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# Essays on Applied Network Theory

Ph.D. Thesis of Elisa Flori

Supervisor: Prof. Francesco Pattarin

Co-supervisor: Prof. Giovanni Solinas

Ph.D. Program Coordinator: Prof. Ylenia Curzi

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# Abstract

This thesis consists of three essays in applied economics. In all articles, we use network analysis techniques to explore critical aspects of global supply chains. In Chapter 1, we examine the resilience properties of the automotive supply chain through the bow-tie taxonomy lens, which arises from customer-supplier relationships in the direct network. We suggest that the extent of shock propagation depends on the bow-tie zone from which the perturbation originates. Moreover, we identify resistance structures within some regions of the network. We offer insights into both the fragility and resilience of different network components and the pathways through which shocks spread. The level of abstraction employed in our study enables the generalization of these findings to other systems depictable as directed graphs. In Chapter 2, we apply agent-based simulation models to evaluate the short-run effects of several lockdown policies on the global automotive industry. Our results reveal the need to consider the specific position of a firm along its supply chain when implementing restrictive measures to business activities. We also show that companies with a high elasticity of substitution for production inputs suffer lower disruptions than those with a more rigid input mix. Therefore, targeted lockdown policies may be less expensive than generalized blocks across entire sectors. These insights allow policymakers to make informed decisions about intervention strategies and recommend that managers adopt flexible supply management approaches. In Chapter 3, we analyze the supply chain network structure of firms listed in the German DAX 30 index. Starting from the literature on buyer-seller matching, we identify four key features of the German economy related to: (i) the heterogeneity of ties (with skewness); (ii) the centrality of larger firms; (iii) the complementarity between large and small firms; (iv) the multi-level hierarchical organization of the national system. These empirical regularities are coherent with recognized properties of international production networks and provide a framework for assessing the resilience of German companies to the recent COVID-19 outbreak. We find that the pandemic crisis significantly impacted focal firms; however, recovery times were shorter for companies that diversify their customer base across multiple sectors. While focal firms are susceptible to exogenous shocks, they can mitigate their negative consequences through diversification.

*Keywords:* network analysis, value chains, focal nodes, supply-chain links, shock resilience.

# Abstract (italiano)

Questa tesi consiste in tre saggi di economia applicata. In tutti gli articoli, utilizziamo tecniche di analisi di rete per esplorare aspetti critici delle catene di fornitura globali. Nel Capitolo 1, esaminiamo le proprietà di resilienza della catena di fornitura automobilistica attraverso la lente della tassonomia bow-tie, che deriva dalle relazioni cliente-fornitore nella rete diretta. Suggeriamo che l'entità della propagazione degli shock dipende dalla zona bow-tie da cui proviene la perturbazione. Inoltre, identifichiamo strutture di resistenza all'interno di alcune regioni della rete. Offriamo spunti di riflessione sia sulla fragilità e sulla resilienza dei diversi componenti della rete, sia sui percorsi attraverso i quali si propagano gli shock. Il livello di astrazione utilizzato nel nostro studio consente di generalizzare questi risultati ad altri sistemi rappresentabili come grafi diretti. Nel Capitolo 2, applichiamo modelli di simulazione basati su agenti per valutare gli effetti a breve termine di diverse politiche di blocco sull'industria automobilistica globale. I nostri risultati rivelano la necessità di considerare la posizione specifica di un'azienda lungo la sua catena di fornitura quando si implementano misure restrittive alle attività commerciali. Mostriamo anche le imprese con un'elevata elasticità di sostituzione dei fattori produttivi subiscono minori interruzioni rispetto a quelle con un mix di fattori produttivi più rigido. Pertanto, politiche di blocco mirate possono essere meno costose dal punto di vista economico rispetto a blocchi generalizzati su interi settori. Queste intuizioni permettono ai responsabili politici di prendere decisioni informate sulle strategie di intervento e raccomandano ai manager di adottare approcci flessibili alla gestione dell'offerta. Nel Capitolo 3, analizziamo la struttura della rete della catena di fornitura delle imprese quotate nell'indice DAX 30 tedesco. Partendo dalla letteratura sul matching acquirente-venditore, identifichiamo quattro caratteristiche chiave dell'economia tedesca relative a: (i) l'eterogeneità dei legami (con skewness); (ii) la centralità delle imprese più grandi; (iii) la complementarità tra grandi e piccole imprese; (iv) l'organizzazione gerarchica multilivello del sistema nazionale. Queste regolarità empiriche sono coerenti con le proprietà riconosciute delle reti produttive internazionali e forniscono un quadro di riferimento per valutare la resilienza delle aziende tedesche alla recente epidemia di COVID-19. Scopriamo che la crisi pandemica ha avuto un impatto significativo sulle aziende focali; tuttavia, i tempi di recupero sono stati più brevi per le aziende che diversificano la loro base di clienti in più settori. Sebbene le imprese focali siano suscettibili agli shock esogeni, possono mitigare le loro conseguenze negative attraverso la diversificazione.

*Parole chiave:* analisi di rete, catene del valore, nodi focali, legami di fornitura, resilienza a shock.

# Chapter 1

## Spread of Perturbations in Supply Chain Networks: The Effect of the Bow-Tie Organization on the Resilience of the Global Automotive System*

with Sandra Paterlini[1], Francesco Pattarin[2], Marco Villani[3,4] and Yi Zhu[1]

[1]Department of Economics and Management, University of Trento
[2]Marco Biagi Department of Economics, University of Modena and Reggio Emilia
[3]Department of Physics, Informatics and Mathematics, University of Modena and Reggio Emilia
[4]European Centre for Living Technology

### Abstract

Many real-world systems are subject to external perturbations, damages, or attacks with potentially ruinous consequences. The internal organization of a system allows it to effectively resist to such perturbations with more or less success. In this work, we study the resilience properties of the global automotive supply-chain by considering the bow-tie structure of the directed network stemming from customer-supplier relationships. Data have been retrieved by Bloomberg supply chain database between 2018 to 2020. Our analysis involves 3,323 companies connected by 11,182 trade links and spanning 135 economic sectors. Our results indicate that the size of propagation of a perturbation depends on the area of the bow-tie structure in which it initially originates. Also, it is possible to identify resistance structures within some bow-tie areas. Thus, we provide insights into the fragility and resilience of different network components and the diffusion paths of perturbations across the system. Interestingly, the level of abstraction used allows our results to generalize beyond the case in question to many systems that can be represented through directed graphs.

*Keywords:* network analysis, perturbation spread, bow-tie model, supply chain, automotive sector

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# 1 Introduction

Many real-world systems are potentially subject to failures or external perturbations that cause disruptions and harmful consequences; for example, adverse events affecting the Internet, power grids, organizations, and natural systems [Albert et al., 2000, Yang et al., 2017, Gao et al., 2016, Pastor-Satorras and Vespignani, 2001, Pilosof et al., 2017, Zhao et al., 2013, Newman, 2018, Kuhla et al., 2023]. The failure of a single node or link can cause a blackout in a power grid or the collapse of an ecological system [Buldyrev et al., 2010, Dunne and Williams, 2009]. Analyzing the size of the impacts shocks cause on complex networks, in terms of how many nodes and links are affected, gives interesting clues about the statics and dynamics of such systems [Villani et al., 2018, Serra et al., 2007]. Furthermore, understanding how the structure of a system determines its response to shocks is crucial because it sheds light on its local and global resilience and how they change after a shock [Cohen et al., 2000, Gao et al., 2016, Strogatz, 2001, Watts, 2002].

Several systems can be effectively represented by directed graphs, where component entities are “nodes” and links between them are “arcs”. Arcs have directions determined by the flows of artifacts that go from one node to another —e.g. information, energy and commodities. Supply chain networks are an example of directed graphs. Suppliers are connected to customers that receive intermediate or final goods and services from them. The existing literature shows that input-output linkages act as pathways for shock propagation in both upstream and downstream directions, potentially amplifying microeconomic disturbances into macroeconomic fluctuations [Acemoglu et al., 2012, Carvalho and Tahbaz-Salehi, 2019, Carvalho et al., 2021]. This is an interesting empirical field for studying the propagation of perturbations in economic systems and to identify some regularities that may have general significance with respect to the representation and investigation of networks [Belhadi et al., 2021, Ivanov and Dolgui, 2020].

