$	Stores the IDs of firms affected by a previous shock	list: [integer]
$network$	The full inter-firm supply network	MetaGraph object
$network_{cg}$	The sub-network containing CG edges and all firms	MetaGraph object
$network_{cs}$	The sub-network containing CS edges	MetaGraph object
$network_{kg}$	The sub-network containing KG edges	MetaGraph object

Table A.3: Firm agent state variables

Variable	Description	Type
A	Productivity level of the firm. How many production units does one unit of labor produce	Float
$capital_{supplier}^{ids}$	IDs of selected capital goods suppliers	list: [integer]
$production_{cap}^{mean}$	Average production capacity	Float
$production_{cap}^{desired}$	Desired production capacity	Float
$price_{unit}$	Unit selling price	Float
$cost_{unit}^{capital}$	Capital cost per unit	Float
$cost_{unit}^{labor}$	Labor cost per unit	Float
$cost_{unit}^{intermediates}$	Intermediate input cost per unit	Float
$cost_{unit}$	Total unit cost	Float
$production_{units}$	Production output in units	Vector of floats
$production_{units}^{possible}$	Maximum feasible production in units	Float
$sales_{units}$	Sales in units	Float
$received_{units,cg}$	Consumer goods units received from suppliers	Float
$received_{units,cs}$	Consumer services units received from suppliers	Float
$demand_{units}^{total}$	History of total demand in units	list: [Float]
$demand_{units,kg}^{unmet}$	Unmet demand	Float
$demand_{units,cg}^{unmet}$	Unmet demand for consumer goods	Float
$demand_{units,cs}^{unmet}$	Unmet demand for consumer services	Float
$inventory_{units}$	Inventory available for sale	Float
$marketshares$	Market shares across regions	Producer
$budget_{cg}$	Budget allocated to consumer goods	Float
$budget_{cs}$	Budget allocated to consumer services	Float
kg_{switch}	Indicator for switching a KG supplier in the current period	Boolean
cg_{switch}	Indicator for switching a CG supplier in the current period	Boolean
cs_{switch}	Indicator for switching a CS supplier in the current period	Boolean
$struck_{flood}$	Indicator whether the firm was affected by a flood	Integer (0/1)
$frac_{destroyed}^{cap}$	Fraction of capital destroyed during flood	Float
$rewire_{risk}$	Propensity to rewire suppliers based on past shocks	Float

A.3. Functions

Table A.4: Relevant model functions

Function	Description
<code>set_supplier_sample_size()</code>	Determines for all firms in the model the number of suppliers they consider to connect with, based on a firm's mean production capacity.
<code>initialize_intermediate_relations()</code>	Determines the IG and IS suppliers and initializes the explicit network, where all firms are nodes and all supplier relationship types (KG, IG, IS) are edges.
<code>aggregate_demand()</code>	Calculates the aggregate demand of all firms per type of market (IG or IS) within a given region (E, NE).
<code>matching_cp_producers()</code>	This function executes the actual matching of firms to their IG and IS suppliers by placing orders.
<code>deliver_cg_units()</code>	For all IG producers within the network, it delivers the received orders to the corresponding buyer firm. It also extracts the units from the supplier's stock.
<code>deliver_cs_units()</code>	For all IS producers within the network, it delivers the received orders to the corresponding buyer firm. It also extracts the units from the supplier's stock.
<code>update_cp_marketshares()</code>	Updates the market share of CG and CS producers within the model.
<code>update_kg_marketshares()</code>	Updates the market share of KG producers within the model.
<code>flood_event()</code>	Executes the flood event within the model, during which firms are selected to experience a shock and a disruption risk is added to them.

Table A.5: Relevant firm agent functions

Function	Description
<code>production_capacity()</code>	A Leontief function that calculates a firm's production capacity.
<code>input_intermediates()</code>	A Cobb–Douglas function that calculates a firm's intermediate input for production, which is an aggregate of <i>ig</i> and <i>is</i> units.
<code>set_desired_intermediates()</code>	Calculates the intermediates (<i>ig</i> , <i>is</i>) a firm would want to buy based on its production capacity and its intermediates in stock.
<code>decide_switch_cp_unmet_demand()</code>	Determines whether a firm replaces an existing intermediate supplier based on unmet demand.
<code>decide_switch_kg_unmet_demand()</code>	Determines whether a firm replaces an existing capital supplier based on unmet demand.
<code>check_better_cp()</code>	Randomly selects one of the firm's current intermediate suppliers and compares it with a newly sampled alternative supplier. If a valid alternative is found, both suppliers are passed to <code>decide_switch_cp_comp()</code> for evaluation.
<code>check_better_kg()</code>	Randomly selects one of the firm's current KG suppliers and compares it with a newly sampled alternative supplier. If a valid alternative is found, both suppliers are passed to <code>decide_switch_kg_comp()</code> for evaluation.
<code>decide_switch_cp_comp()</code>	Evaluates whether the sampled alternative intermediate supplier is more competitive than the current supplier. If so, the existing supplier relationship is removed and replaced by a new edge to the alternative supplier.
<code>decide_switch_kg_comp()</code>	Evaluates whether the sampled alternative KG supplier is more competitive than the current supplier. If so, the existing supplier relationship is removed and replaced by a new edge to the alternative supplier.

Function	Description
<code>sample_new_cp_supplier_marketshare()</code>	The function returns an alternative IG or IS supplier based on the market share of suppliers.
<code>sample_new_capital_supplier_marketshare()</code>	The function returns an alternative KG supplier based on the market share of suppliers.
<code>sample_new_cp_supplier_risk()</code>	Selects a new CP supplier for a firm based on the supplier's disruption risk.
<code>sample_new_capital_supplier_risk()</code>	Selects a new KG supplier for a firm based on the supplier's disruption risk.
<code>rewire()</code>	Determines and applies the appropriate rewiring behavior for a firm, depending on the scenario and market type.
<code>is_KG()</code>	Takes a firm ID and checks if it is a capital goods producer
<code>is_CG()</code>	Takes a firm and checks if it is a consumer/intermediate goods producer.
<code>is_CS()</code>	Takes a firm ID and checks if it is a consumer/intermediate service producer.

B

Network verification code fragments

This Appendix presents the code fragments used to verify the networks. It checks the consistency of the sub-networks with the full network during initialization and throughout the model run when switching suppliers.

Listing B.1: Network verification code within initialization

```
1 # Verification: test if the network is filled correctly
2
3 println("\n-----")
4 println("NETWORK VERIFICATION")
5 println("-----")
6
7 println("Nodes: $(nv(model.network))")
8 println("Edges: $(ne(model.network))")
9
10 if model[11004] == model.network[11004]
11     println("Node data correctly assigned for firm 11004")
12 else
13     println("Node data not correctly assigned for firm 11004")
14 end
15
16 p_id = 11004
17 code = code_for(model.network, p_id)
18
19 out_codes = outneighbors(model.network, code)
20 in_codes = inneighbors(model.network, code)
21
22 out_labels = label_for.(Ref(model.network), collect(out_codes))
23 in_labels = label_for.(Ref(model.network), collect(in_codes))
24
25 # are there nodes without edges (firms without suppliers)
26 isolated = Int[]
27
28 for code in 1:nv(model.network)
29     if isempty(inneighbors(model.network, code))
30         push!(isolated, label_for(model.network, code))
31     end
32 end
33
34 if isempty(isolated)
35     println("No firms without suppliers found.")
36 else
37     println("Firms without suppliers:")
```

```

38     println(isolated)
39 end

```

Listing B.2: Supplier consistency verification code within initialization

```

1 println("\n-----")
2 println("SUPPLIER CONSISTENCY CHECK (Firm $p_id)")
3 println("-----")
4
5 println("Stored KG suppliers: ", model[p_id].capital_supplier_ids)
6
7 println("KG suppliers (network): ",
8     filter(id -> id in model.national_economy.all_kg, collect(in_labels)))
9
10 println("CG suppliers (network): ",
11     filter(id -> id in model.national_economy.all_cg, collect(in_labels)))
12
13 println("CS suppliers (network): ",
14     filter(id -> id in model.national_economy.all_cs, collect(in_labels)))

```

Listing B.3: Sub-network consistency verification code within initialization

```

1 println("\n-----")
2 println("SUBNETWORK CHECK")
3 println("-----")
4
5 in_labels_cg_network = label_for.(Ref(model.network_cg), collect(inneighbors(model.network_cg,
6     code)))
7 in_labels_cs_network = label_for.(Ref(model.network_cs), collect(inneighbors(model.network_cs,
8     code)))
9 in_labels_kg_network = label_for.(Ref(model.network_kg), collect(inneighbors(model.network_kg,
10     code)))
11
12 println("CG suppliers (network_cg): ", collect(in_labels_cg_network))
13 println("CS suppliers (network_cs): ", collect(in_labels_cs_network))
14 println("KG suppliers (network_kg): ", collect(in_labels_kg_network))

```

Listing B.4: Output of the consistency verification code within initialization

```

1 =====
2 NETWORK VERIFICATION
3 =====
4 Nodes: 1050
5 Edges: 13404
6 Node data correctly assigned for firm 11004
7 No firms without suppliers found.
8
9 -----
10 SUPPLIER CONSISTENCY CHECK (Firm 11004)
11 -----
12 Stored KG suppliers: [11043, 11018]
13 KG suppliers (network): [11018, 11043]
14 CG suppliers (network): [10025, 10040, 10116, 10143, 10204, 10349]
15 CS suppliers (network): [10373, 10531, 10566, 10606, 10630, 10656]
16
17 -----
18 SUBNETWORK CHECK
19 -----
20 CG suppliers (network_cg): [10025, 10040, 10116, 10143, 10204, 10349]
21 CS suppliers (network_cs): [10373, 10531, 10566, 10606, 10630, 10656]
22 KG suppliers (network_kg): [11018, 11043]

```

23 =====

Listing B.5: Network consistency verification code within switch_kg()

```

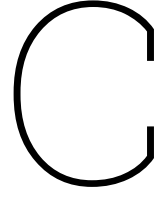
1
2 # retrieve the suppliers for all types from the full network
3
4 suppliers_list = p.capital_supplier_ids
5
6 producer_node = code_for(model.network, p_id)
7 network_neighbors = inneighbors(model.network, producer_node)
8
9 all_network_suppliers = label_for.(Ref(model.network), collect(network_neighbors))
10
11 kg_suppliers_network = filter(
12     s -> s in model.national_economy.all_kg,
13     all_network_suppliers
14 )
15
16 cg_suppliers_network = filter(
17     s -> s in model.national_economy.all_cg,
18     all_network_suppliers
19 )
20
21 cs_suppliers_network = filter(
22     s -> s in model.national_economy.all_cs,
23     all_network_suppliers
24 )
25
26 # check the consistency of the KG supplier list with the full network, if not consistent,
    return an error
27
28 if sort(suppliers_list) != sort(kg_suppliers_network)
29
30     mismatch = setdiff(kg_suppliers_network, suppliers_list)
31
32     println("\n[KG SUPPLIER MISMATCH]")
33     println("Producer: ", p_id)
34
35     println("\nMismatch (KG): ", mismatch)
36     println("\nModel supplier list: ", suppliers_list)
37     println("\nNetwork KG suppliers: ", kg_suppliers_network)
38
39     @assert 1 == 2
40 end
41
42 cs_suppliers_sub = get_cs_suppliers(p_id, model) # function to get the suppliers from the sub-
    network CS
43 cg_suppliers_sub = get_cg_suppliers(p_id, model) # function to get the suppliers from the sub-
    network CG
44
45 # check the consistency of the CS sub-network with the full network, if not consistent, return
    an error
46
47 if sort(cs_suppliers_network) != sort(cs_suppliers_sub)
48
49     mismatch = setdiff(cs_suppliers_network, cs_suppliers_sub)
50
51     println("\n[CS SUPPLIER MISMATCH]")
52     println("Producer: ", p_id)
53

```

```

54     println("\nMismatch (CS): ", mismatch)
55     println("\nNetwork CS suppliers: ", cs_suppliers_network)
56     println("\nSubnetwork CS suppliers: ", cs_suppliers_sub)
57
58     @assert 1 == 2
59 end
60
61 # check the consistency of the CG sub-network with the full network, if not consistent, return
    an error
62
63 if sort(cg_suppliers_network) != sort(cg_suppliers_sub)
64
65     mismatch = setdiff(cg_suppliers_network, cg_suppliers_sub)
66
67     println("\n[CG SUPPLIER MISMATCH]")
68     println("Producer: ", p_id)
69
70     println("\nMismatch (CG): ", mismatch)
71     println("\nNetwork CG suppliers: ", cg_suppliers_network)
72     println("\nSubnetwork CG suppliers: ", cg_suppliers_sub)
73
74     @assert 1 == 2
75 end
76
77 # check the consistency of the KG sub-network with the full network, if not consistent, return
    an error
78
79 kg_suppliers_network_sub = label_for.(Ref(model.network_kg), collect(inneighbors(model.
    network_kg, code_p_id)))
80
81 if sort(kg_suppliers_network) != sort(kg_suppliers_sub)
82
83     mismatch = setdiff(kg_suppliers_network, kg_suppliers_sub)
84
85     println("\n[KG SUPPLIER MISMATCH]")
86     println("Producer: ", p_id)
87
88     println("\nMismatch (KG): ", mismatch)
89     println("\nNetwork KG suppliers: ", kg_suppliers_network)
90     println("\nSubnetwork KG suppliers: ", kg_suppliers_sub)
91
92     @assert 1 == 2
93 end

```



Sensitivity analysis

This appendix presents the sensitivity analysis performed on EMERGO in order to evaluate how uncertainty in input parameters influences the main outcomes of the system. Because the model captures both economic dynamics and network formation processes, it is essential to understand which assumptions drive the observed behavior and to what extent the results are robust to variations in the parameters.

C.1. Selection of input parameters

The first step is the selection of relevant input parameters. This choice was guided by three considerations: (i) uncertainty in parameter estimation, (ii) structural assumptions embedded in the model, and (iii) expected influence on key system dynamics.

The following parameters were selected for analysis:

- $\phi_K^{desired}$
- $\phi_I^{desired}$
- $max_{cp}^{considered}$
- $min_{cp}^{considered}$
- $max_{kg}^{considered}$
- $min_{kg}^{considered}$
- $\gamma_{switch,p}^{price}$
- $\gamma_{switch,p}^{unmet}$

The parameter $\phi_I^{desired}$ was included because there is uncertainty regarding the appropriate level of inventory within the system. This parameter directly affects firms' ordering behavior and therefore has a strong influence on supplier relationships and the network structure. The parameter $\phi_K^{desired}$ serves the same purpose, but then for the kg inventory targeting. It is therefore included to capture potential asymmetries between intermediates and capital goods dynamics.

The supplier range parameters ($max_considered$ and $min_considered$ for both CG/CS and KG suppliers) were included because they are based on modeling assumptions. These parameters are the maximum and minimum KG or CG/CS suppliers considered for a firm and therefore directly influence the density of the supplier network. Varying them allows testing how sensitive network formation and supplier selection are to structural assumptions about market structure.

Finally, the switching parameters $\gamma_{switch,p}^{price}$ and $\gamma_{switch,p}^{unmet}$ were included because a simplifying assumption was made that switching behavior is identical across CG and CS suppliers on the one hand, and KG suppliers on the other hand. Testing these parameters allows evaluation of whether this assumption influences system outcomes.

C.2. Outcomes of interest

The sensitivity analysis focuses on outcomes that have been used throughout the research and are central to the study. These include indicators of economic dynamics as well as network metrics. These outcomes jointly capture both the economic and structural behavior of the model. The reason only the metrics for the full network are chosen is that it is assumed that when a model outcome is sensitive to a particular parameter in the full network, it is also sensitive in the sub-networks and vice versa.