In this article, we first check if nodes in the global automotive supply chain network can be effectively represented by a bow-tie structural model [Broder et al., 2000], initially introduced in studies about the world-wide-web [Avrachenkov et al., 2007, Tawde et al., 2004, Broder et al., 2000, Timár et al., 2017] and extended, albeit with slightly different meanings, to other areas, like biological systems and the management of complex social organizations [Friedlander et al., 2015, Ghosh Roy et al., 2021, Tieri et al., 2010, Culwick et al., 2016, Muniz et al., 2018]. Our analyses suggest that the bow-tie model is a good representation of the supply chain network. Furthermore, we are interested in the influence the bow-tie structure has in shaping the paths of perturbations across the network. In fact, the analysis of the structure of the system could allow the study of its resilience: static structural features and dynamic responses to perturbations are closely connected [Fiksel, 2003]. Therefore, we carried out several simulations of perturbations under different scenarios and identified some significant determinants of resilience in the supply-chain, bow-tie like, network. While it is well known that having (few) big hubs improves network resilience when perturbations start by randomly hitting some nodes, we find that the position of nodes —or relative density of them— in the areas of the bow-tie structure is also very important. We argue that this is because of the spread of perturbations through sequences of directed arcs connecting nodes ("paths") depends on their connections and, therefore, on the area they belong to. To our knowledge, we are the first to suggest such an analysis in the scientific literature. By relying on our unique dataset of 3,323 companies (nodes) from the global automotive sector, connected by 11,182 trade relations (arcs) and collected from the Bloomberg platform, we provide new insights into the characteristics of the global automotive supply chain network (Section 2). In particular, the directionality of supplier-customer relationships leads to the spontaneous emergence of five major areas, as described in Broder et al. [2000] and Fujita et al. [2019] (Section 3). By applying such taxonomy, we can better understand the percolation of avalanches and shocks within the system and then evaluate network resilience and robustness (Section 4). This allows us to characterize some stylized facts about the global automotive network. Eventually, we examine the network robustness to avalanches and shocks at different levels and show that the automotive supply chain network is more resilient than random networks and networks with the same degree distribution, while also quantifying the impact delivered by nodes belonging to different bow-tie areas.

## 2 Data

The data collection procedure started by identifying and retrieving all automobile, motorcycle, construction machinery and heavy-duty vehicles manufacturers available in the Bloomberg Supply Chain database in April 2021; such companies are called "focal companies", and we recovered 165 of them. Then, the final dataset was built (1) by identifying and selecting the main suppliers and customers of focal companies and then (2) by identifying and selecting the main suppliers and customers of the latter[1,2], (the network therefore includes the focal nodes

[1]Bloomberg defines "main" as top-ranking suppliers and customers according to revenues or cost of goods sold. The number of main suppliers and customers is not the same for every company and typically is in the range of a few to twenty units.

[2]This approach follows Bellamy et al. [2014]. They used Bloomberg's Supply Chain Relationship Database (SPLC) to recreate a network of connections between 3,106 companies to understand how administrative envi-

and the nodes which can be reached staring from them in 1 or at most 2 steps - see Figure 1).

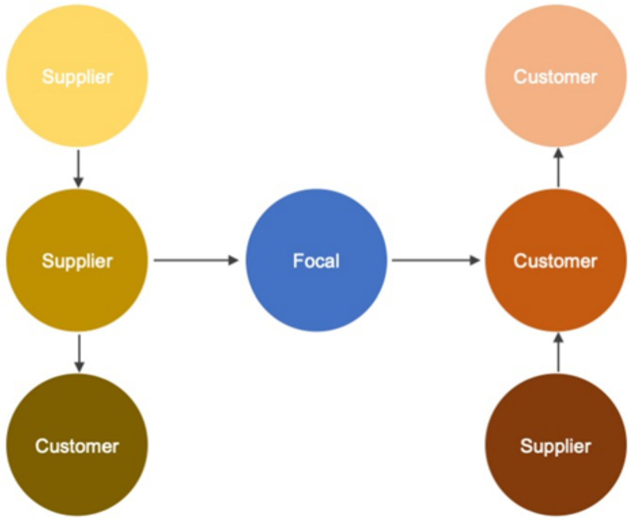



**Figure 1:** Exemplification of focal company, supplier, and customer. Circles are nodes and arrows are directed arcs connecting them; the direction of any arc follows the flow of goods and services from a company to another.

Notice that some companies are both suppliers and customers —they have both incoming and outgoing arcs— some are only suppliers —do not have any incoming arc— and some are only customers —do not have any outgoing arc (see Table 1).

| **Type of node** | **Absolute frequency** | **Relative frequency (%)** |
|---|---|---|
| Supplier and consumer | 1,192 | 35.87 |
| *of which: Focal firms* | *92* | *2.77* |
| Only supplier | 1,201 | 36.14 |
| *of which: Focal firms* | *25* | *0.75* |
| Only consumer | 930 | 27.99 |
| *of which: Focal firms* | *48* | *1.44* |
| **Total** | **3,35** | **100.00** |

**Table 1:** Distribution of network nodes by role.

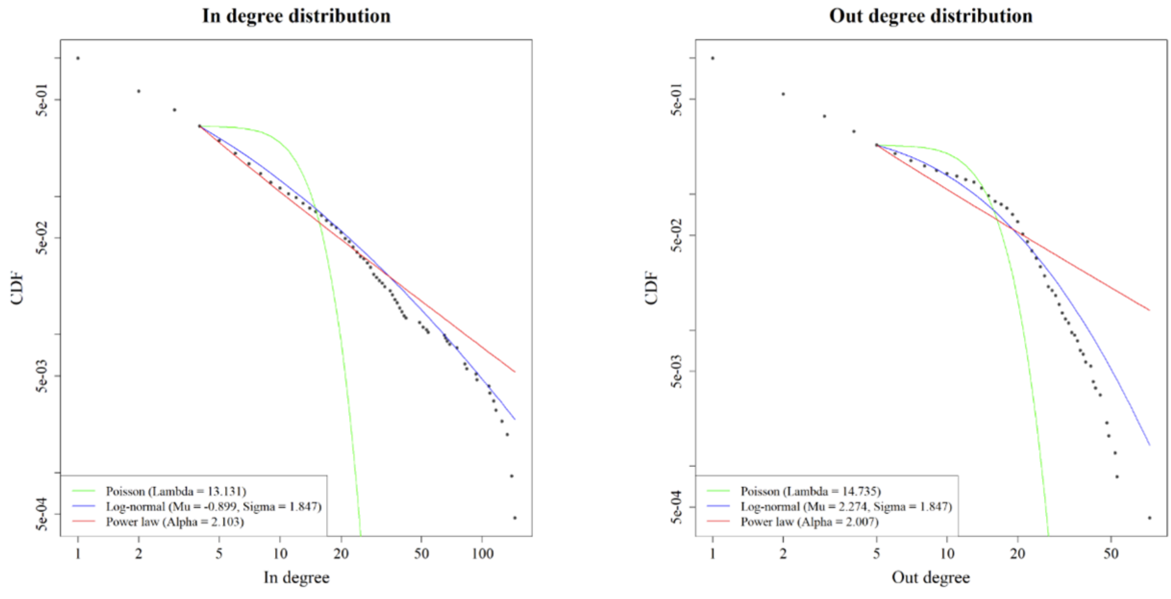
The final supply chain network dataset consists of 3,323 companies (nodes) connected by 11,182 trade relations (arcs). For all companies we know: (a) their size, measured by the average annual sales (USD millions) over the 2018-2020 fiscal years; (b) the region they are legally established in; (c) their economic activity sector according to Morgan Stanley Capital International and Standard & Poor's GICS® taxonomy[3]. So, besides the number of nodes and arcs that char-

ronmental innovations (AEIs) relate to environmental disclosure.

[3]The Global Industry Classification System (GICS) consists of 11 sectors, 24 industry groups, 69 industries

acterize the automotive supply chain network, we can provide a measure of its size based on average 2018-2020 total sales. This amounts to about 27 billion USD, out of which focal companies generate 2,890 billion USD (11%). We estimate the market share of focal companies in the global automotive market to be about 79%[4]. The network is weakly connected by construction, as we discarded isolated nodes. The network diameter is 20, which means that the longest of all shortest (or "geodesic") paths connecting any two nodes is 20 arcs.