- The total inventory
- The real GDP
- The network density for the full network
- The maximum eigenvector centrality for the full network
- The maximum degree centrality for the full network
- The network modularity for the full network
- The average clustering coefficient for the full network

C.3. Methodological approach: Morris approach

Given the computational complexity of the model, the Morris method was initially selected as a suitable global sensitivity analysis technique. According to Sczygiol and Dyja (2007), the Morris method is particularly appropriate for computationally expensive models, as it provides a small number of model samples.

Three choices need to be made for using Morris as SA, p , representing the number of levels for each input parameter, and the lower and upper bound for each input parameter and the number of samples. Petersen et al. (2019) discuss that a p of larger than four is appropriate. Moreover, it recommends starting with approximately 100 samples and gradually increasing the sample size until the results stabilize and no significant changes in sensitivity rankings are observed.

The choices for the upper and lower bounds have been made based on experience with the model and its constraints. For example, if the lower bound for $\min_{cp}^{considered}$ and $\min_{kg}^{considered}$ is set to 1 or lower, firms may end up with only a single supplier. This can lead to instability in the model, as it increases the sensitivity of firms, threatening to break the model. At the same time, setting the upper bound for $\max_{cp}^{considered}$ and $\max_{kg}^{considered}$ too high may result in an overly complex network structure, where firms are connected to a large number of suppliers. This increases computational complexity.

In addition, the lower and upper bounds for $\phi_K^{desired}$ and $\phi_I^{desired}$ have been chosen with the requirement in mind that sufficient inventory must be maintained for the model to function properly, particularly in the case of intermediate goods. If these values are too low, firms tend to understock, which can disrupt production flows, while excessively high values may lead to inefficient overstocking and break the dynamics of the system. The choices are listed below:

- p : 8, one for each parameter
- lowerbound: [0.1,0.1,5,3,4,2,0.1,0.1], following the order of the variables given above
- upperbound: [0.5,0.9,12,8,10,6,1.0,1.0], following the order of the variables given above
- *samples*: 100

Based on these choices, an initial Morris setup was implemented using the `GlobalSensitivity.jl` package in Julia. The implementation followed the standard Morris screening procedure, where trajectories are generated across the predefined parameter space, and effects are computed for each input variable.

C.4. Results of the Morris approach

During implementation, several limitations of the Morris method became apparent in the context of this model. First, the method was not well-suited for analyzing the supplier density parameters (`min_considered` and `max_considered` values). These parameters are discrete in nature, as they define integer-based

bounds for the number of suppliers. Morris, however, relies on small steps in continuous parameter spaces. As a result, sampled variations were rounded back to identical integer values, leading to effectively no change between the parameter values in samples. Therefore, analyzing the sensitivity of EMERGO for density was not well-suited for the Morris approach.

Second, the model exhibited extreme sensitivity to $\phi_I^{desired}$ and $\phi_K^{desired}$. Even small changes in these parameters led to structural breakdowns of the model. Initially, this resulted in firm bankruptcies, which then cascaded through the system, eventually leading to complete model collapse. This behavior persisted even when the parameter ranges were significantly reduced. These results suggest that the model is highly sensitive to inventory targets for intermediates and capital goods.

Since these parameters directly affect the inventory within the model, small changes can lead to two reasons for the model to break: excessive buying behavior of firms to accumulate inventory when the parameter is set too low, or insufficient buffering capacity when the parameter is set too high. The latter case appears particularly relevant for the CS and CG sectors, where baseline values (0.3) are relatively low in order to stimulate higher inventory buffers. This sensitivity indicates that the model may not yet be fully robust with respect to these behavioral parameters.

C.5. Alternative approach: PAWN method

In order to still include the supplier range parameters ($\min_considered$ and $\max_considered$ values for KG and CG/CS) in the sensitivity analysis, an alternative method was considered: the PAWN approach.

PAWN is a distribution-based sensitivity analysis method that uses the Kolmogorov–Smirnov statistic to compare the unconditional and conditional cumulative distribution functions of model outputs (Wang & Solomatine, 2019). This allows it to capture the influence of input parameters on output distributions.

An important advantage of PAWN is that it can handle discrete input variables, making it suitable for the supplier range parameters that could not be analyzed using Morris. In addition, PAWN requires fewer simulations, around 2000, than variance-based methods such as Sobol, which makes it computationally more efficient for expensive models. As shown by Parreira et al. (2024), PAWN achieves reliable sensitivity estimates at a lower number of samples than Sobol-based approaches.

For this PAWN method, the same output variables are used as mentioned before. As for the input parameters, only $\phi_K^{desired}$ and $\phi_I^{desired}$ are removed, leaving the analysis with the following parameters: $\max_{cp}^{considered}$, $\min_{cp}^{considered}$, $\max_{kg}^{considered}$, $\min_{kg}^{considered}$, $\gamma_{switch,p}^{price}$ and $\gamma_{switch,p}^{unmet}$. The lower and upperbound listed above still count for this parameters

To generate the samples and vary the input parameters, Latin Hypercube Sampling (LHS) is used, which is the same sampling technique used for the PAWN SA in the paper from Parreira et al. (2024). LHS is a stratified sampling technique in which the range of each input parameter is divided into N equally probable intervals, and exactly one sample is drawn from each interval per parameter (Iman, 2006). By combining these stratified marginal samples across dimensions, LHS achieves a large coverage of the input space compared to simple random sampling, despite requiring fewer samples.

However, this technique is only used to vary $\gamma_{switch,p}^{price}$ and $\gamma_{switch,p}^{unmet}$, as LHS is not usable for the discrete variables: $\max_{cp}^{considered}$, $\min_{cp}^{considered}$, $\max_{kg}^{considered}$ and $\min_{kg}^{considered}$. For these variables, a discrete stratified sampling procedure was used instead. Each discrete parameter's range was first enumerated as the full set of integer values it could take (see upper and lower bounds from before). This set was then repeated and randomly shuffled until it matched the required sample size of $N = 2000$. This approach ensures that each integer value within a parameter's range is represented approximately an equal number of times in the samples. This is better than relying on uniform random draws, which over-or under-sample values by chance.

An additional constraint was added to the parameters to preserve the logical structure=: for each firm, the minimum considered number of suppliers must be strictly smaller than the maximum considered number of suppliers. To enforce this, $\max_{cp}^{considered}$ and $\max_{kg}^{considered}$ were sampled first, after which $\min_{cp}^{considered}$ and $\min_{kg}^{considered}$ were sampled conditionally, with their upper bound capped at one less than the corresponding sampled maximum value for that same simulation run. This prevented the

generation of invalid parameter combinations (a minimum supplier range larger than the maximum) that would not correspond to a sensible rule.

For each of the N sampled parameter combinations, a single simulation run was executed with a fixed random seed ($seed = 42$), ensuring that differences in model output across runs could be attributed to the sampled input parameters rather than to stochastic variation between simulations. Each run simulated the $T = 700$ time steps, with the two flood shocks at $t = 300$ and $t = 500$. During each run, the outcomes, selected earlier, were collected and, after all simulations were done, merged into a single combined dataset, which served as the input for the PAWN sensitivity analysis.

The PAWN sensitivity analysis is then executed using $N = 2000$ samples across the six remaining parameters. For each of the seven outcomes, the time series of each output variable was first aggregated by taking the mean across all time steps. The full set of results, including the minimum, mean, median, maximum, and coefficient of variation of the KS statistic across the ten conditioning intervals, is then calculated. For this version, the sensitivity analysis is increased to 2000 compared to the 1000 runs earlier. However, the results do not show significantly different results to the 1000 runs earlier.

C.6. Results approach: PAWN method

The full set of results is reported in Table C.1. Figure C.1 visualizes the results from this table in a heatmap, using the mean of the KS statistics across the ten conditioning intervals as the PAWN sensitivity index for each parameter-outcome combination.

The results show a clear distinction between the supplier range parameters and the switching weight parameters. The switching weight parameters $\gamma_{switch,p}^{price}$ and $\gamma_{switch,p}^{unmet}$ exhibit consistently low mean KS values across all seven outcomes, ranging between 0.06 and 0.10. This indicates that, within the tested ranges, the model's economic and network outcomes are relatively insensitive to how fast firms want to switch to new suppliers based on unmet demand or competitiveness.

In contrast, the supplier range parameters show higher sensitivity. $max_{cp}^{considered}$ is shown to be the most influential parameter for the network structure outcomes. This is consistent with the expectation that the maximum number of CG/CS suppliers a firm considers directly constrains how densely and how unevenly connected the network can become, since it sets the upper bound on how many connections a firm can establish for CG and CS suppliers. Notably, this does not count towards the maximum KG suppliers a firm can have.

$min_{cp}^{considered}$ also shows a moderate effect on network density, which is logical considering it directly affects the density of the network and the average clustering coefficient. Although this effect is weaker than for the maximum value. This suggests that while the lower bound on the number of CG and CS suppliers plays a role in shaping the network structure, the upper bound is the more decisive constraint.

For the economic outcomes, the pattern differs. $min_{kg}^{considered}$ is dominant for real GDP, total inventory, and maximum degree centrality, while $max_{cp}^{considered}$ has little influence on these outcomes. This indicates that economic performance and the degree distribution of the network are governed primarily by the minimum number of KG suppliers a firm must have. This could be explained by the fact that this lower bound determines the redundancy available to firms when a KG supplier is lost following a flood shock, directly affecting their ability to replace damaged capital.

Overall, the heatmap in Figure C.1 reveals two groups of sensitive outcomes: the network structure metrics (network density, average clustering coefficient, maximum eigenvector centrality, network modularity) are primarily driven by $max_{cp}^{considered}$, while the economic and degree-based outcomes (real GDP, total inventory, maximum degree centrality) are primarily driven by $min_{kg}^{considered}$. The remaining parameters, $max_{kg}^{considered}$, $min_{cp}^{considered}$, and the two switching weights, do not play a significant role.

C.7. Robustness of the model

Taken together, these findings suggest that the model is selectively robust. On the one hand, the rewiring-related findings central to this study appear relatively trustworthy: the supplier range parameters ($max_{cp}^{considered}$, $min_{kg}^{considered}$) and the switching weight parameters show moderate KS values rather than values approaching 1 or signs of model breakdown. This indicates that small uncertain-

ties in these structural assumptions are unlikely to produce fundamentally different outcomes, which is reassuring given that SQ3 and SQ4 rely directly on these parameters.

However, the extreme sensitivity to utilization parameters $\phi_K^{desired}$ and $\phi_I^{desired}$ identified by attempts to execute the Morris method, together with the instability triggered by even a modest increase in the intermediate input coefficient ν , indicates that the model is not fully robust. It functions reliably only within a narrow parameter range that was chosen to preserve model stability, rather than being derived from empirical estimation.

The robustness of the model should therefore be understood as conditional rather than absolute. Provided that the utilization parameters and intermediate coefficient remain within their narrow range, the PAWN results suggest that the conclusions regarding network restructuring and resilience are relatively stable under variation of the remaining, rewiring-related parameters: number of supplier ranges and switching weights. From this, conditional robustness, the findings reported in this thesis are reasonably certain, while also emphasizing that the model's overall stability remains reliant on a small set of parameter choices that were not empirically grounded.

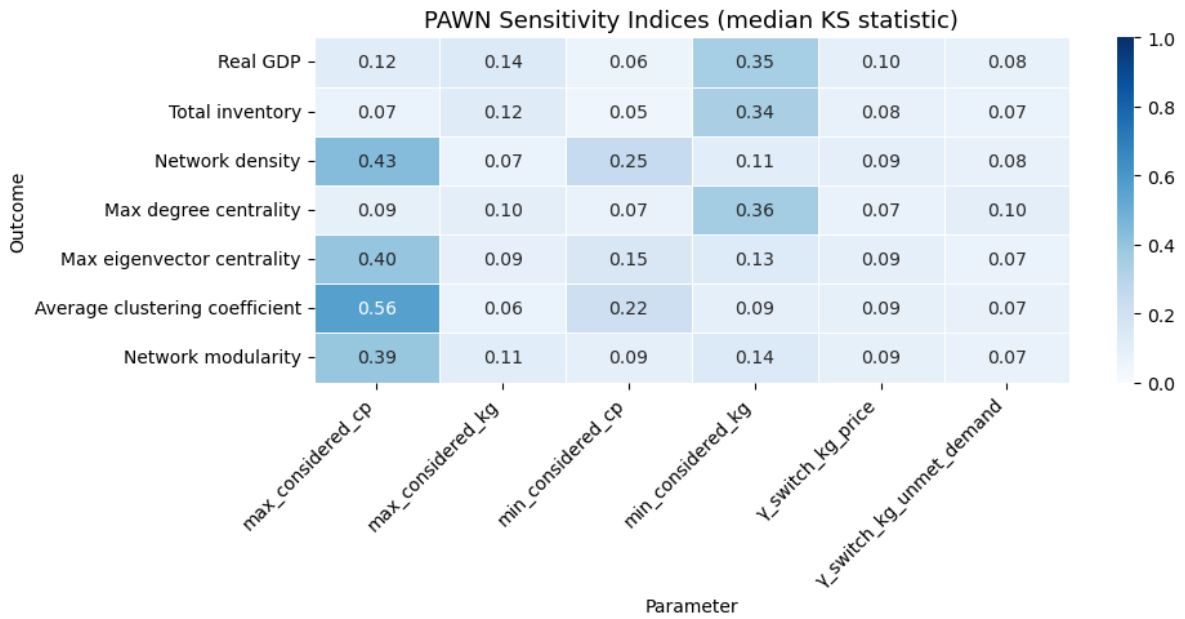


Figure C.1: PAWN sensitivity indices (median Kolmogorov–Smirnov statistic) for each model outcome and input parameter, where darker cells indicate greater influence of the parameter on the outcome's distribution

Table C.1: PAWN sensitivity indices (KS statistics) per outcome and parameter.