Another way to analyze the network is by examining the in- and out-degree distributions. Using a Maximum-Likelihood-based schema [Clauset et al., 2009][5], we fit three probability distributions to these degrees: Poisson, Log-normal, and Power law. The comparison methods used are: (1) visual inspection of the cumulative degree distributions on a log-log scale to identify the best fit to the empirical distribution; (2) computation of the Kolmogorov-Smirnov (KS) distance between the fitted and empirical distributions to quantify differences; and (3) statistical tests to assess the significance of these differences, accounting for sampling variability [Gillespie, 2024]. These comparisons were applied to both in- and out-degree distributions. Fitted and empirical degree distributions are depicted in Figure 2.




(a) (b)

**Figure 2:** Empirical and fitted degree distributions on log-log scale. (a) In-degrees. (b) Out-degrees. Fitting is performed by Maximum Likelihood.

and 158 sub-industries, where each level is more granular than its predecessors so that, for example, an industry is a more specific definition of economic activity that an industry group (Global Industry Classification Standard (GICS®) Methodology, retrieved 7 June 2021). We collected data on sub-industries.

[4]According to IBISWorld, Global Car & Automobile Sales (retrieved 12 August 2021), the average size of the global automotive market over the same period was 3,690 billion USD.

[5]"Tail nodes" are defined based on their in- and out-degrees; nodes with degrees higher than the first quartile of the overall distribution are considered tail nodes. For in-degrees, this corresponds to nodes with at least five upstream edges, while for out-degrees, the threshold is four downstream edges.

Figure 2 clearly shows that the Poisson distribution provides a poor fit in both cases, indicating that the global supply-chain network cannot be described as a random graph. On the other hand, the Log-normal and Power law distributions provide a better fit [Barabási, 2017, Sheridan and Onodera, 2018]. This observation aligns with other studies, suggesting formation mechanisms where node connectivity is significant, similar to "preferential attachment" [Albert and Barabási, 2002]. Preferential attachment mechanisms naturally lead to the emergence of hubs, where some nodes become critical intermediaries for network connections.

Turning to the KS distance results, Table 2 shows that the Poisson distribution performs substantially worse than both the Log-normal and Power law distributions (lower KS values indicate a better fit). The Log-normal distribution generally emerges as the preferred model. However, the KS values for Log-normal and Power law are relatively close for in-degrees. This prompted us to compute likelihood-ratio (LR) statistics to further distinguish between the two models. As Clauset et al. [2009] and Gillespie [2024] explain, the LR test is directional, meaning its interpretation depends on how the alternative hypothesis is posed against the null. The null hypothesis is:

H0: Log-normal and Power law distributions are indistinguishable.

The two alternatives, marked as "1" and "2" are:

H1: Log-normal is better than Power law.

H2: Power Law is better than Log-normal law.

Therefore, if we reject H0 against H1 and do not reject it against H2, then we can safely conclude that the Log-normal law is a better representation of the degree distribution than the Power law. The marginal probability values of these tests for in-degrees are, respectively, 0.019 and 0.981; therefore, Log-normal is favored to Power Law[6].

| **Theoretical distribution** | **In-degree** | **Out-degree** |
|---|---|---|
| Poisson | 0.5182 | 0.3945 |
| Log-normal | 0.0342 | 0.0909 |
| Power law | 0.0384 | 0.1219 |

**Table 2:** KS distances between theoretical probability laws and empirical degree distributions.

[6] For the out-degree distribution, Log-normal is favored to Poisson- and Power-law at $< 0.0001$ significance level of the test. Also, Log-normal is favored to Poisson at $< 0.0001$ significance level of the test for in-degree distribution.

This distinction between Log-normal and Power law is noteworthy. While both distributions suggest mechanisms of network formation involving uneven connectivity, they differ in their implications. Preferential attachment is often linked to the Power law, as it describes scenarios where new connections preferentially attach to already well-connected nodes. However, the Log-normal distribution may indicate additional factors, such as node heterogeneity or growth constraints, which modulate the strictness of the preferential attachment mechanism. The findings suggest that while preferential attachment might contribute to the network's structure, other dynamics, such as variations in node capabilities or resource limits, could also play a role. This underscores the complexity of real-world networks and highlights the need for multifaceted interpretations of their degree distributions.

# 3 Bow-tie organization of the automotive network

In the automotive system, the directionality of supplier-customer relationships leads to the spontaneous emergence of a network bow-tie structure. The bow-tie structure comprises five major areas, as described in Broder et al. [2000] and Fujita et al. [2019]. We thus examine what the network components are according to this taxonomy. Here, the "strongly connected component" (Scc) is the largest collection of nodes that can be reached from any other node in the network through directed arcs[7]. The "in component" (In) is the set of nodes that cannot be reached from the Scc but point to it. Nodes that belong to the "out component" (Out) can be reached from the Scc but do not point to it. The in- and out-component nodes may be connected through "tube" nodes (Tubes), bypassing the Scc. Also, some marginal nodes called "tendrils" (Tendrils) are connected to in- and out-component nodes with outgoing and incoming arcs, respectively (see Figure 3)[8].

[7]Some strongly connected components may exist within other areas. In this case, however, they are only within them and therefore share part of their characteristics (see Section 4). Thus, we call Scc the main area, and references to any minor Scc's will be correctly disambiguated.

[8]Since our network is weakly connected by construction, there are no isolated components. Also, note that the in- and out-component areas may have nodes interconnecting inside them, but it is not possible to reach any node from any other within them. The same applies to tubes and tendrils areas.

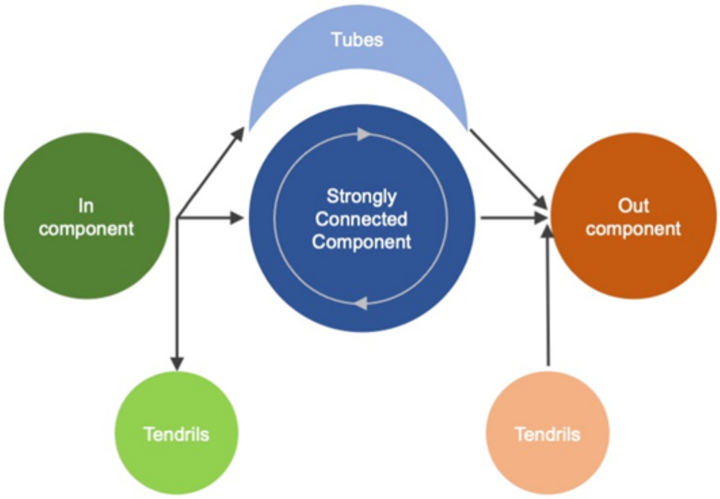



**Figure 3:** Taxonomy of network components according to the bow tie model. The five network components are represented by circles. Arrows exemplify the directed connections of nodes belonging to each component. Scc is the largest area where from each node it is possible to reach any other node; In, the area that has only one directional paths towards the Scc; Out, the area reachable from the Scc where paths lead to nodes that have not any further exit; Tubes, the zone that directly connects In and Out zones; Tendrils, one or more sets of nodes that start from the In zone and directly reach the border of the system, or that reach the Out zone starting from the border.

The features of the automotive supply chain network are in Table 3. Tubes are a residual component (21 nodes or 0.6% of the total), which means that most connections are intermediated by nodes belonging to the Scc. This component sums up to 755 nodes (22.7% of the total) with 58 focal nodes. Also, in- and out-components are both important, together with tendrils (2,547 nodes or 76.6% of the total).

To determine whether the identified areas are large or small, we compare the bow-tie organization of systems where there is not any specific construction rule. Here, we use networks consisting of the same number of nodes and connections as the automotive's, but where: (i) connections are uniformly distributed, as in Erdős-Rényi or "random" network —Rnd hereafter— or (ii) the connectivity distribution of each node is preserved, but each link is randomly redirected, which we call "redirected networks" —Rid in the following. As shown in Table 3, in Rnd networks, the Scc is very large, comprising more than 90% of the network, while every other zone occupies a fraction of less than 4% of the system, resulting in a network configuration quite distant from the actual automotive network. On the contrary, the Rid graph has Scc, In and Out areas of similar size to those of the actual network. These facts support the hypothesis that the distribution of the connectivity of nodes determines the size of the bow-tie areas. We notice that the automotive system has small number of strongly connected components which do not belong to the main Scc area; this is not the case in either Rnd or Rid artificial networks.

| **Components** | **Actual network** | | **Rnd network** | **Rid network** |
|---|---|---|---|---|
| | Count | Frequency (%) | Frequency (%) | Frequency (%) |
| Scc | 755 (*58*) | 22.7 | 92.4 ± 0.2 | 29.0 ± 0.9 |
| In | 1,071 (*18*) | 32.2 | 3.9 ± 0.5 | 35.0 ± 0.9 |
| Out | 883 (*72*) | 26.6 | 3.7 ± 0.4 | 25.0 ± 0.9 |
| Tubes | 21 (*1*) | 0.6 | 0 ± 0.0 | 0.36 ± 0.3 |
| Tendrils | 593 (*16*) | 17.8 | 0.03 ± 0.02 | 10.5 ± 0.9 |

**Table 3:** Comparison of actual and simulated Rnd and Rid networks morphology. In the first two columns we show the count and percent frequency of nodes by type of network component they belong to; figures in brackets are the number of focal nodes. In the last two columns, we show the percent frequency of nodes by type of network component they belong to. In the case of Rnd networks and scale-free Rid networks, averages on simulated ensembles of 10 networks are shown; the ± margin is three standard deviations from the mean.