Outcome	Parameter	Min	Mean	Median	Max	CV
Real GDP	$max_{cp}^{considered}$	0.06	0.11	0.12	0.15	0.28
Real GDP	$min_{cp}^{considered}$	0.04	0.08	0.06	0.17	0.55
Real GDP	$max_{kg}^{considered}$	0.05	0.17	0.14	0.36	0.56
Real GDP	$min_{kg}^{considered}$	0.23	0.39	0.35	0.62	0.38
Real GDP	$\gamma_{switch,p}^{price}$	0.05	0.09	0.10	0.16	0.31
Real GDP	$\gamma_{switch,p}^{unmet}$	0.04	0.08	0.08	0.11	0.32
Total Inventory	$max_{cp}^{considered}$	0.05	0.08	0.07	0.16	0.42
Total Inventory	$min_{cp}^{considered}$	0.05	0.07	0.05	0.11	0.35
Total Inventory	$max_{kg}^{considered}$	0.09	0.15	0.12	0.32	0.50
Total Inventory	$min_{kg}^{considered}$	0.25	0.35	0.34	0.47	0.22
Total Inventory	$\gamma_{switch,p}^{price}$	0.04	0.07	0.08	0.11	0.29
Total Inventory	$\gamma_{switch,p}^{unmet}$	0.05	0.08	0.07	0.14	0.37

Outcome	Parameter	Min	Mean	Median	Max	CV
Network density	$max_{cp}^{considered}$	0.29	0.48	0.44	0.73	0.30
Network density	$min_{cp}^{considered}$	0.12	0.25	0.25	0.40	0.35
Network density	$max_{kg}^{considered}$	0.06	0.07	0.07	0.08	0.11
Network density	$min_{kg}^{considered}$	0.08	0.11	0.11	0.14	0.24
Network density	$\gamma_{switch,p}^{price}$	0.05	0.09	0.09	0.19	0.42
Network density	$\gamma_{switch,p}^{unmet}$	0.04	0.08	0.08	0.10	0.26
Max degree centrality	$max_{cp}^{considered}$	0.07	0.10	0.09	0.17	0.34
Max degree centrality	$min_{cp}^{considered}$	0.05	0.07	0.07	0.12	0.33
Max degree centrality	$max_{kg}^{considered}$	0.06	0.15	0.10	0.36	0.67
Max degree centrality	$min_{kg}^{considered}$	0.21	0.35	0.36	0.46	0.26
Max degree centrality	$\gamma_{switch,p}^{price}$	0.06	0.08	0.07	0.11	0.21
Max degree centrality	$\gamma_{switch,p}^{unmet}$	0.08	0.10	0.10	0.14	0.21
Max eigenvector centrality	$max_{cp}^{considered}$	0.26	0.43	0.40	0.66	0.29
Max eigenvector centrality	$min_{cp}^{considered}$	0.07	0.17	0.15	0.31	0.47
Max eigenvector centrality	$max_{kg}^{considered}$	0.06	0.10	0.09	0.19	0.44
Max eigenvector centrality	$min_{kg}^{considered}$	0.05	0.12	0.13	0.18	0.37
Max eigenvector centrality	$\gamma_{switch,p}^{price}$	0.05	0.09	0.09	0.14	0.26
Max eigenvector centrality	$\gamma_{switch,p}^{unmet}$	0.05	0.07	0.07	0.10	0.20
Avg clustering coefficient	$max_{cp}^{considered}$	0.42	0.60	0.57	0.81	0.22
Avg clustering coefficient	$min_{cp}^{considered}$	0.11	0.22	0.22	0.36	0.38
Avg clustering coefficient	$max_{kg}^{considered}$	0.05	0.06	0.06	0.07	0.09
Avg clustering coefficient	$min_{kg}^{considered}$	0.08	0.09	0.09	0.11	0.15
Avg clustering coefficient	$\gamma_{switch,p}^{price}$	0.05	0.09	0.09	0.17	0.35
Avg clustering coefficient	$\gamma_{switch,p}^{unmet}$	0.05	0.08	0.07	0.11	0.22
Network modularity	$max_{cp}^{considered}$	0.19	0.41	0.39	0.73	0.40
Network modularity	$min_{cp}^{considered}$	0.07	0.13	0.09	0.23	0.47
Network modularity	$max_{kg}^{considered}$	0.08	0.12	0.11	0.19	0.31
Network modularity	$min_{kg}^{considered}$	0.08	0.14	0.14	0.20	0.32
Network modularity	$\gamma_{switch,p}^{price}$	0.05	0.09	0.09	0.12	0.27
Network modularity	$\gamma_{switch,p}^{unmet}$	0.06	0.08	0.07	0.11	0.20

D

Network metrics plots

This appendix presents the figures for each network metric across all experiments.

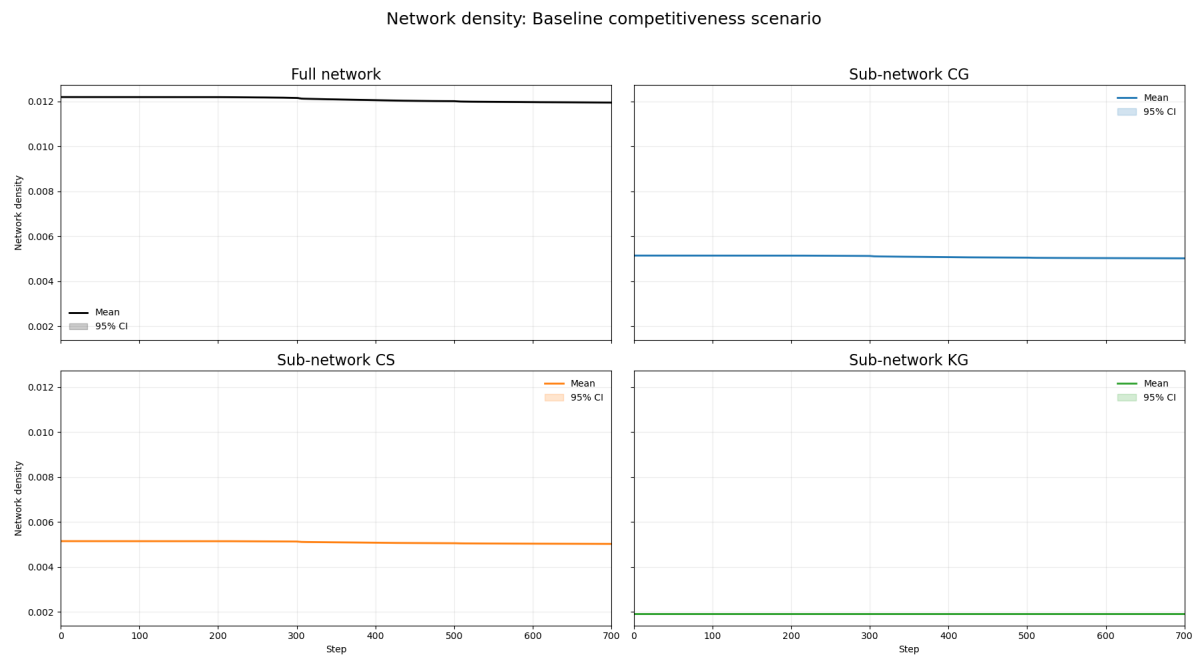


Figure D.1: The evolution of the network density in the baseline competitiveness scenario for all network types

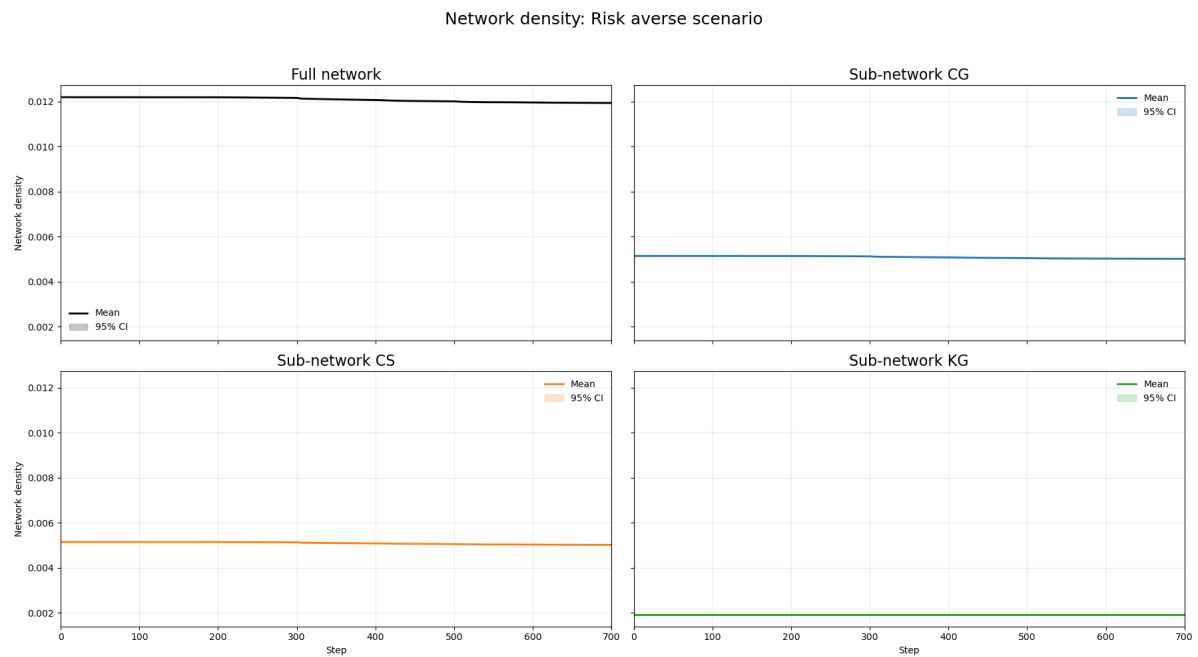


Figure D.2: The evolution of the network density in the risk-averse scenario for all network types

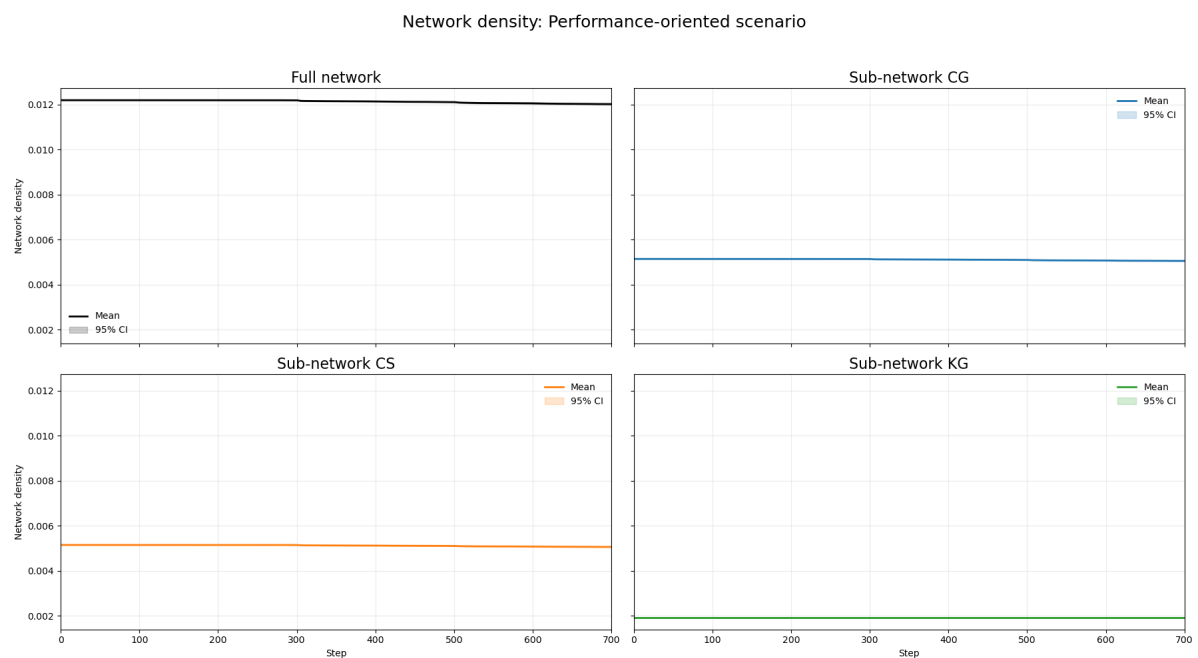
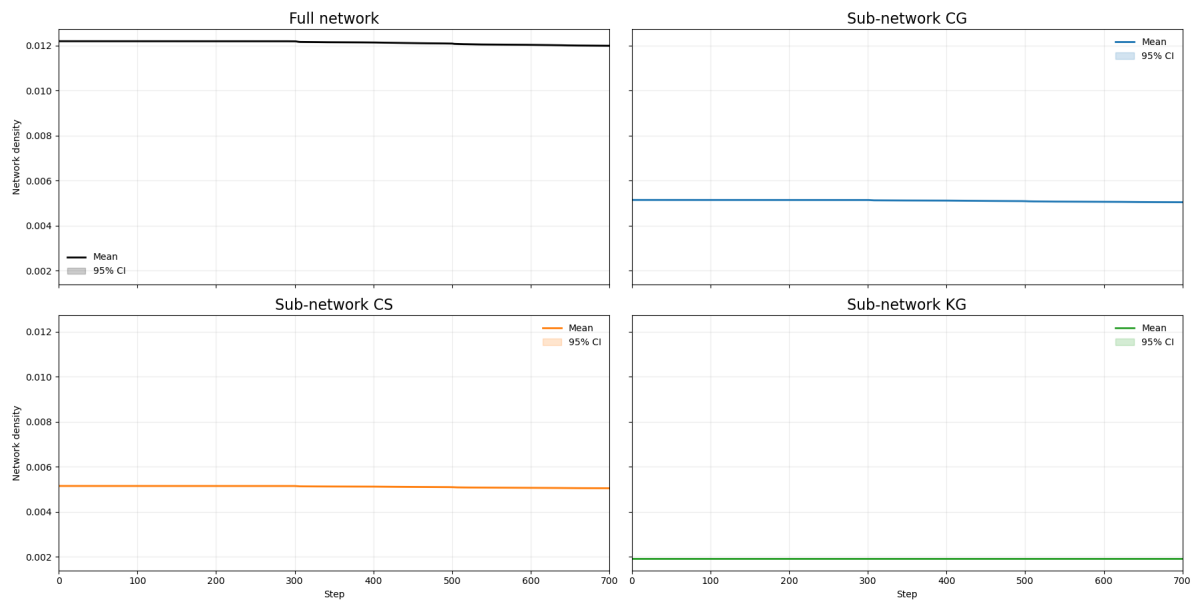
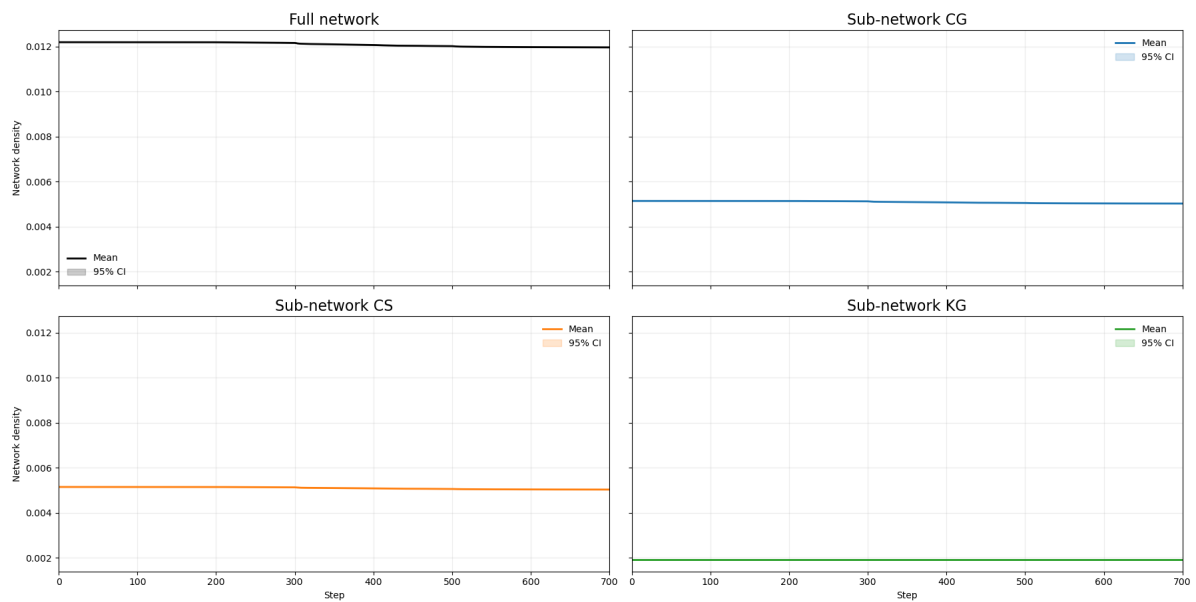


Figure D.3: The evolution of the network density in the performance-oriented scenario for all network types