It is interesting that the extension of the In and Out areas of the automotive network are both larger than 25% of the whole system. Indeed, a very similar structure was found in early World-Wide-Web related searches [Broder et al., 2000]. Our interpretation is that the extension of such zones depends on the nature of the actual system, but also on the procedure we followed to map it (see Section 2). We think the latter aspect is important and worth further investigation, because similar sampling schemes are common — e.g., Dong et al. [2022]. We do not pursue this line here, but we deem that this topic is not enough studied in the extant published research, as far as we know.

# 4 Diffusion of perturbations in the automotive system

## 4.1 Introduction

In this section we discuss the propagation of perturbations across the supply chain network. All simulated perturbations start from a single node of the system; this way, we examine the risk connected to each node and map the local and global resilience characteristics of the network.

We envision several scenarios that differ because of the resiliency of nodes to perturbations. First, in the case of a "rigid" production technologies, every supply relationship of a node is essential, so that the loss of any incoming link leads to a node stop operating and to its failure. This position corresponds to situations in which the missing supplier supplies essential and otherwise not replaceable parts; alternatively, one can think of short-term scenarios, in which agents do not have enough time to look for alternative suppliers. Second, in the case of "flexible" technology, we assume that a node stays operative even if it loses some of its suppliers and does not fail. In this way it is possible to simulate situations in which a node can deal (at least partially and / or up to a certain point) with supply shortages — for example, by making use of small local suppliers, or by producing the necessary utilities by itself. The difference between the two technological scenarios involves the maximum size of the affected part of the system, but the transmission mechanism is very similar. In the following we can therefore refer to the rigidity scenario. Under these assumptions, we examine the resilience of the network over the short term, where firms cannot effectively respond to perturbations by changing their technology, suppliers, or customers[9].

Given the nature of the perturbations we propose, the bow-tie organization of the system influences its resilience properties; indeed, the position and the final size of the network regions involved by perturbations strongly depends on the bow-tie area where the initial disturbance happens. We assume two types of perturbations:

1. "Avalanches", where the propagation of perturbations spreads along the supplier-customer direction; any perturbation hitting a node involves its outgoing links — i.e., it goes downstream.

2. "Shocks", the same as above plus upstream propagation of perturbations, because if a node loses all its main customers, then it fails; in this case, the customer-supplier relationships also play a role.

The asymmetry in the propagation of perturbations, downstream only (1) or downstream and upstream (2), is significant, because it allows to investigate the resilience of the network in diverse conditions. Beyond the specific case of the automotive supply-chain we examine, our analyses may provide insights about the effects of perturbations in similar systems, such as socio-technological networks, chemical reaction systems, or gene regulation networks.

## 4.2 Avalanches

In our simulations, the cascade of avalanche perturbations starts from a single node; we hit every node in the network, one at a time, and see what the outcomes are. The main evidence we collected is:

[9] This is in line with most extant research, such as Inoue and Todo [2019]. Investigating proactive responses to shocks is an interesting topic but beyond the scope of this article. We leave it for future investigation.

1. As expected, if the first perturbated node belongs to the Scc area, then every other Scc node is hit. The failure of Scc nodes leads to perturbations in the Out component, so that all its nodes are obliterated. This does not depend on which specific Scc node is first hit; any perturbation in the Scc leads to the failure of all Out nodes.

2. If the first perturbated node belongs to the In zone, then all downstream nodes are involved until the cascade of perturbations reaches the Scc area. Then, the avalanche continues as above, so that the size of the disruption is the same plus some nodes in the In zone[10].

3. If the initial node belongs to the Out zone, then the cascade of perturbations will only hit downstream nodes until it reaches the edge of the system: here the avalanche ends. Consequently, the cascades of perturbations starting from the Out zone are very small in size.

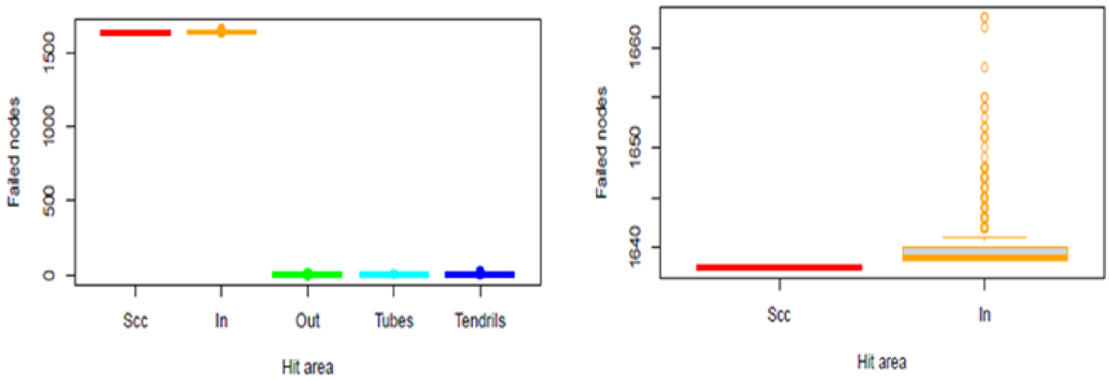
4. If the initial node belongs to a Tube, the avalanche involves only some of the nodes of that zone and their downstream in the Out area. Thus, the cascades of perturbations starting from this zone are very small in size.

5. Finally, if the initial node belongs to a Tendril connected to the In zone, then the avalanche involves only the nodes of such area downstream. If the initial node belongs to the Tendril area connected to the Out zone, then the avalanche involves the downstream nodes of that structure and the nodes of the Out zone downstream of the Tendril structure.

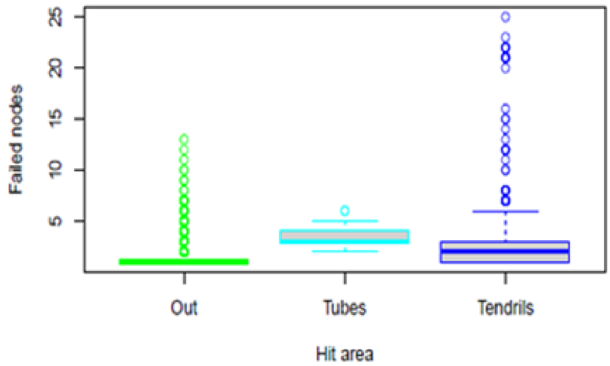
The size distribution of avalanches in the automotive supply chain exhibits a bimodal pattern, with many large avalanches (cases 1 and 2) and many small ones (cases 3, 4, and 5), as shown in Figure 4. Remarkably, the typical size of these avalanches closely corresponds —and is sometimes identical— to the combined size of the Scc and Out zones. This alignment suggests a strong dependency of the system vulnerability on the structural position of the perturbed node within the network. The results reveal that the extent of damage caused by a single node's perturbation is not merely a function of the node's degree or immediate connections but is intrinsically tied to the node's positional role within the more extensive network topology. Figure 3 shows that nodes within the Scc region are highly central. When avalanches affect these nodes, the repercussions are extensive, underscoring their systemic importance. Interestingly, a similar dynamic is observed for nodes in the In zone. Despite not being centrally located, perturbations in these nodes propagate through directed pathways to the Scc, amplifying their

[10] Sometimes it happens that an avalanche starting in the In zone hits some nodes belonging to Tubes, because one or more of the failed nodes in the In zone are suppliers of one or more nodes belonging to the Tubes zone. However, tubes have few nodes (see Table 3), so they are not worth discussing.

impact. Thus, sensitive nodes are not limited to the most central ones but extend to those with structural connectivity to critical network areas. What makes this result particularly noteworthy is the interconnected nature of the vulnerabilities. While it might be intuitive that central nodes in the Scc are critical, the cascading sensitivity of In nodes highlights that the network vulnerability is not only determined by individual node properties but also by the interplay between topological zones. Targeted disruptions in peripheral regions can still result in catastrophic system-wide effects due to their directional influence on the Scc.