Network density: Strategic selection scenario

**Figure D.4:** The evolution of the network density in the strategic selection scenario for all network types

Network density: Performance-risk trade-off scenario

**Figure D.5:** The evolution of the network density in the performance-risk trade-off scenario for all network types

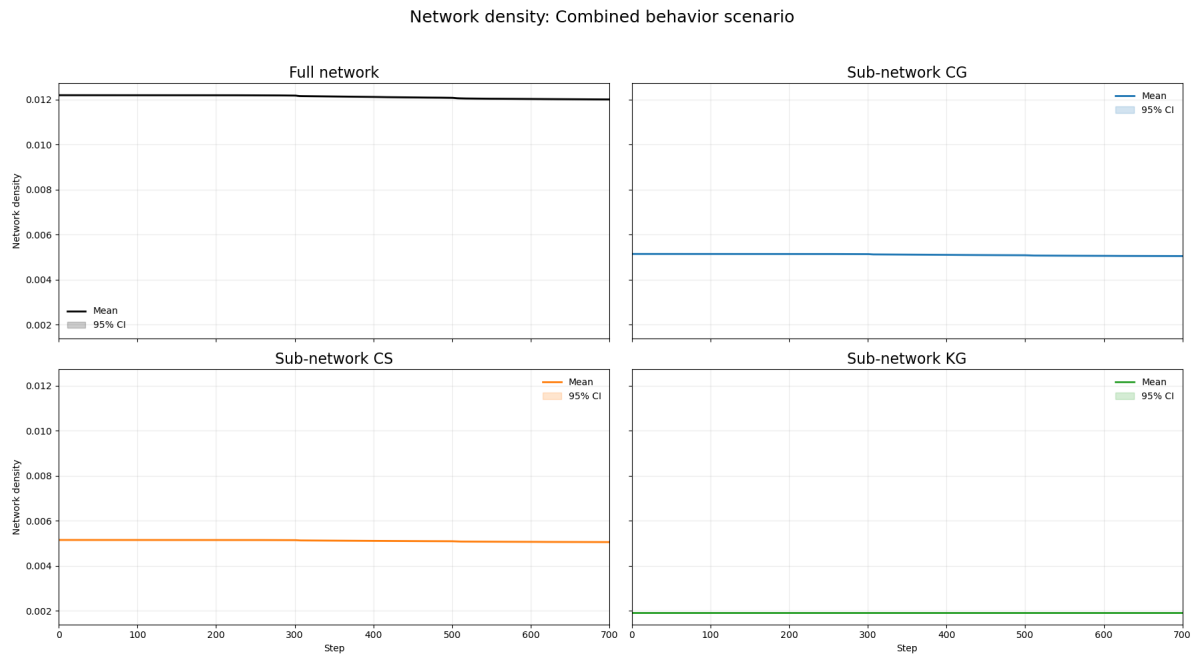


Figure D.6: The evolution of the network density in the combined behavior scenario for all network types

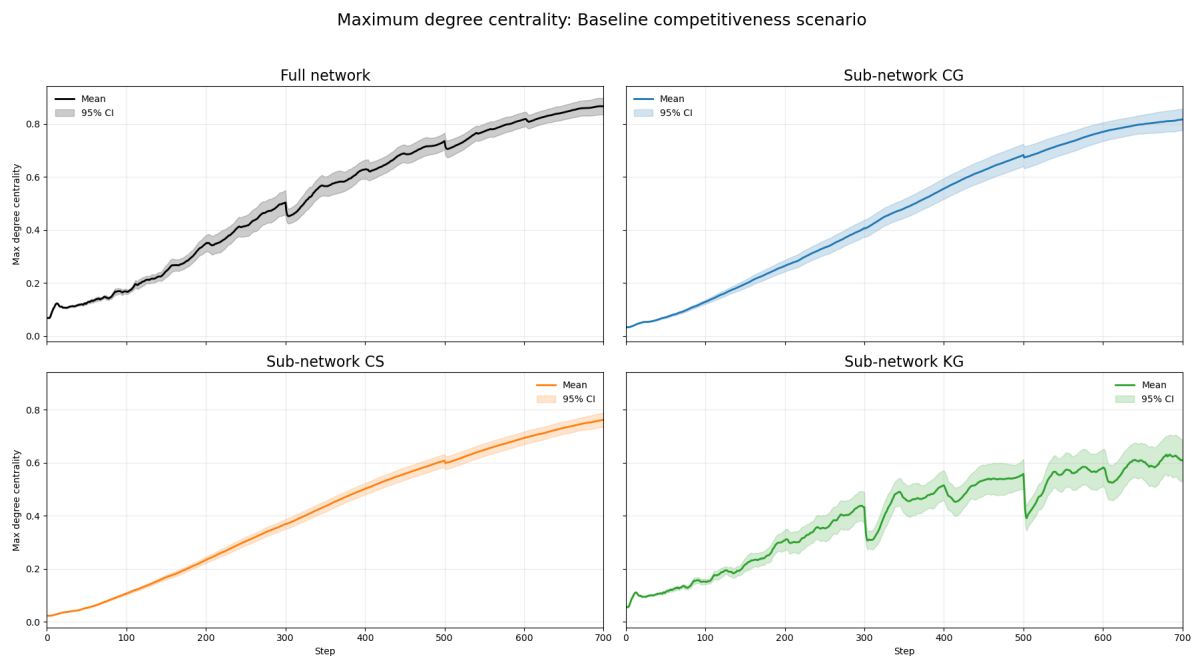
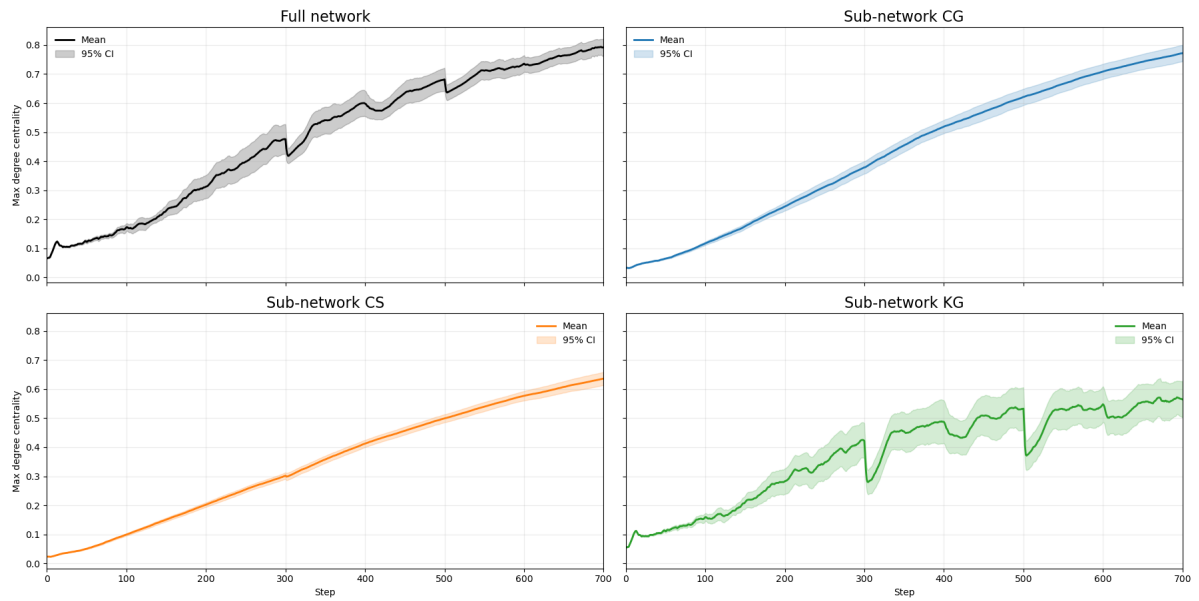


Figure D.7: The evolution of the maximum degree centrality in the baseline competitiveness scenario for all network types

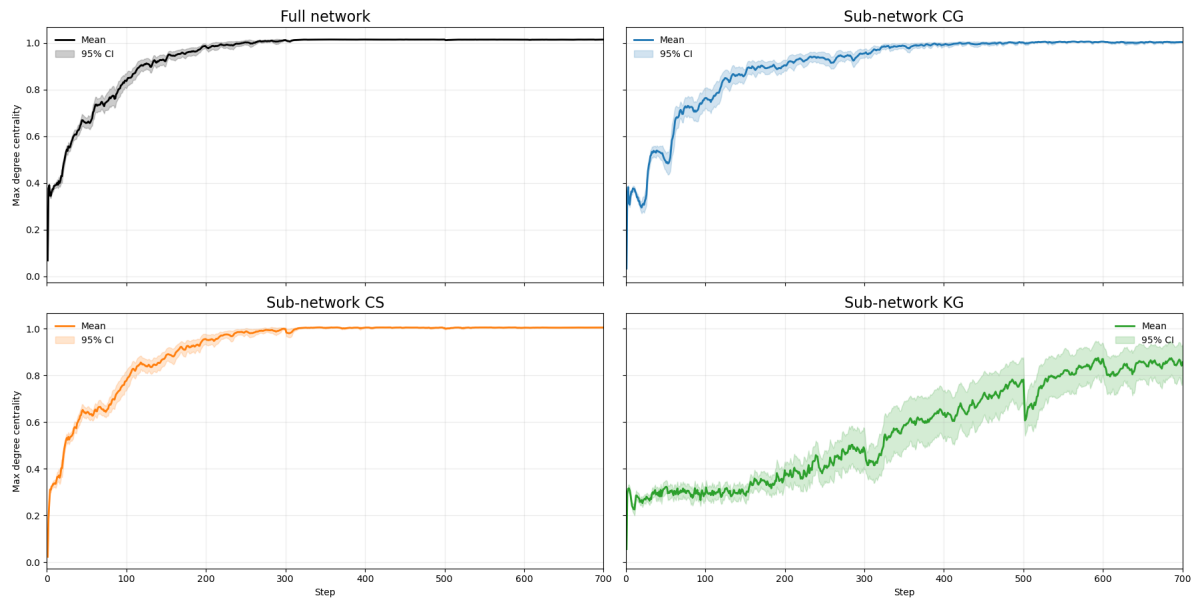
Maximum degree centrality: Risk averse scenario

**Figure D.8:** The evolution of the maximum degree centrality in the risk-averse scenario for all network types

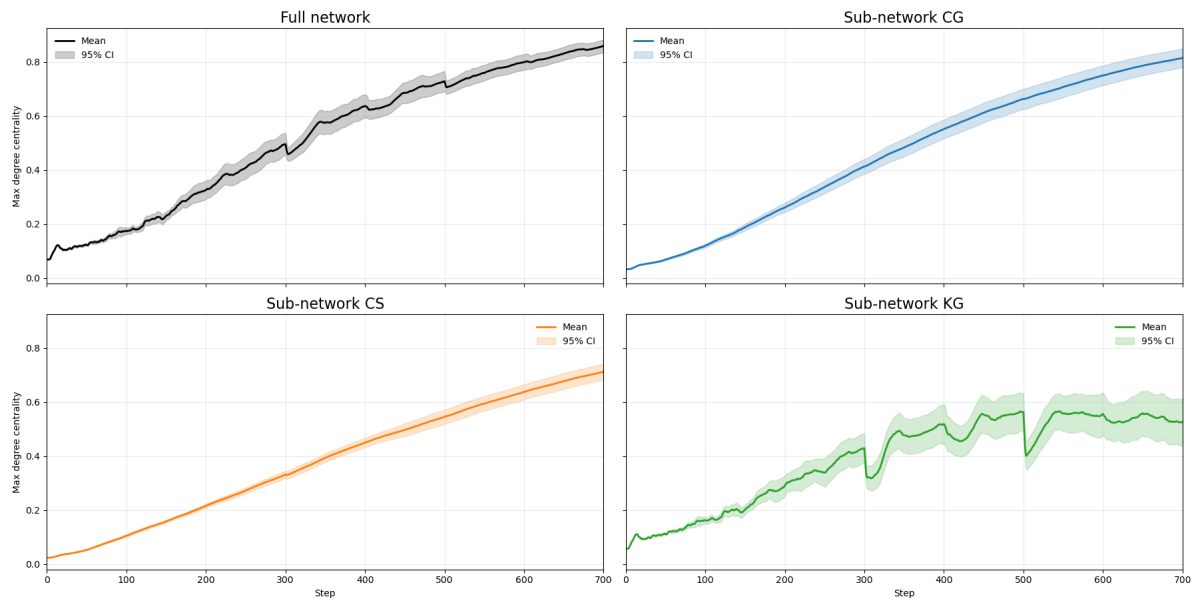
Maximum degree centrality: Performance-oriented scenario

**Figure D.9:** The evolution of the maximum degree centrality in the performance-oriented scenario for all network types

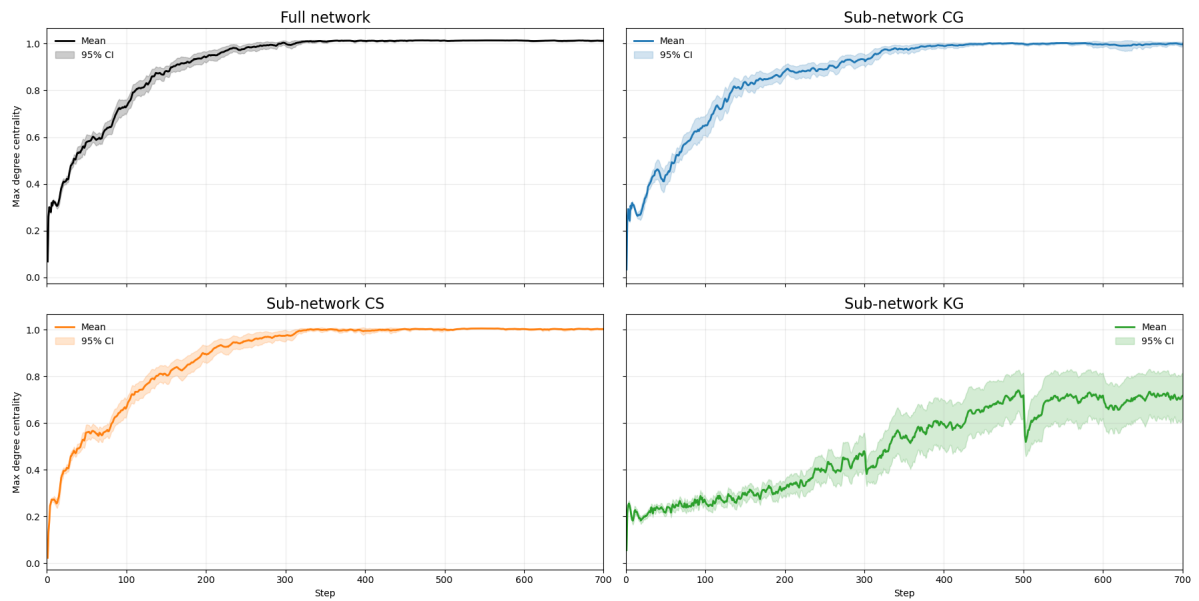
Maximum degree centrality: Strategic selection scenario

**Figure D.10:** The evolution of the maximum degree centrality in the strategic selection scenario for all network types

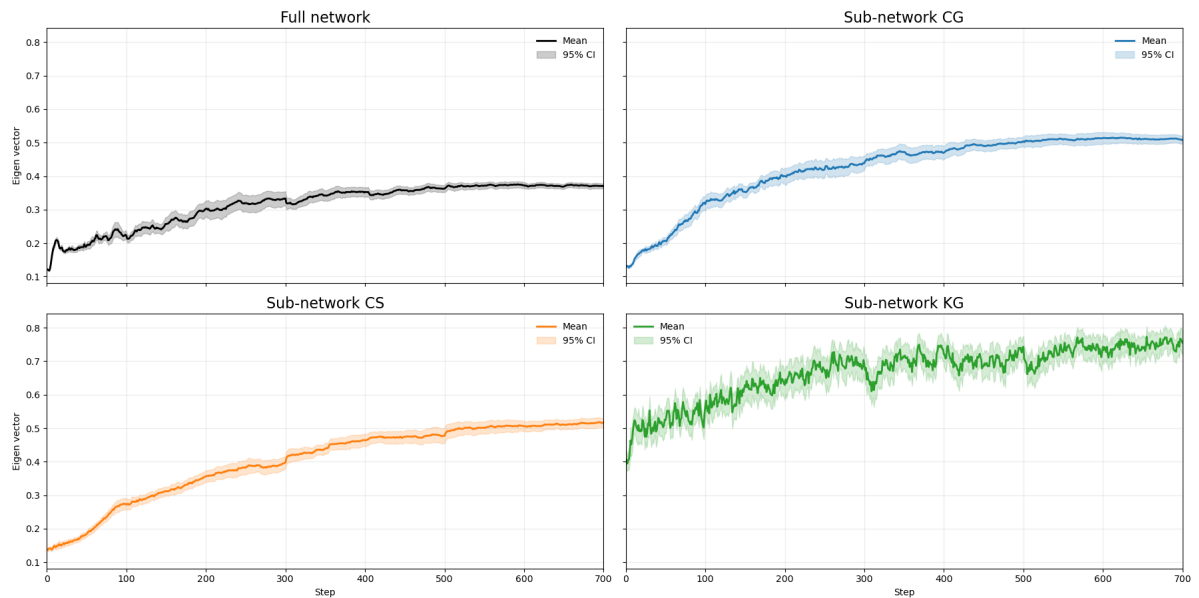
Maximum degree centrality: Performance-risk trade-off scenario