(a) (b)




| Percent of failed nodes | |
|---|---|
| Minimum | 0.03 |
| Average | 27.1 |
| Median | 49.3 |
| Maximum | 50 |

Note: Median is Scc + Out

(c) (d)

**Figure 4:** Distribution of avalanches. (a) Count of nodes involved by avalanches starting in the Scc, In, Out, Tubes and Tendrils areas. (b) Details of avalanches starting in the Scc and In zones, their variances are very small. (c) Details of avalanches starting in the Out, Tubes and Tendrils zones. The little number of outliers suggests that there are different propagation paths within some small zones. (d) Statistics about the size of the avalanches, as fractions of hit nodes in the whole network.

Another interesting statistics concerns the number of times each node is involved in one of 3,323 possible avalanches; we call this “susceptibility”, in line with Serra et al. [2004]. There are nodes often involved, while other almost never are. As expected, Scc and Out nodes exhibit large susceptivity, while In, Tubes and Tendrils are basically unaffected by avalanches (see Figure 5). The same analysis can be applied also to random networks (Rnd) and redirected networks (Rid). The size distribution of the avalanches is again bimodal, and the observation that the typical size of the avalanches is close to the sum of the size of the Scc and Out zones remain valid. However, the large size of the Scc zone of Rnd networks leads to a particular bimodality, in which more than 96% of avalanches involve a very narrow range close to 96% of the system. The automotive network is therefore much more robust than a corresponding Rnd system. On the other hand, the size distribution of avalanches of a Rid system is substantially similar to that of the automotive network, despite the median size of avalanches is slightly higher than its, because the larger size of the Scc and Out zones.

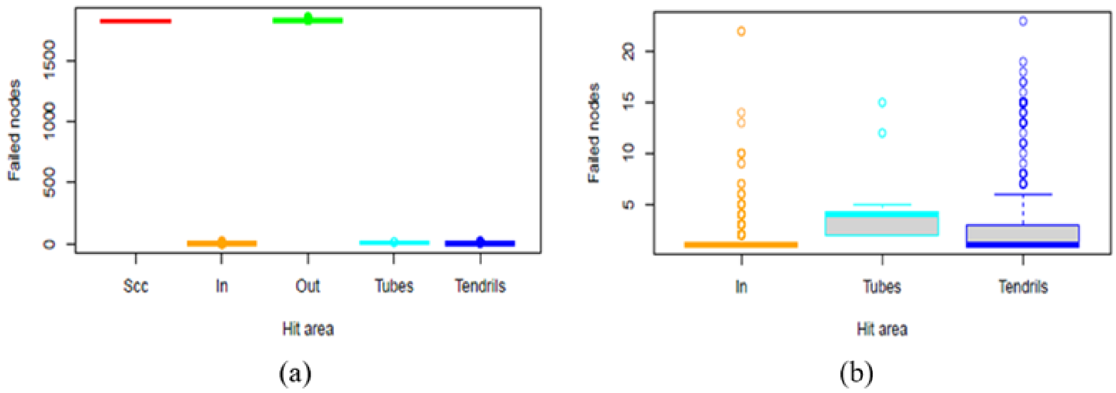



**Figure 5:** The bimodal distribution of susceptivities in case of avalanches. (a) The boxplot graph in which we indicate the fraction of times each node is involved in one of 3323 possible ava-lanches, calculated based on the node belonging to Scc, In, Out, Tubes and Tendrils areas. (b) A magnification focused only on nodes belonging to In, Tubes and Tendrils zones. The presence of outliers (however very small — see part (a) of this figure) indicates the possibility of different avalanches propagation paths.

## 4.3 Shocks

Shocks are like avalanches, but they are characterized by an additional process involving possible retro-propagations of perturbations in the customer-supplier direction, which results in more nodes potentially involved. The main evidence we get for shocks is:

1. If the first hit node belongs to the Scc area, all nodes of the Scc and Out zone are involved, as for the case of avalanches. Furthermore, most if not all the nodes belonging to the In zone often lose their customers and are then perturbated. This does not happen in avalanches. Also, some Tendril nodes originating from the in component fail. Finally, nodes in the Out zone are also perturbated, causing the involvement of all their customers in the Tendrils. However, the cascade of perturbations can be interrupted by resistance structures present in Tubes.

2. When the first hit node belongs to the In zone, all downstream nodes are perturbated until the cascade reaches the Scc: from here, the shock will continue as already described, involving the whole Out zone and parts of Tubes and Tendrils. So, shocks starting from

the In zone typically have a bigger size than shocks starting in the Scc area. Again, the cascade of perturbations can be stopped by resistance structures present in Tubes.

3. If the first hit node belongs to the Out zone, then the cascade of perturbations affects all downstream nodes until it reaches the edge of the system: here the cascade ends. Nodes belonging to the Scc zone are not involved because they have at least one additional customer in the Scc zone not hit by any perturbation. Nodes in the Tendril area of the Out zone can be involved, but sometimes the propagation can be stopped by resistance structures. Nodes in Tubes can be involved, and in the absence of resistance structures the propagation of perturbations can reach the border of the In zone, where it stops because the nodes belonging there have at least one customer in the same zone or in the Scc area. Therefore, shocks originating in the Out area necessarily limited in size.

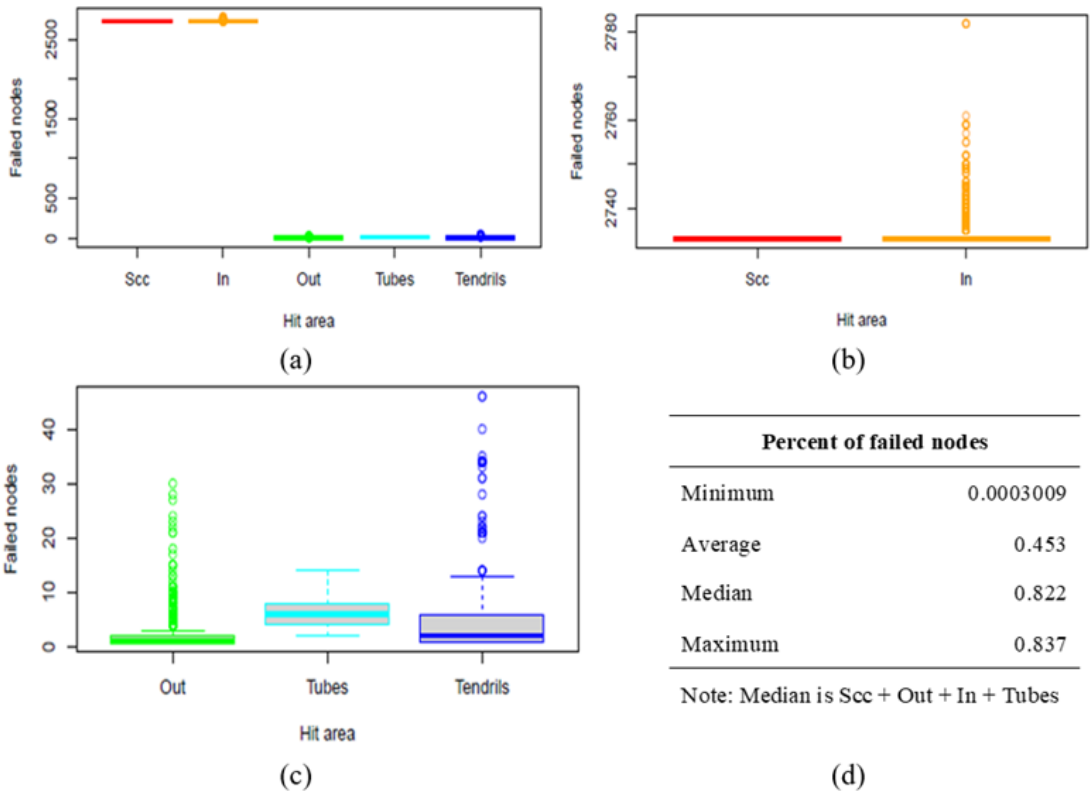
4. When the first hit node belongs to a Tube, the shock involves its nodes downstream and also the downstream nodes of the Out area. In the absence of resistance structures, the propagation can reach the border of the In zone, but here it stops because the nodes belonging to the In zone have at least one customer in the In zone or in the Scc area. So, perturbations starting in Tubes are very small in size.