**Figure D.11:** The evolution of the maximum degree centrality in the performance-risk trade-off scenario for all network types

Maximum degree centrality: Combined behavior scenario

**Figure D.12:** The evolution of the maximum degree centrality in the combined behavior scenario for all network types

Maximum eigenvector centrality: Baseline competitiveness scenario

**Figure D.13:** The evolution of the maximum eigenvector centrality in the baseline competitiveness scenario for all network types

Maximum eigenvector centrality: Risk averse scenario

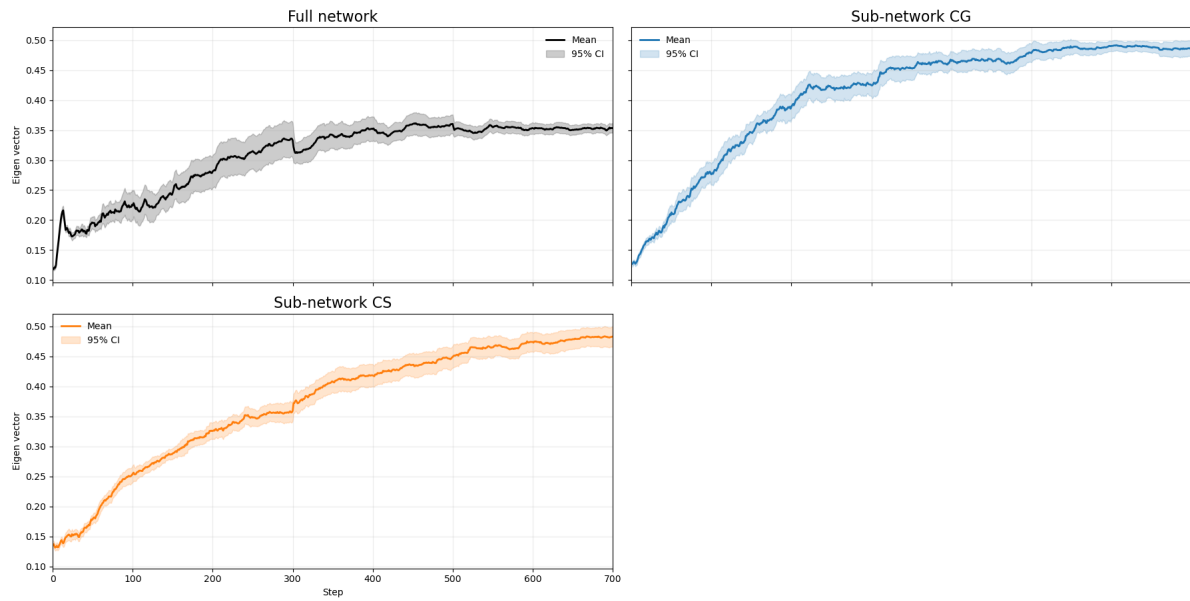


Figure D.14: The evolution of the maximum eigenvector centrality in the risk-averse scenario for all network types

Maximum eigenvector centrality: Performance-oriented scenario

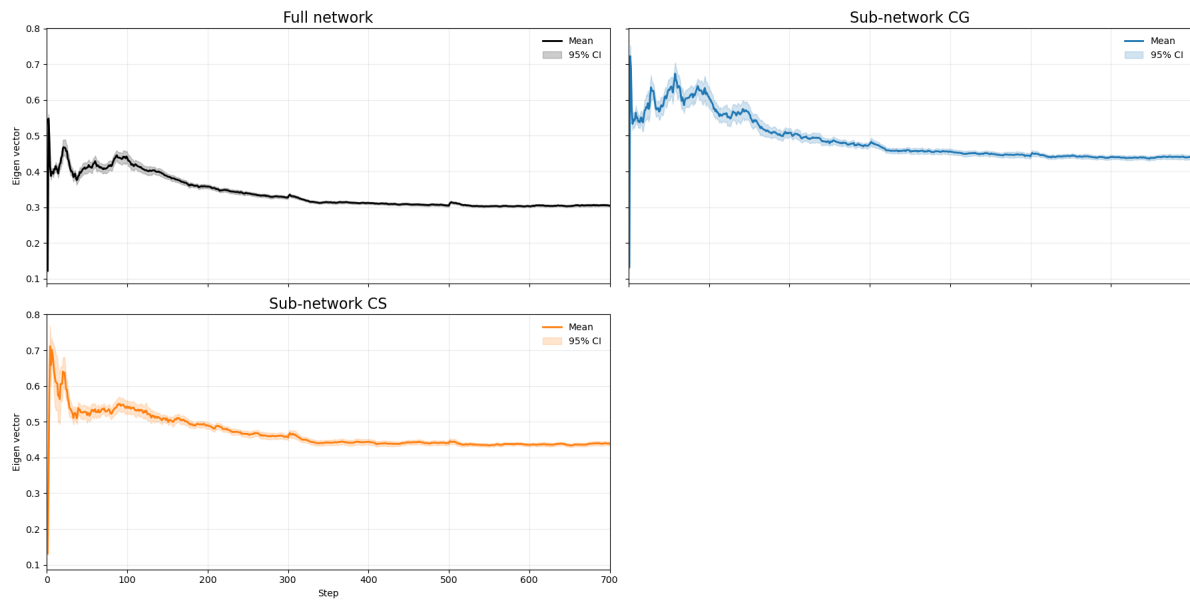


Figure D.15: The evolution of the maximum eigenvector centrality in the performance-oriented scenario for all network types

Maximum eigenvector centrality: Strategic selection scenario

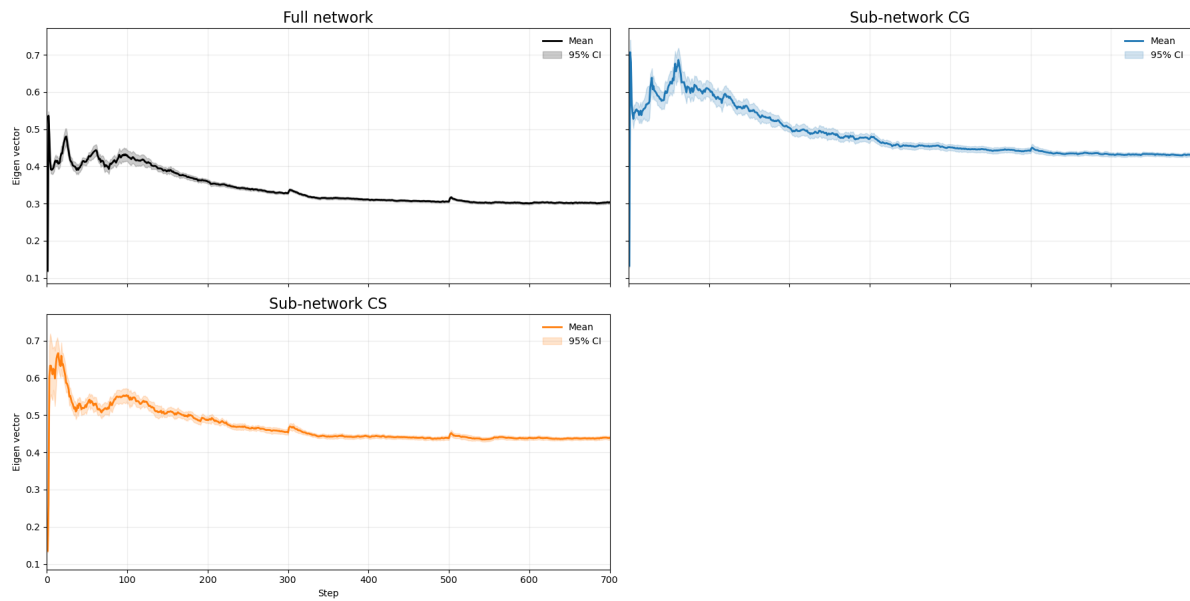


Figure D.16: The evolution of the maximum eigenvector centrality in the strategic selection scenario for all network types

Maximum eigenvector centrality: Performance-risk trade-off scenario

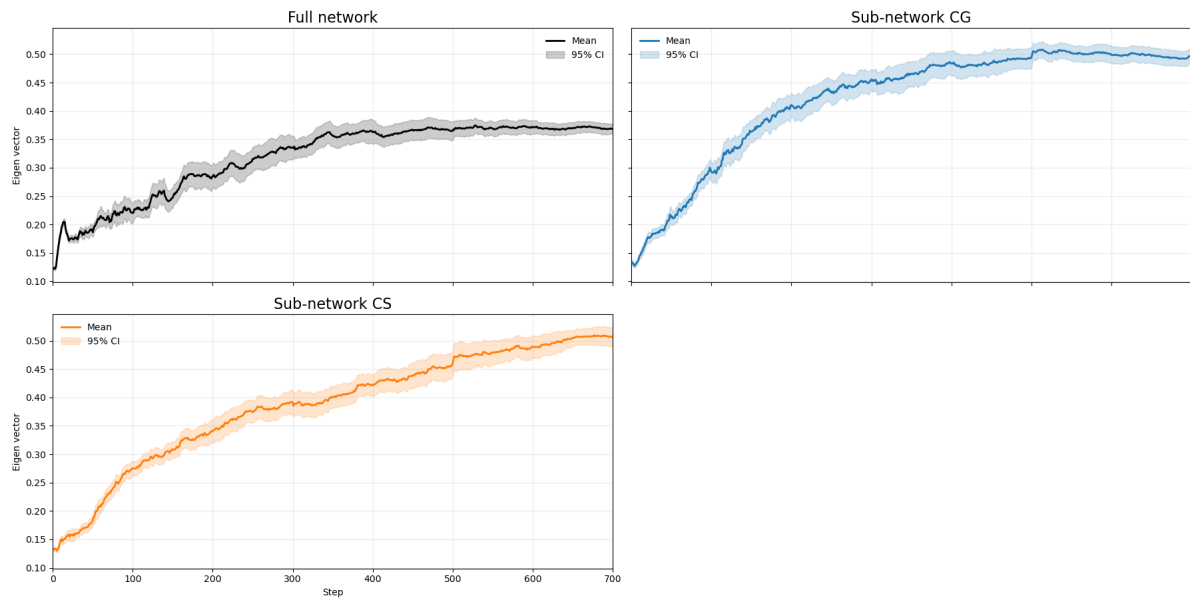


Figure D.17: The evolution of the maximum eigenvector centrality in the performance-risk trade-off scenario for all network types

Maximum eigenvector centrality: Combined behavior scenario

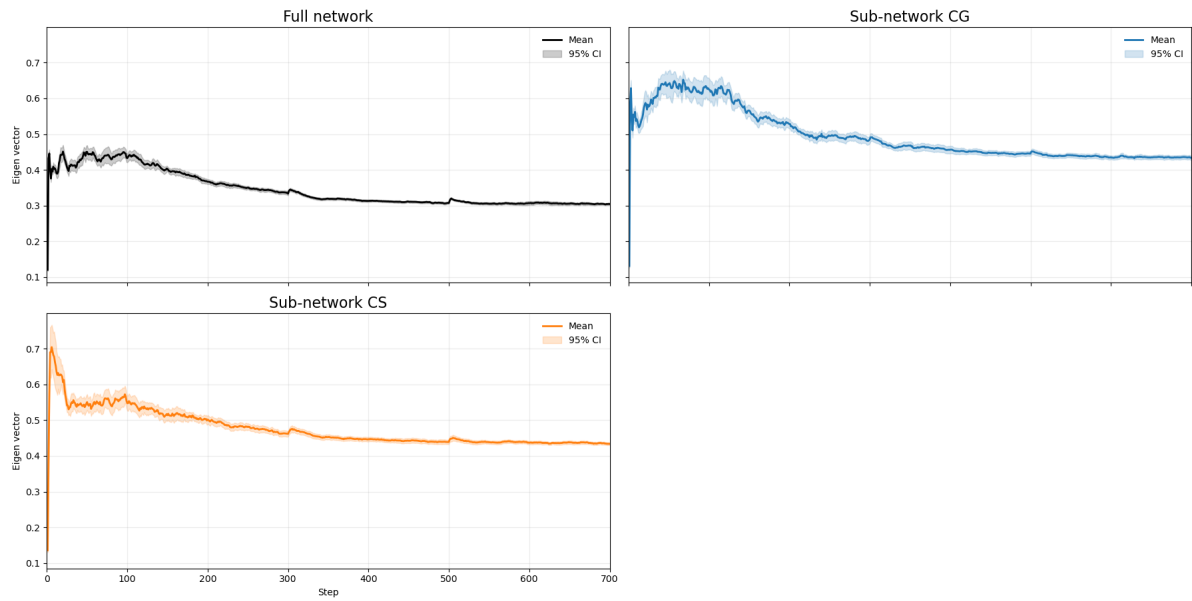


Figure D.18: The evolution of the maximum eigenvector centrality in the combined behavior scenario for all network types