5. Finally, if the first hit node belongs to a Tendril connected to the In zone, then the shock involves only the nodes of that area downstream — with exceptions in case of resistance structures. If the first hit node belongs to a Tendril connected to the Out zone, then the perturbation involves the Tendril and Out nodes downstream: in some cases, some Out nodes lose all customers and back-propagate the perturbation. In any case, perturbation ends once it reaches the Scc area. The shocks originating in a Tendril area are limited in size.

Obviously, shocks have larger effects than avalanches (see Figure 6). However, the asymmetry of the propagation of perturbations creates the conditions for the emergence of resistance structures that can interrupt the retro-propagation of a shock along the supply chain network. A first large resistance structure is the Scc area. While initial-seeded shocks in the In zone can invade the Scc area, which is downstream, none of the initial-seeded shocks in the Out zone can involve Scc nodes via the back-propagation of perturbations in the customer-supplier sense[11]. This resistance is due to the fact that each node belonging to the Scc has at least one

[11] Although, back propagations through Tubes can reach the In zone because they bypass the Scc. frontier (which is upstream with respect to the Scc zone), but once they have reached the frontier, they cannot invade the In zone, because the nodes of this zone have at least one customer in the In zone itself or in the Scc, areas not reached by the shock.

customer belonging to the same area; therefore, the back-propagation in the upstream direction is ineffective. It is interesting to note that this property could allow to block the propagation of shocks in the customer-supplier direction, even if it were not necessary to lose all customers to damage a node.




| Percent of failed nodes | |
|---|---|
| Minimum | 0.0003009 |
| Average | 0.453 |
| Median | 0.822 |
| Maximum | 0.837 |

Note: Median is Scc + Out + In + Tubes

**Figure 6:** The bimodal distribution of shocks. (a) The boxplot graph in which we indicate the fraction of the system involved by the shocks with initial source in the Scc, In, Out, Tubes and Tendrils areas. (b) A magnification focused only on shocks started in the Scc and In zones (the variances are very small). (c) A magnification focused only on shocks started in the Out, Tubes and Tendrils zones. The presence of outliers (however very small — see part (a) of this figure) indicates the possibility of different propagation paths within the various (small) zones. (d) Statistics about the size of the shocks. Obviously, given the bimodality of the distribution, the average is an abstraction (no avalanche size corresponds to the average value); the median size is close to the sum of the dimensions of the Scc, Out, In and Tubes areas (most part of the avalanches affect these areas).

A second-level resistance is local Scc's in the Out, Tubes and Tendrils areas which, because of the conformation of the structure they are immersed in, in some cases they are not bypassed by back-propagation (see Figure 7)[12]. Once groups of nodes are able to resist back-propagation, they can in turn become bases for defending their customers upstream, and thus preserve large areas. As anticipated, given the size and sparseness characteristics of the systems we simulated, these structures are unlikely in the case of random linking; indeed, we only found them in the actual automotive network.

[12] Again, in case it is not necessary to lose all customers to damage a node. Also, secondary Scc's may be the core of larger resistance structures.

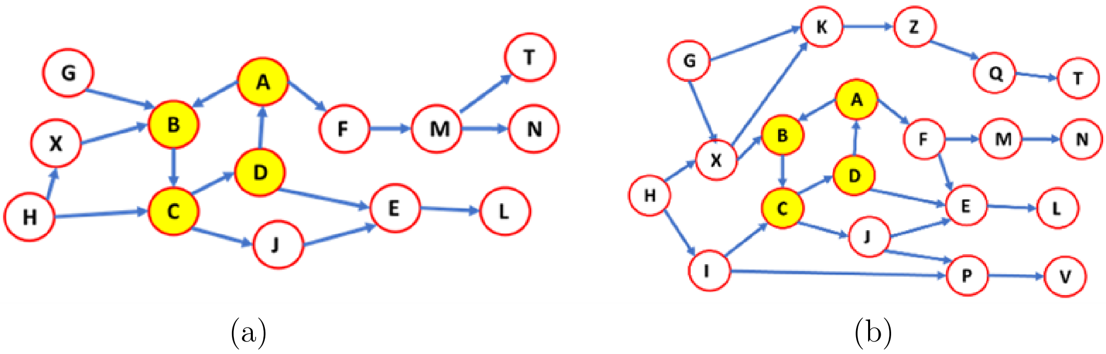



**Figure 7:** Resistance structures (in yellow) immersed in an area (In, Out, Tube or Tendril) where the flow of material globally proceeds in only one direction. From left to right: (a) back propagations coming from T, N or L are blocked, because sooner or later they only hit nodes that have at least one client not involved in the shock; (b) back propagations are blocked. It should be noted that nodes X and I do not belong to the local Scc, but the Scc guarantees that they have at least one not failed customer.

Summing up, it never happens that an initial perturbation hitting a node in the Out zone gives rise to large shocks. In case of shocks, the risk (susceptibility) connected to nodes belonging to the Scc and Out zones are basically the same as for avalanches, while the susceptibility of a big part of the nodes belonging to other areas considerably increases. This effect is visible in the boxplots of Figure 8, where we notice a strong bimodality of susceptibility for In, Tubes and Tendrils areas; this is because a subset of the nodes is protected by the resistance structures — definitely more effective for nodes belonging to the Tubes and Tendrils areas.

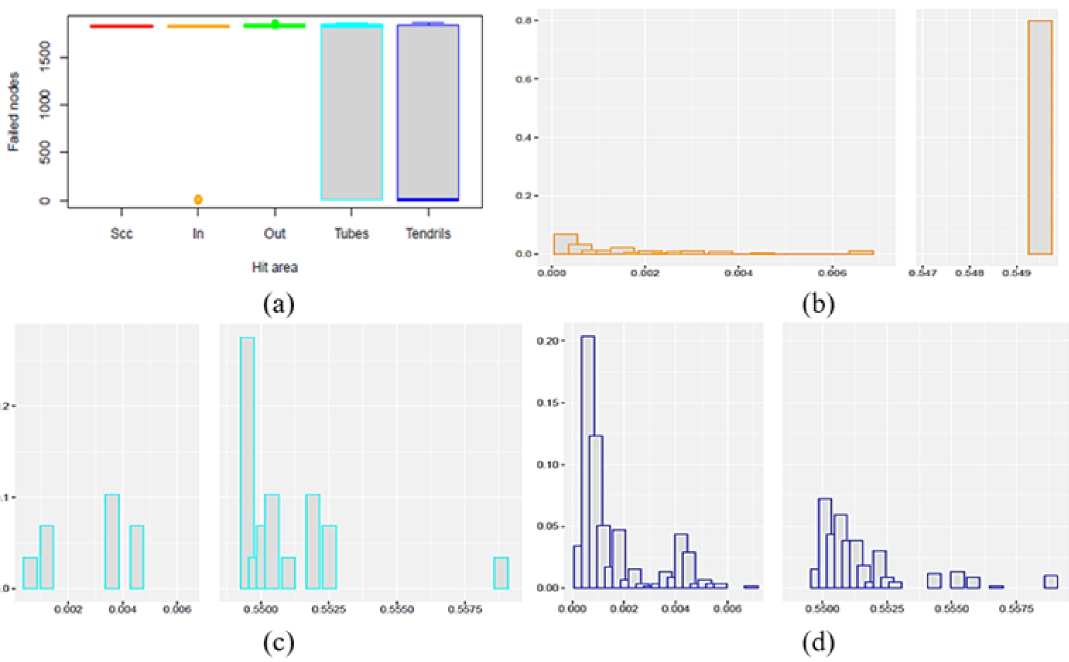



**Figure 8:** The distribution of susceptivities in case of shocks: (a) boxplot of the percent fraction of cases where each node is involved in one of 3,323 possible shocks, by the zone it belongs to in the bow-tie model. The appearance of the boxplots relating to the In, Tubes and Tendrils areas, indicates a bimodal distribution. (b) The bimodal nature of the susceptibility in the In area, where a small fraction of nodes have low susceptibilities, while the majority of nodes are hit by perturbations. (c) The bimodal nature of the susceptibility in the Tubes area. (d) The bimodal nature of the susceptibility in the Tendrils area. Here, the resistance structures are particularly effective.

The shock propagation analysis can be repeated for random networks (Rnd) and redirected networks (Rid). The size distribution of the shocks is again bimodal, and the observation that the typical size of the avalanches is close to the sum of the size of the Scc, Out, In and Tubes areas remains valid. However, the large size of the main Scc zone of the Rnd networks and the small size of Tubes and Tendrils lead to a situation in which more than 96% of shocks involve 3,321 nodes out of 3,323. The automotive network is therefore more robust than a corresponding Rnd configuration. On the other hand, the size distribution of shocks of a Rid system is substantially like that of the automotive network: the size of 55% of the shocks is close to 2,973 (3,001 being the sum of the Scc, Out, In and Tubes zones) up to a maximum size of 2,986[13], while the remaining 45% is composed by small shocks, with a maximum size of 19. No major shocks are generated from the Out area.

# 5 Discussion and Conclusion

In this study, we aim to understand the diffusion path of perturbation by examining the properties of the global automotive supply-chain sampled from the Bloomberg database between 2018 to 2020. The directionality of supplier-customer relationships leads to the spontaneous emergence of five major areas according to the bow-tie organization [Broder et al., 2000, Fujita et al., 2019]. The application of such taxonomy —a large Scc, In, Out, Tubes, and Tendrils— allows us to better understand the diffusion of perturbations, be them avalanches or shocks, across the system and to evaluate the network resilience and robustness.

The effects of perturbations are strongly dependent on the different areas of the bow-tie where they originate. We can identify Scc and In nodes as those that generate the greatest avalanches and shocks. Still, when looking at susceptivity, avalanches strongly affect Scc and Out nodes, which are the largest involved areas; shocks might also impact In, Tubes and Tendrils. Scc nodes are central in the network, thus we expect them to be capable of producing a larger impact on the entire system when hit, while Out nodes are largely affected by avalanches and shocks. It is interesting to note that In nodes, although not as central as those in the Scc area, are the origin of large avalanches and shocks. On the contrary, an initial a perturbation generated in the Out zone never gives rise to large avalanches or shocks.

Our results indicate that a shock, as expected, involves more nodes than an avalanche, due to an additional process involving possible back-propagations of perturbations in the customer-

[13] The typical size of shocks for Rid is larger than that for the automotive system, because the slightly larger size of the Scc, In and Out zones.

supplier direction. However, it is interesting to note that in this case it is possible to identify interesting resistance structures, based on zones that appear locally and are organized as Scc's — including but not limited to the main bow-tie Scc area. In general, when is not necessary to lose all clients to make a node fail, these Scc's may be the core of larger resistance structures.

Finally, we examined the network robustness to avalanches and shocks and show that the automotive supply chain network is more resilient than both random networks and redirected networks with the same degree distribution.

The capability of a system to recover quickly and effectively to a planned performance level after an unexpected disruption depends on its structure, as well as on the specific resistance of its nodes [Hearnshaw and Wilson, 2013, Behzadi et al., 2020]. In supply-chain systems, efforts to build resilience can be made both at the firm or supply-chain level. The latter level depends on the connections of firms in the network; this requires an understanding of its structure and of the way nodes interact with each other [Hearnshaw and Wilson, 2013, Ozdemir et al., 2022]. In this sense, to improve supply chain resilience, it is imperative to understand the supply chain network topology [Kim et al., 2011].

In this work we used the division into "bow-tie" areas to better understand the consequence of perturbations applied in different parts of a system that can be represented by a directed graph. We notice that the central area Scc, although significant, does not actually generate the largest perturbations (which start from the nodes belonging to the In area): it is instead the area most often affected by avalanches and shocks, being involved both by perturbations that depart from it, both by the perturbations coming from the In area. The same fate is shared by the Out zone, towards which all these perturbations converge. Interestingly, avalanches and shocks from the Out, Tubes an Tendrils zone never take on significant dimensions. Finally. the nodes belonging to Tubes and Tendrils are almost never involved in avalanches (while a fraction of them can be involved very frequently by shocks).

Based on the bow-tie model, we can therefore identify the areas and nodes starting from which perturbations can have a great impact on the system and therefore indicate the zones where is useful to intensify the risk management and mitigation strategies. These insights may also apply to other real-world systems organized according to bow-tie structures.

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# Chapter 2

## Evaluation of the Pandemic Impact on Global Automotive Supply Chain through Network Analysis*

with Sandra Paterlini[1], Francesco Pattarin[2] and
Marco Villani[3,4]

[1]Department of Economics and Management, University of Trento
[2]Marco Biagi Department of Economics, University of Modena and Reggio Emilia
[3]Department of Physics, Informatics and Mathematics, University of Modena and Reggio Emilia
[4]European Centre for Living Technology

### Abstract

In 2020, several countries implemented restrictive measures on a wide range of business activities as a crucial step to control the rapid spread of the COVID-19 pandemic. In the urgency of the situation, many nations swiftly implemented extensive and stringent lockdown measures, causing significant disruptions to global supply chains and inflicting severe consequences on the worldwide economy. In hindsight, we now contemplate whether implementing targeted restrictions, considering the understanding of supply chain networks, could have mitigated the negative impacts. In this regard, we direct our attention to the global automotive sector. First, we examine the features of its supply chain network (SCN), using original data on 3,323 companies linked by 11,182 trade connections. Second, we assess the short-term effects of different lockdown policies through agent-based simulation models. Our findings suggest that not all companies play the same role in the supply chain, so that the specific position of a company shall be considered when adopting lockdown measures. Furthermore, companies with a high elasticity of substitution for production inputs are less affected by restrictions than those with a rigid input mix. Therefore, targeted lockdown policies may be less costly than those where all companies in some sectors are locked down. Our results may provide policymakers with valuable information about the relative costs of different lockdown interventions. Also, we suggest company managers to adopt flexible supply management strategies.

*Keywords:* network analysis, global automotive sector, supply chain, COVID-19

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# 1 Introduction

The automotive industry uses inputs from a wide variety of other industrial firms. It provides vehicles to final consumers and other industries: automobiles, motorbikes, trucks, and heavy-duty vehicles. In any case, its outputs are semi-durable goods, since nowadays their typical operating life is less than a decade, due to either wear-out or obsolescence. This has made the automotive industry a strong driver of economic growth, employment, and innovation, which has a pivotal role in the worldwide economy through local and global value chains [Garcia et al., 2020].

As vehicles have become complex artifacts with many functionalities beyond their basic purposes —i.e., mobility, transportation, and duties— their production processes require many materials, components, and services from diverse firms and countries, such as metals, chemicals, semiconductors, and software. The automotive sector has become globally connected, as many companies within and outside of it have gradually come to share complementary goods and services, often specializing in specific areas (e.g., Toyota in hybrid engines, German carmakers in diesel ones, Pirelli making tires, Google or Apple providing connectivity services). Blázquez and González-Díaz [2016] analyzed the structural characteristics of the auto industry's network between 1996 and 2009. They used data from 172 countries and found that the auto network has become increasingly widespread and integrated. Consequently, global supply chains have become the foundational organization of the automotive industry, forming a competitive yet cooperative network [Gunasekaran and Ngai, 2004].

Since the 1980s, modes of production originating in Japan and based on lean and just-in-time processes have become a standard, as they have dramatically reduced operating costs. This requires quick and sure deliveries of components to vehicle makers; there is probably no carmaker that can continue producing at normal levels if some of the material inputs it needs are not delivered in less than a month's time.

In the 21st century, many challenges have affected the automotive industry's demand and supply side. Sales have decreased due to the burden of global economic recessions, tax hikes in several countries, strict environmental standards, and the transition towards electric vehicles. [Garcia et al., 2020]. The sudden and quick spread of the COVID-19 outbreak has imposed an unprecedented disruption on automotive companies and supply chains, causing considerable losses worldwide. The evolution of the pandemic has resulted in governments' decisions to quarantine the workforce and suspend the activities of many key businesses. For instance, Volkswagen and Hyundai shut down their automotive assembly plants in China and South Korea, and Nissan halted its production in Africa and the Middle East.