Network modularity: Baseline competitiveness scenario

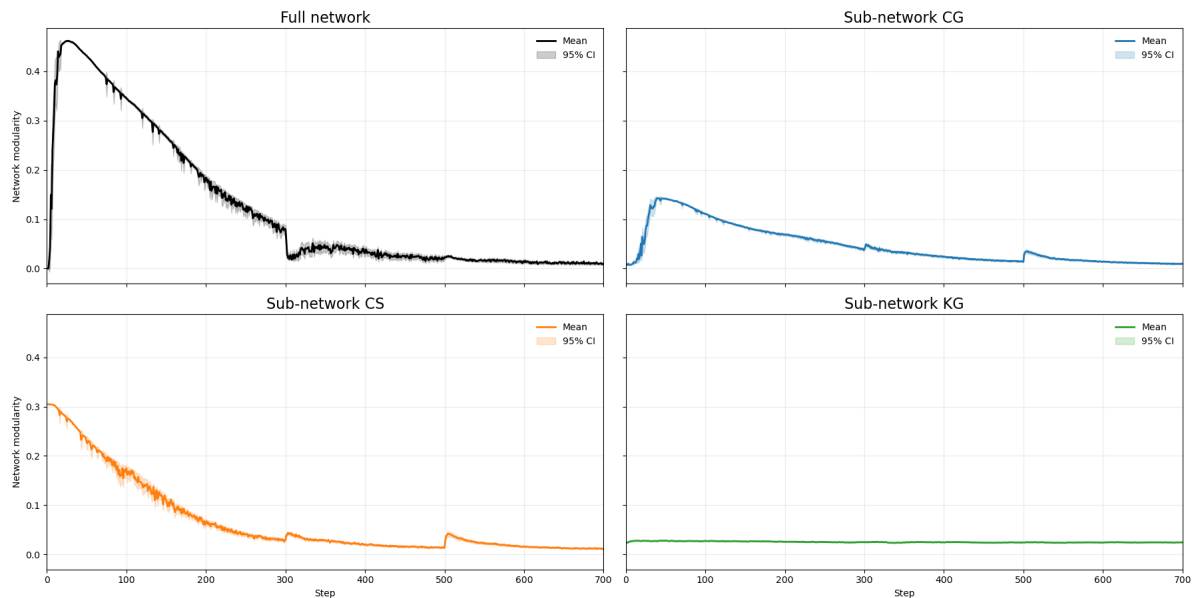
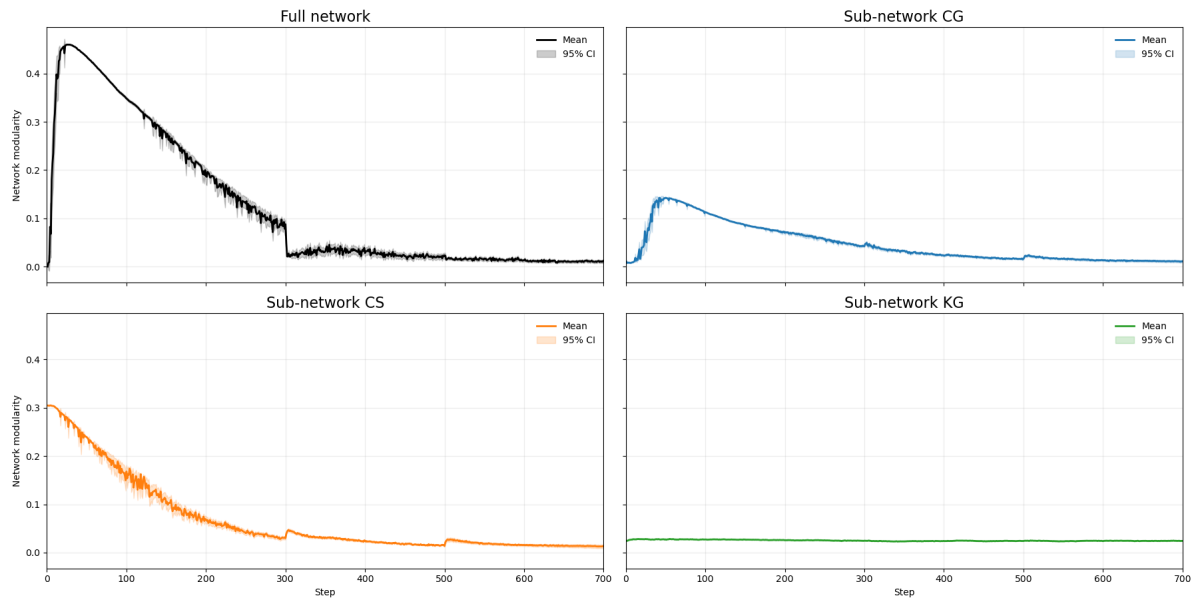
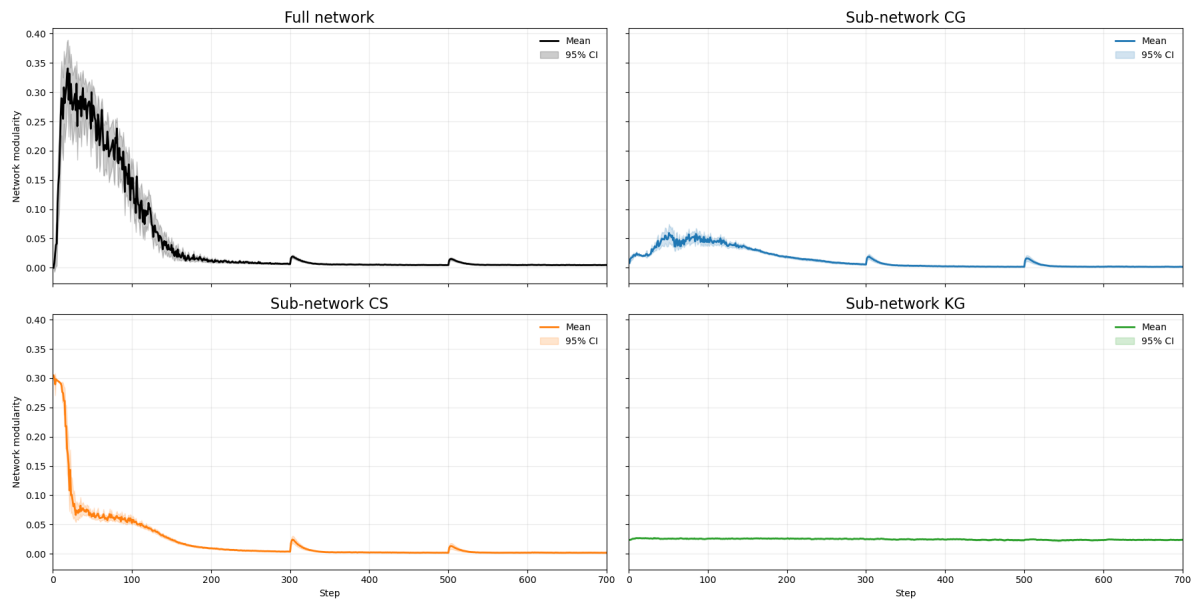


Figure D.19: The evolution of the network modularity in the baseline competitiveness scenario for all network types

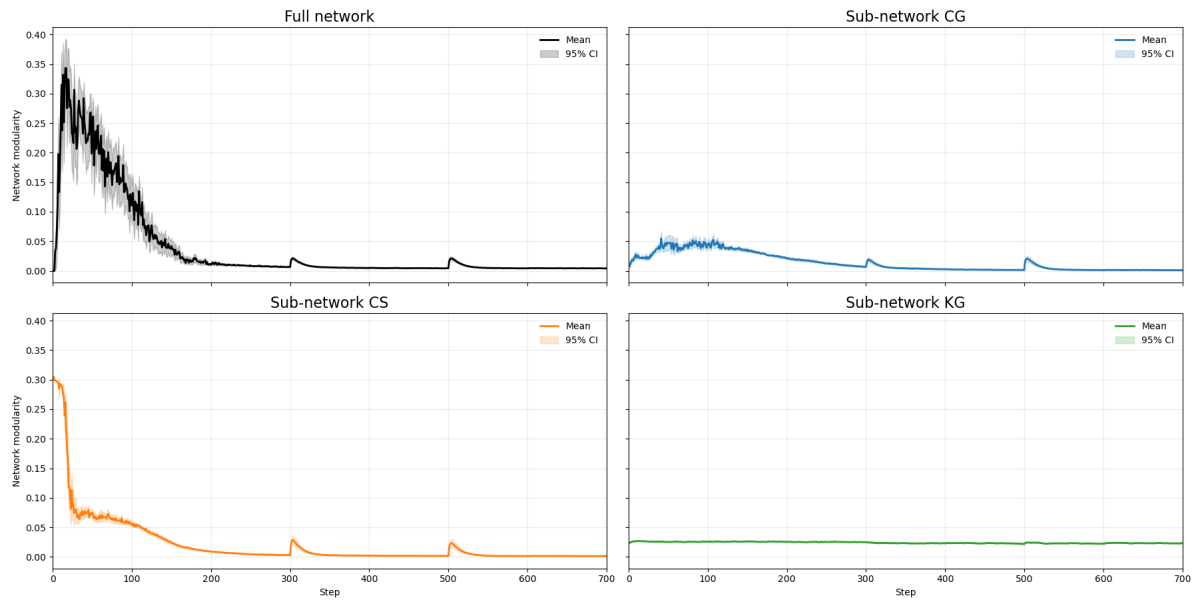
Network modularity: Risk averse scenario

**Figure D.20:** The evolution of the network modularity in the risk-averse scenario for all network types

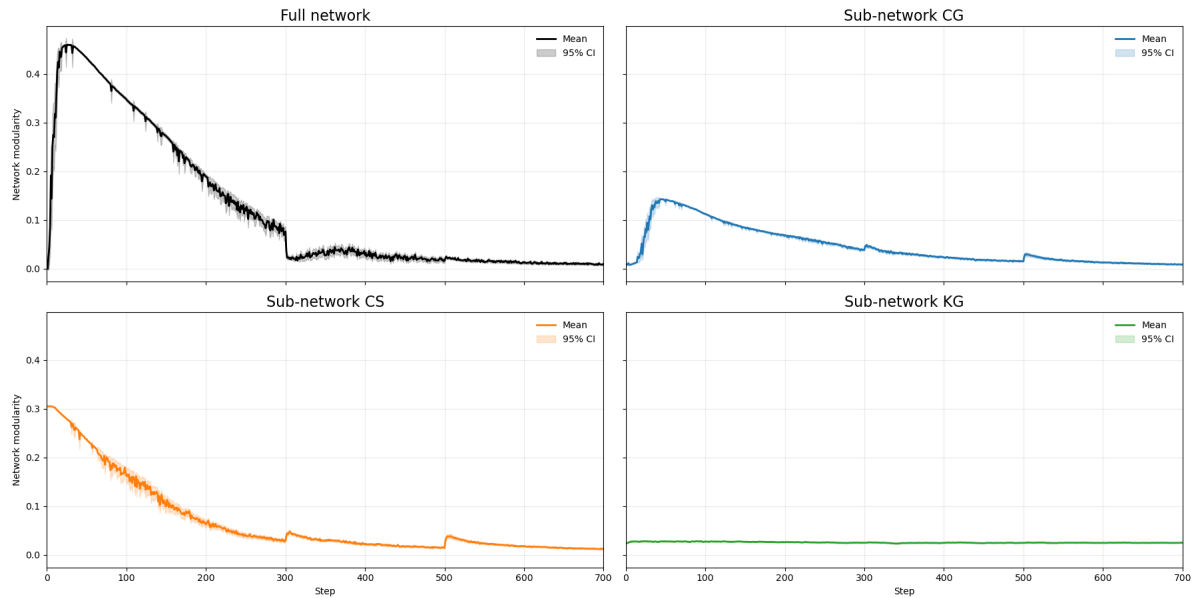
Network modularity: Performance-oriented scenario

**Figure D.21:** The evolution of the network modularity in the performance-oriented scenario for all network types

Network modularity: Strategic selection scenario

**Figure D.22:** The evolution of the network modularity in the strategic selection scenario for all network types

Network modularity: Performance-risk trade-off scenario

**Figure D.23:** The evolution of the network modularity in the performance-risk trade-off scenario for all network types

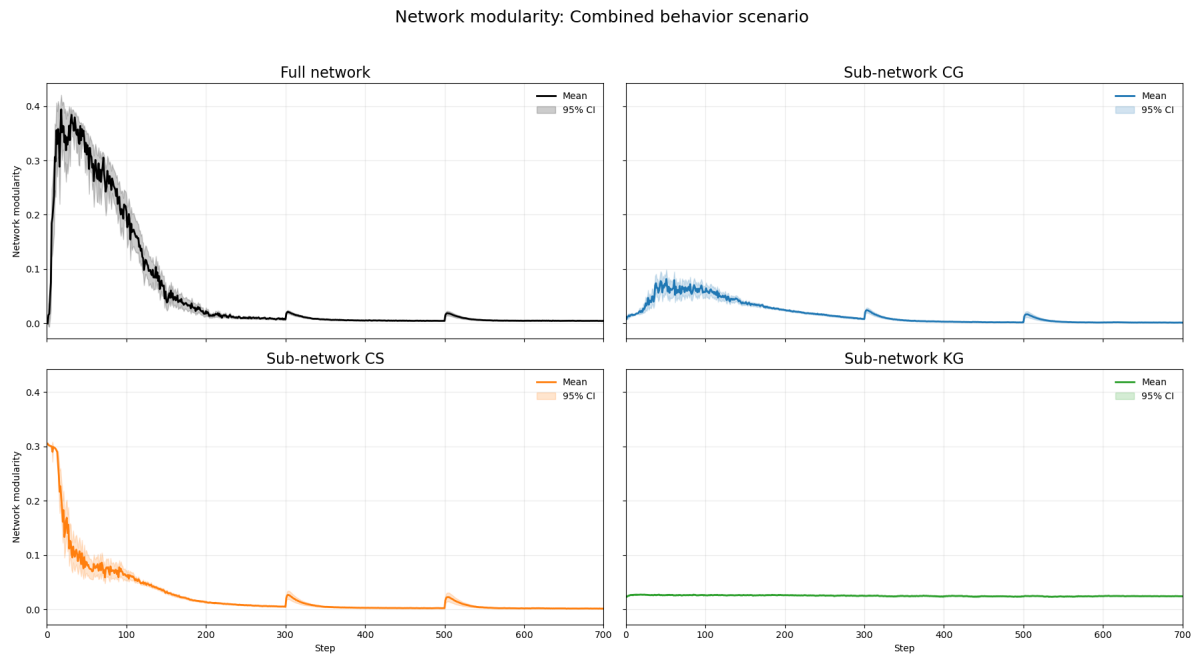


Figure D.24: The evolution of the network modularity in the combined behavior scenario for all network types

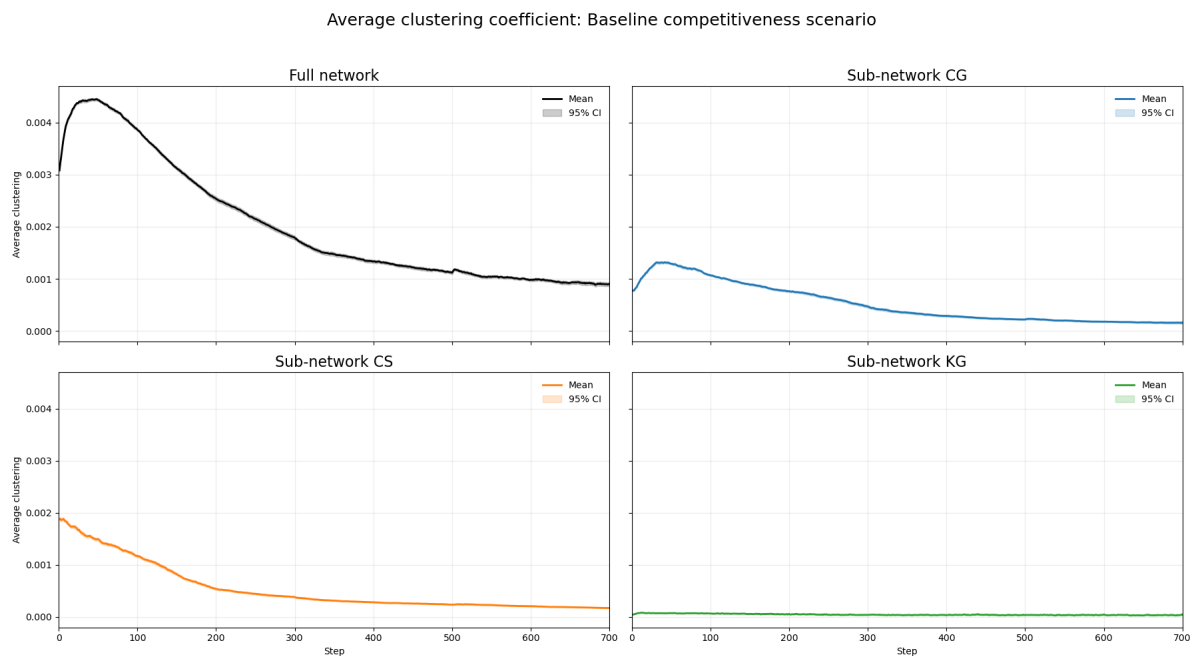
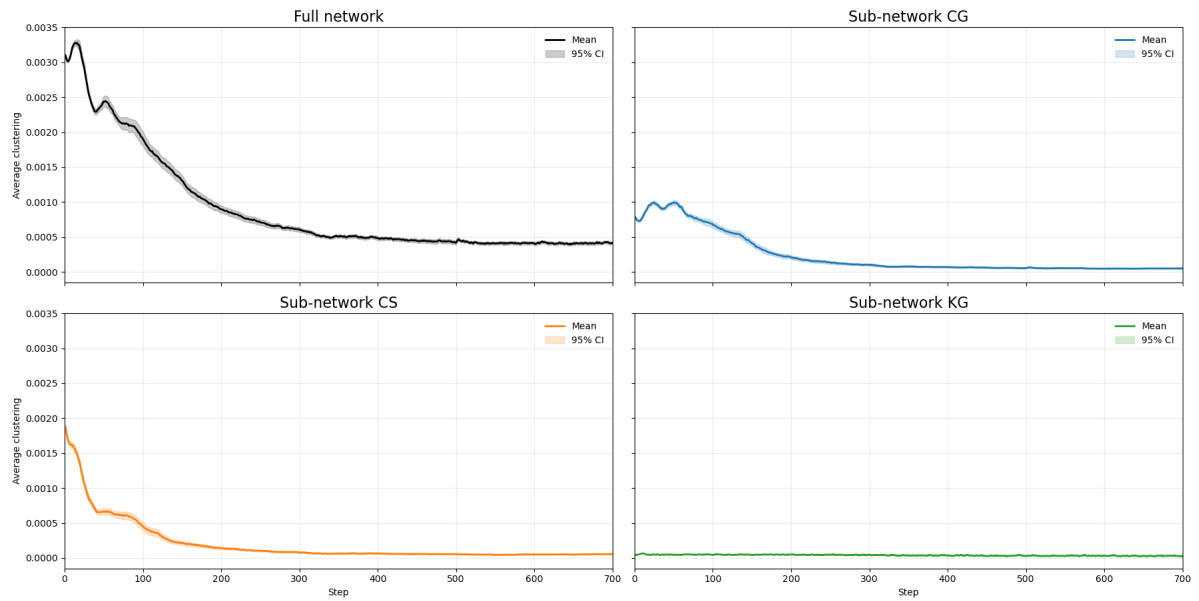
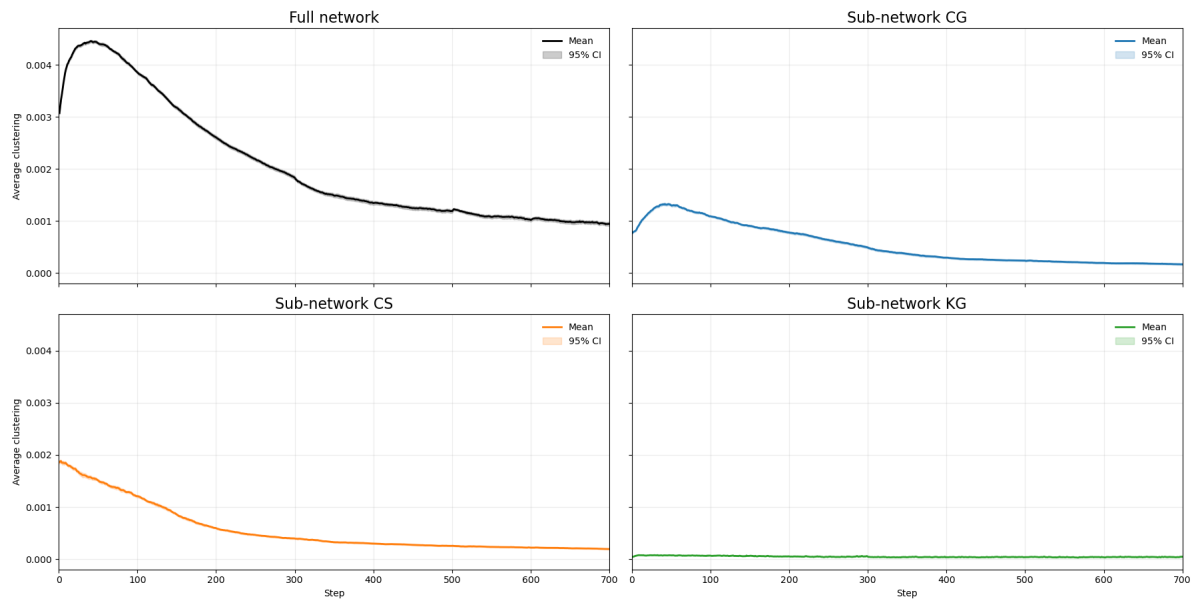


Figure D.25: The evolution of the average clustering coefficient in the baseline competitiveness scenario for all network types

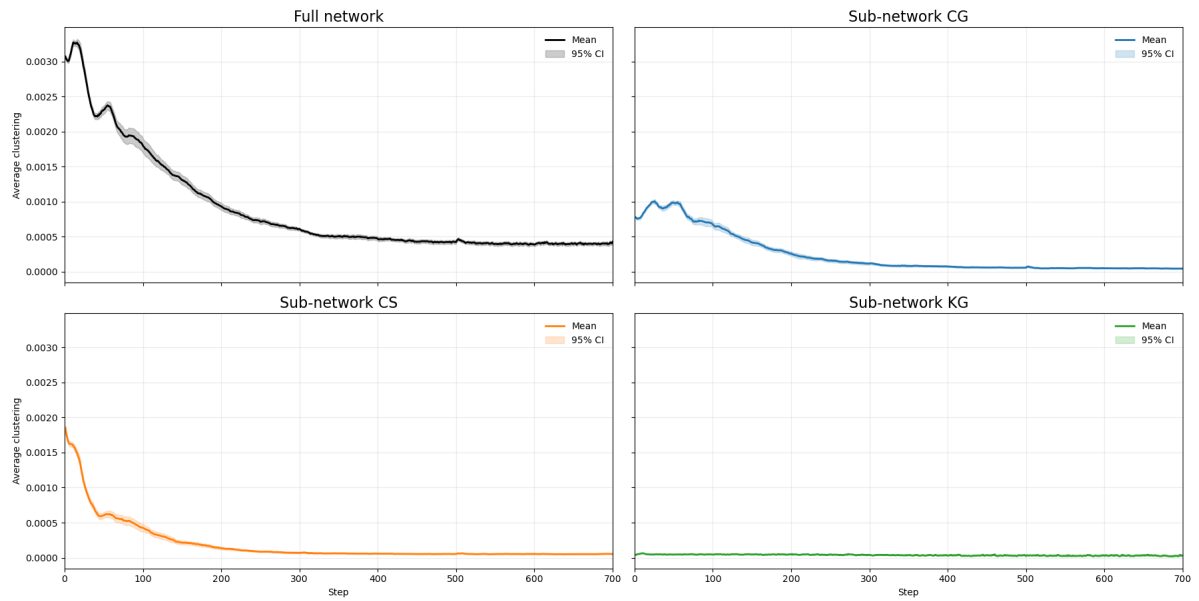
Average clustering coefficient: Performance-oriented scenario

**Figure D.26:** The evolution of the average clustering coefficient in the performance-oriented scenario for all network types

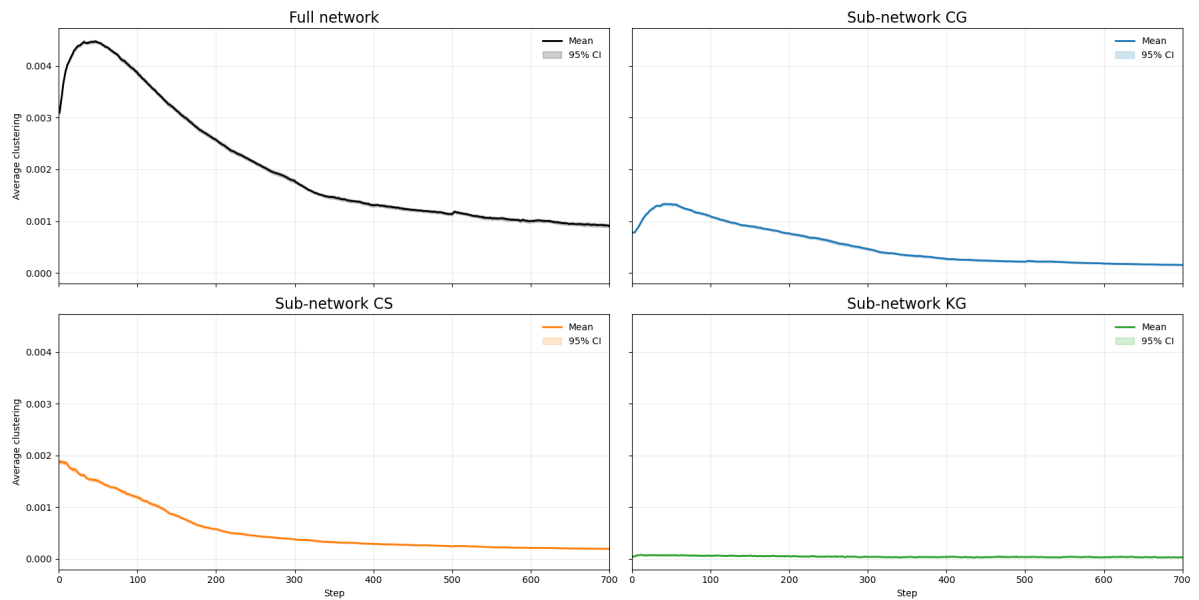
Average clustering coefficient: Risk averse scenario

**Figure D.27:** The evolution of the average clustering coefficient in the risk-averse scenario for all network types

Average clustering coefficient: Strategic selection scenario

**Figure D.28:** The evolution of the average clustering coefficient in the strategic selection scenario for all network types

Average clustering coefficient: Performance-risk trade-off scenario

**Figure D.29:** The evolution of the average clustering coefficient in the performance-risk trade-off scenario for all network types

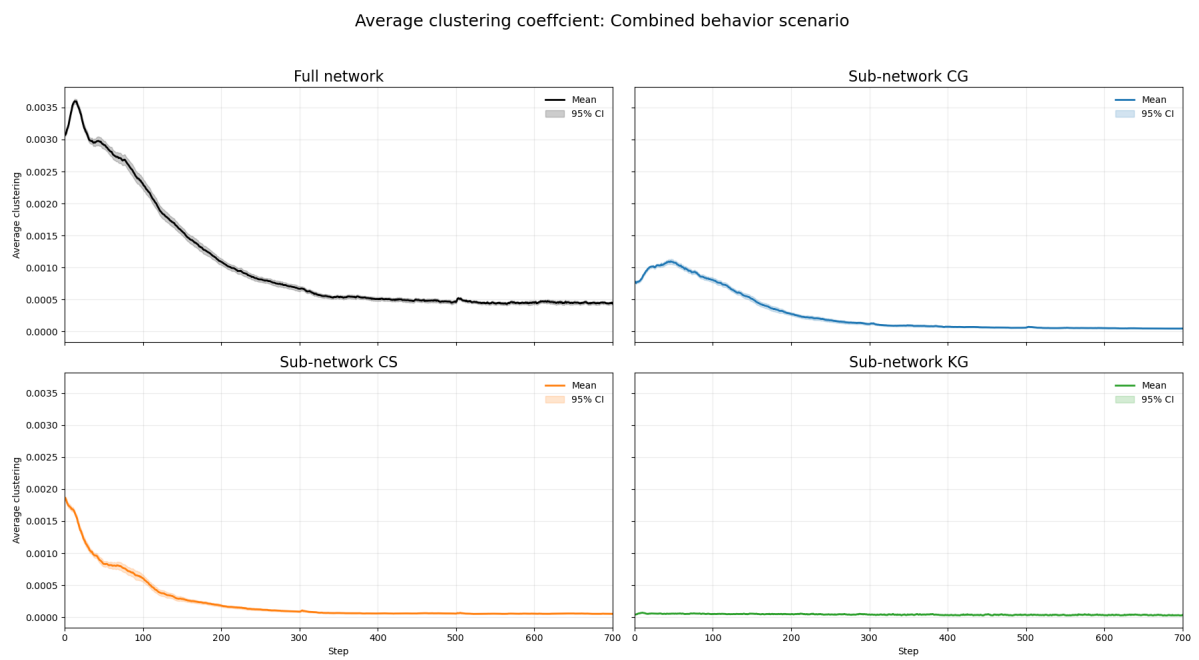


Figure D.30: The evolution of the average clustering coefficient in the combined behavior scenario for all network types

Resilience analysis data

This appendix presents the data used to execute the resilience analysis. It shows the aggregate inventory plots for each network type across all scenarios. These plots serve as resilience curves from which resilience metrics are derived. Moreover, the code of the function that calculates and returns the resilience metrics is presented as well as the table with the resilience metrics results.

E.1. Resilience curve

It should be noted that in the figures, the Total, CG, and CS inventories share the same y-axis to facilitate comparison. However, the scale for the KG inventory has been adjusted, as inventory levels in this market are considerably lower. Without this adjustment, the KG results would not be clearly visible.

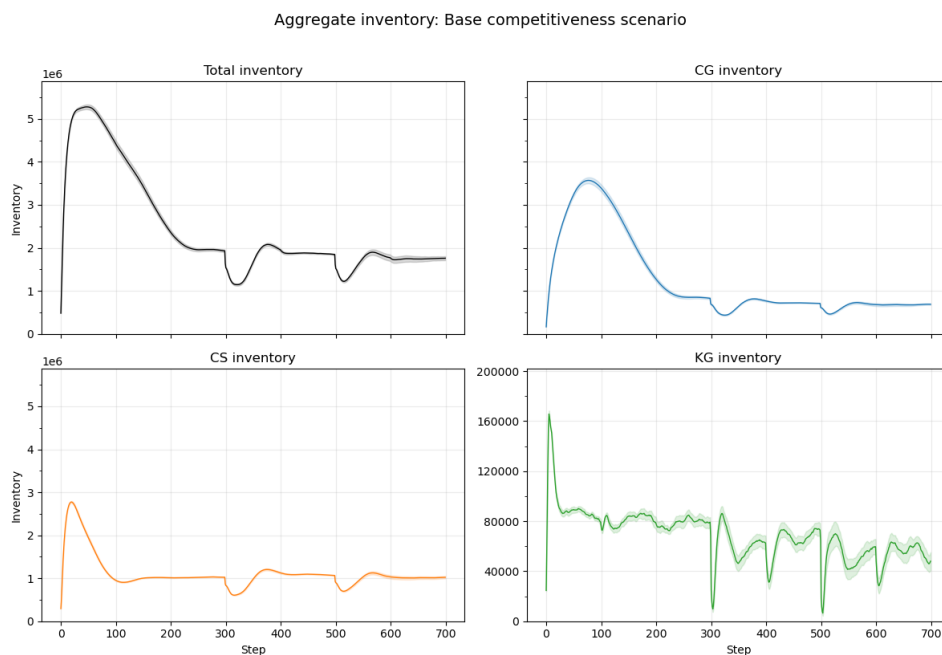


Figure E.1: The evolution of the total inventory within the economy as well as the inventories for each unit type, which is used as a resilience curve for the Baseline competitiveness scenario

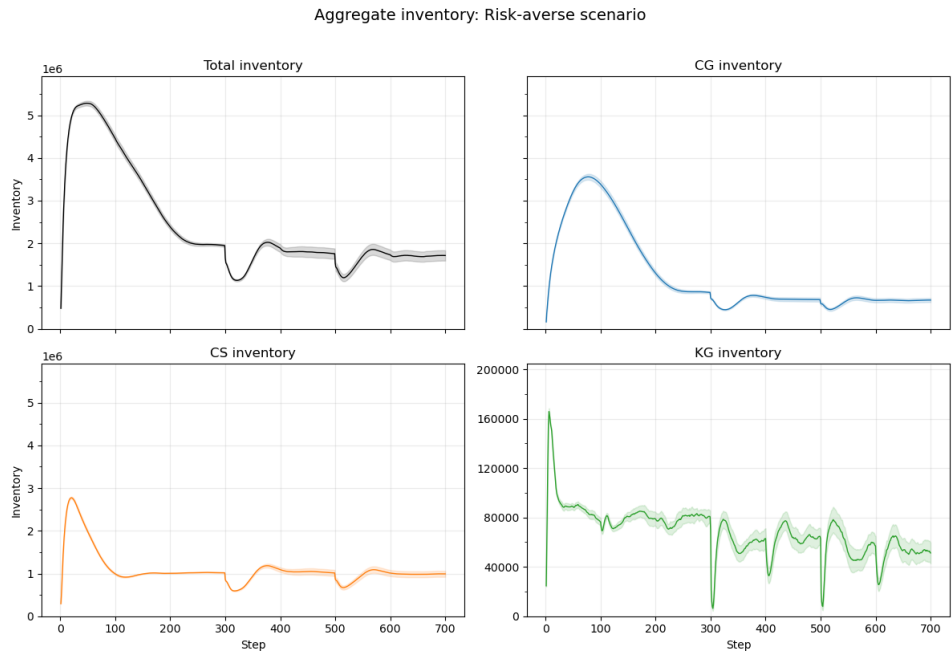


Figure E.2: The evolution of the total inventory within the economy as well as the inventories for each unit type, which is used as a resilience curve for the Risk-averse scenario

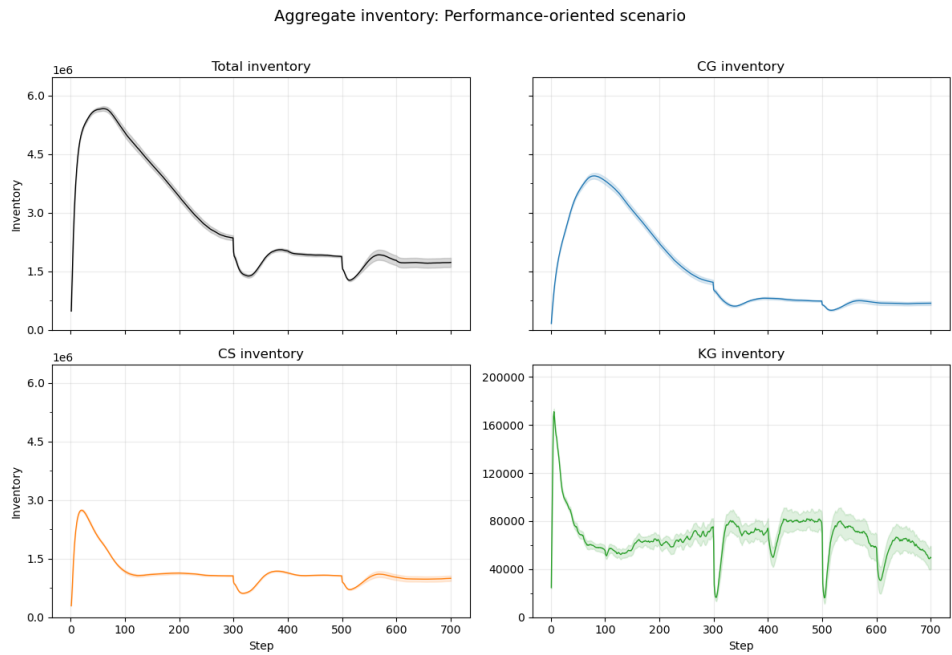


Figure E.3: The evolution of the total inventory within the economy as well as the inventories for each unit type, which is used as a resilience curve for the Performance-oriented scenario

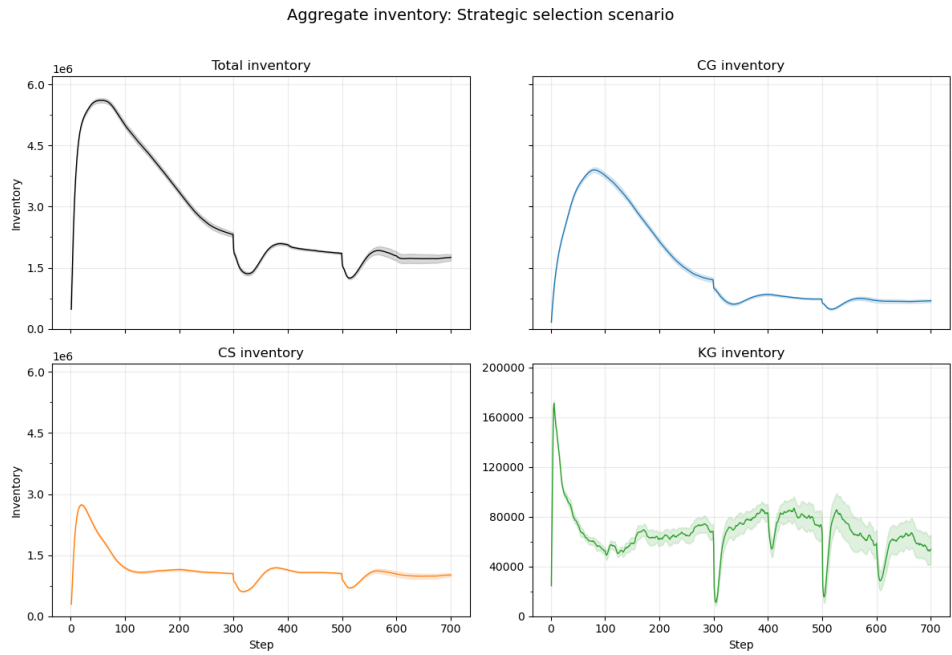


Figure E.4: The evolution of the total inventory within the economy as well as the inventories for each unit type, which is used as a resilience curve for the Strategic selection scenario

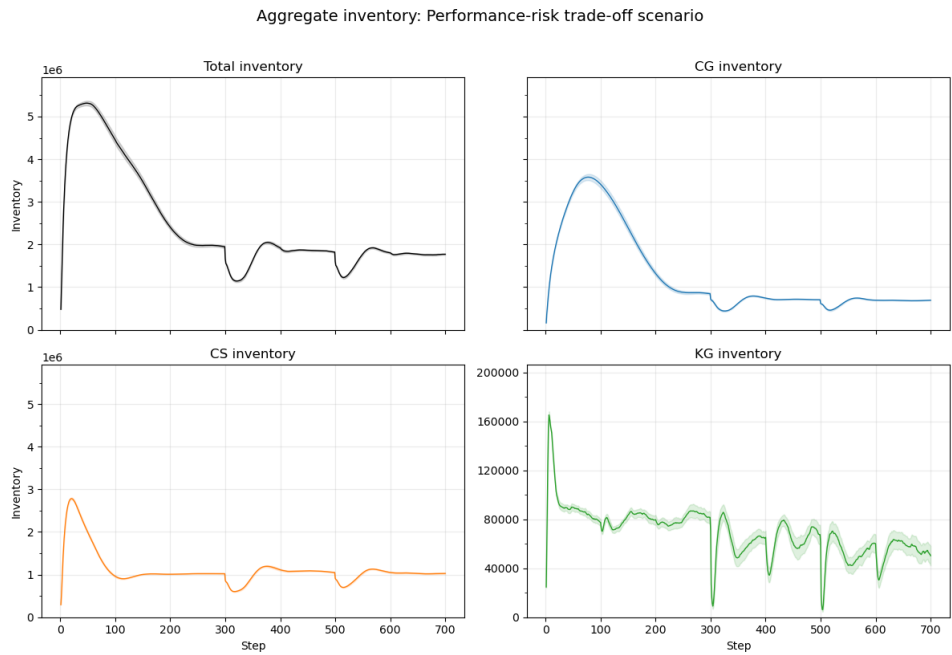


Figure E.5: The evolution of the total inventory within the economy as well as the inventories for each unit type, which is used as a resilience curve for the Performance-risk trade-off scenario

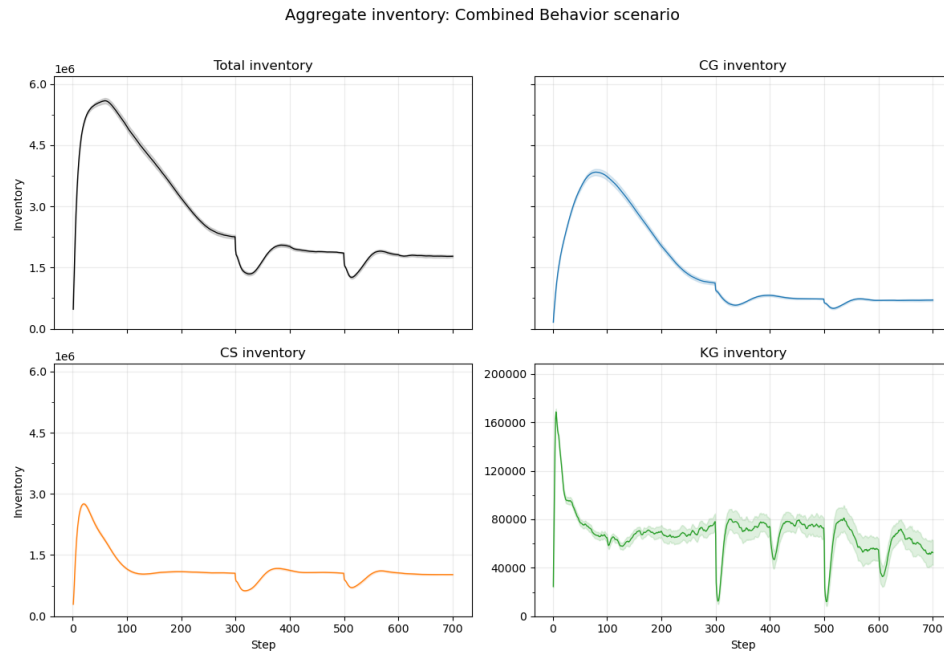


Figure E.6: The evolution of the total inventory within the economy as well as the inventories for each unit type, which is used as a resilience curve for the Combined behavior scenario

E.2. Resilience calculation code

As explained in the research design a window needs to be chosen which will point out the time in which the minimum value of the performance metric is identified as well as to calculate the endure duration. After analyzing the resilience curves a window of 100 was decided, because after both shocks the trend stabilizes again within the 100 steps after the shock.

Listing E.1: Function that calculates the resilience metrics

```

1 def shock_metrics(df, col, shock_step, window=100, tol=0.01, steady_window=20):
2     """
3     Returns:
4     - depth of impact
5     - endure duration
6     - time of minimum
7     - recovery ratio (pf / p0)
8     """
9
10    series = df.set_index("step")[col]
11
12    # p0 (pre-shock value)
13    p0 = series.loc[shock_step - 1]
14
15    # post-shock window
16    post = series.loc[shock_step: shock_step + window]
17
18    # minimum (impact)
19    p_min = post.min()
20    t_min = post.idxmin()
21    depth = p_min - p0
22
23    # endurance (time near trough)
24    band = p_min * (1 + tol)
25    after_min = series.loc[t_min:]
26    endure_duration = (after_min > band).idxmax() - t_min

```

```

27
28 # pf = steady-state recovery value (average of last part of window)
29 pf = series.loc[shock_step + window - steady_window : shock_step + window].mean()
30
31 # recovery ratio
32 recovery_ratio = round(pf / p0, 2)
33
34 return depth, endure_duration, recovery_ratio,
35
36 print("For KG shock 1:", shock_metrics(df_mean, 'invent_kg_total', 300, window=100, tol=0.01))
37 print("For CG shock 1:", shock_metrics(df_mean, 'invent_cg_total', 300, window=100, tol=0.01))
38 print("For CS shock 1:", shock_metrics(df_mean, 'invent_cs_total', 300, window=100, tol=0.01))
39 print("For Total shock 1:", shock_metrics(df_mean, 'total_inventory', 300, window=100, tol
    =0.01))
40 print("For KG shock 2:", shock_metrics(df_mean, 'invent_kg_total', 500, window=100, tol=0.01))
41 print("For CG shock 2:", shock_metrics(df_mean, 'invent_cg_total', 500, window=100, tol=0.01))
42 print("For CS shock 2:", shock_metrics(df_mean, 'invent_cs_total', 500, window=100, tol=0.01))
43 print("For Total shock 2:", shock_metrics(df_mean, 'total_inventory', 500, window=100, tol
    =0.01))

```

E.3. Resilience metrics

This section presents Table E.1 with the results of the resilience metrics derived from the resilience curve and the code from the previous section.

Table E.1: Resilience metrics across scenarios, network types, and shocks

Scenario	Network type	Shock	Depth of impact	Endure duration	Restored performance
Baseline competitive-ness	Full network	1	-785738.53	6	1.05
Baseline competitive-ness	Full network	2	-626021.88	3	0.98
Baseline competitive-ness	Sub-network CG	1	-392265.63	4	0.96
Baseline competitive-ness	Sub-network CG	2	-248708.04	3	0.97
Baseline competitive-ness	Sub-network CS	1	-417833.35	4	1.14
Baseline competitive-ness	Sub-network CS	2	-367375.38	4	1.0
Baseline competitive-ness	Sub-network KG	1	-69343.41	1	0.81
Baseline competitive-ness	Sub-network KG	2	-66416.44	1	0.78
Risk-averse	Full network	1	-816304.67	5	1.01
Risk-averse	Full network	2	-563256.05	3	1.01
Risk-averse	Sub-network CG	1	-404428.75	4	0.9
Risk-averse	Sub-network CG	2	-228675.71	3	1.0
Risk-averse	Sub-network CS	1	-424136.22	4	1.12
Risk-averse	Sub-network CS	2	-343899.95	3	1.03
Risk-averse	Sub-network KG	1	-74542.72	1	0.76
Risk-averse	Sub-network KG	2	-56810.14	1	0.87
Performance-oriented	Full network	1	-975162.6	6	0.87

Continued on next page

Scenario	Network type	Shock	Depth of impact	Endure duration	Restored performance
Performance-oriented	Full network	2	-500,000	4	0.97
Performance-oriented	Sub-network CG	1	-611124.66	5	0.66
Performance-oriented	Sub-network CG	2	-237295.28	5	0.97
Performance-oriented	Sub-network CS	1	-446491.57	4	1.1
Performance-oriented	Sub-network CS	2	-351431.56	4	0.99
Performance-oriented	Sub-network KG	1	-58887.69	1	0.95
Performance-oriented	Sub-network KG	2	-62744.12	1	0.78
Strategic selection	Full network	1	-965683.66	6	0.90
Strategic selection	Full network	2	-608894.1	3	0.99
Strategic selection	Sub-network CG	1	-597050.1	6	0.69
Strategic selection	Sub-network CG	2	-250290.89	4	0.97
Strategic selection	Sub-network CS	1	-442850.36	4	1.11
Strategic selection	Sub-network CS	2	-353787.45	4	1.02
Strategic selection	Sub-network KG	1	-55793.81	1	1.23
Strategic selection	Sub-network KG	2	-56915.84	1	0.86
Performance-risk trade-off	Full network	1	-806149.99	5	1.02
Performance-risk trade-off	Full network	2	-597323.26	4	1.01
Performance-risk trade-off	Sub-network CG	1	-405372.5	5	0.91
Performance-risk trade-off	Sub-network CG	2	-245868.05	3	1.0
Performance-risk trade-off	Sub-network CS	1	-418801.9	4	1.13
Performance-risk trade-off	Sub-network CS	2	-350051.3	3	1.02
Performance-risk trade-off	Sub-network KG	1	-72413.48	1	0.8
Performance-risk trade-off	Sub-network KG	2	-61252.94	1	0.85
Combined behavior	Full network	1	-909719.17	6	0.91
Combined behavior	Full network	2	-595496.91	3	0.99
Combined behavior	Sub-network CG	1	-542421.84	5	0.73
Combined behavior	Sub-network CG	2	-228546.37	3	0.96
Combined behavior	Sub-network CS	1	-430199.07,	4	1.09
Combined behavior	Sub-network CS	2	-351584.45	3	1.02
Combined behavior	Sub-network KG	1	-65612.13	1	0.97
Combined behavior	Sub-network KG	2	-60781.59	1	0.76