Since 2000, many epidemics and natural catastrophes have shocked supply chains, such as the 2003 SARS epidemic in China, the 2009 H1N1 epidemic in the US, the 2004 tsunami in Indonesia, and the 2011 earthquake in Japan. Most of these events, however, were limited to specific geographical areas and lasted only a short time, allowing for quick recoveries to normal operating conditions. Comparatively, in terms of its scope and magnitude, COVID-19 has profoundly affected global supply chains at all stages, from the primary sources to the final customers [Xu et al., 2020]. Furthermore, the lockdown ripple effects have lingered much longer than in past shocks, significantly hitting the economic activities of many companies, especially those unable to change sourcing strategies due to rigid technologies or the type of markets in which they operate.

We believe that knowing the morphology of the automotive supply chain at a granular level may help to gain insight about how and why the effects of COVID-19 shocks were such. Therefore, we reconstructed the global automotive supply chain over the 2018 to 2020 period at the single company level. We first identified their leading suppliers and customers from 165 world manufacturers of vehicles, be they automobiles, motorcycles, trucks, and heavy-duty vehicles. Then we searched for the companies connected to them, again, as suppliers and customers. Thus, we got a network of 3,323 companies spanning 135 industries and 16 geographical areas, connected by 11,182 mutual trades connections. To our knowledge, this is one of the few researches considering such an extensive network. For instance, Kito and Ueda [2014] used a series of regularly published surveys, each providing quantitative information on structural transitions in the supply networks of 200 auto parts. However, the data is limited to first-level incoming links. This means that they fail to identify the customers of the assemblers and to capture the second-level business relationships of the suppliers and customers themselves.

We used this dataset for two purposes. First, we examined the supply chain, highlighting its main economic and systemic features from a network viewpoint. Second, we studied the effects of various lockdown policy scenarios on it through agent-based models (ABMs henceforth) under a complex system approach without pre-establishing any configuration of the final outcomes and looking at short-term effects. To this end, we consider two factors: (i) the sustainability of the production process of firms, in terms of capacity, when they lose suppliers and may, therefore, become short of productive inputs; (ii) how firms react when they lose customers.

The objective of this paper is not to replicate the long-term consequences experienced by individual firms, including failures or reopening, but rather to elucidate the general systemic effects in the short run. In this perspective, Inoue and Todo [2019] investigated the economic aftermath of the 2011 Great East Japan earthquake. Their findings showed that a few weeks of disruption or a significant reduction in production activity could exert a substantial impact on a country's GDP.

The originality of our study is twofold. First, analyzing the global automotive supply chain at the level of second-tier individual companies through network analysis tools. Given that cross-border trades are a crucial aspect of the automotive industry, the high level of detail in the network we reconstructed offers an updated representation of the companies involved and their relationships. Second, using ABMs to simulate the effects of lockdown policies on the automotive supply chain. Most research on the effects of natural disasters and epidemics does not consider cross-border connections between companies. We hypothesize some network perturbations, benchmarked to the lockdown measures adopted in Italy from the end of March 2020. We chose Italy as it was the first country to be hit by the COVID-19 pandemic outside of China and implemented one of the strictest lockdown measures in the world. Detailed data from the Italian National Institute of Statistics about the shutdown of economic sectors were used to identify the industries subject to restrictions[1]. Our simulation results offer valuable information to policymakers regarding the relative costs of different lockdown policy interventions and highlight the limitations of generalized lockdown policies. Future research could use alternative models to analyze network structure, such as the riskiness of a node based on its geographic location, by assessing country-country exposure as proposed by Chakraborty et al. [2024].

The article is structured as follows. Section 2 contextualizes our research within the relevant literature. Section 3 details the data collection process for our analyses and presents the characteristics of the global automotive SCN. Section 4 describes the agent-based modeling method we used and discusses our simulation results. Section 5 concludes.

[1] Link. Retrieved on 12 May 2020.

# 2 Literature review

Several authors have studied the economic effects of exogenous shocks from natural disasters, such as earthquakes, hurricanes, and tsunamis, and their propagation through supply chains. As Zhu et al. [2022] point out, the aggregate economic impacts of such shocks are examined mainly through three different methodologies: general economic equilibrium, agent-based simulation, and econometric methods. These differ by specific theoretical assumptions and the kind of data they rely on and have been recently applied to understand and evaluate the economic impact of the COVID-19 crisis. As Ivanov [2020] states, the consequences of the pandemic are comparable to a natural disaster that compromises supply chains because it hits final demand and causes shortages of inputs and workforce, both in the short and long terms. We do not agree with this view, as we notice an important difference between these two kinds of shocks. While natural disasters mainly disrupt physical infrastructures and impact the workforce and demand only at the local level, possibly with indirect global effects, the pandemic did not hit infrastructures and firms but had direct global effects on their operations, both on the workforce and on final demand. This is an important difference. Once a disaster is over, the investments to replace damaged infrastructures have positive effects on economic activity, the labor market and demand, which may help to start firms' recovery in the short-term. Recovering from a pandemic is different, because it takes a longer time, and the process is not straightforward. Economic agents react by reducing their expectations to face uncertainty and, even if no physical infrastructure is compromised, normal economic activity is disrupted both on the demand and supply side; firms reduce their operations and investments, some of the workforce is laid off, and the demand for goods and services goes down [Baldwin and Di Mauro, 2020, Basurto et al., 2023]. Therefore, we believe it is essential to explore and model the complex interplay of such factors to understand the reactions of economic systems to the pandemic crisis and its consequences. This approach will help us make sense of an evolving situation that may be unstable in the short run. In a similar vein, Henriet and Hallegatte [2008] delved into the short-term consequences of Hurricane Katrina in the USA. They argued that the economic costs associated with the hurricane were contingent upon the heterogeneous nature of the productive system structure. The results of their simulations indicate that the probability of failures was lower for firms that had many customers and suppliers, as well as large inventories; this is consistent with the idea that risk management of operations improves robustness. Hallegatte [2012] further investigated the consequences of Hurricane Katrina, focusing on the role of the goods and services heterogeneity within sectors, pointing out that a significant negative influence of this factor on production bottlenecks would increase the total economic losses caused by a natural disaster. Kashiwagi et al. [2021] showed that connections of companies with their suppliers and customers had been damaged by Hurricane Sandy —which hit the East Coast of the USA in 2012— reducing sales growth. They provided evidence that propagation effects were mitigated in cases of vertical integration, where internal exchange of resources prevailed over market trades, thus acting as a safeguard and reducing uncertainty. Seetharam [2018] argued that potentially ignoring interregional connections emerging from multi-plant firms' internal networks underestimate the impact of hurricanes on supply chains. In particular, the author deems that the natural disasters effects may propagate spatially. Inoue and Todo [2019] analyzed how shocks spread through supply chains by using data from the Great Eastern Japan earthquake of 2011, the fourth largest earthquake in the world since 1900. They found that direct losses were smaller than indirect ones because companies not actually affected by the earthquake suffered the failure of their providers based in the hit regions[2]. In assessing how input-output links acted as a transmission channel for the 2011 Great East Japan earthquake, Carvalho et al. [2021] defined extremely detailed assumptions regarding the shock propagation along supply chains. They emphasize that a company's position within the network and the flexibility to substitute labor, materials, and intermediate goods play a critical role in determining the severity of shock propagation. The scholars found that such propagation is more widespread and severe when inputs are highly specific and complex to replace, a constraint influenced not only by technology and production techniques but also by the firm's market positioning within the supply chain.

Following the outbreak of COVID-19 and the subsequent restrictions on social and economic activities, researchers have been examining the impact on the economy, both locally and globally. A strand of studies has investigated the economic shock propagation of the pandemic through supply chains. Inoue and Todo [2020] examined the possible impacts of lockdown measures in Tokyo at the firm level across Japan from a complex system perspective and concluded that, although the production of the locked-down sectors in Tokyo is 21.3% of the national production, restrictions would result in an 86% reduction of the overall daily GDP (1.25 trillion Yen) in a month's time. To identify the network structure through which the economic effects of lockdowns in different regions interact with each other, Inoue et al. [2020] simulated an agent-based model of actual supply chain data from 1.6 million companies in Japan. Their findings revealed that the economic impact of lockdowns varied significantly across regions,

[2]Their estimate was that the total cumulated loss over a one-year period after the shock was 11.4 trillion yen or 2.3% of Japan GDP; this amounts to more than a hundred times the total direct effect suffered by hit firms.

depending on whether and to what extent the regions they traded with were also subject to restrictions. This highlights the necessity of interregional policy coordination to decrease the economic loss caused by lockdown policies. Similarly, in analyzing the global supply chain effects of a set of idealized lockdown scenarios, Guan et al. [2020] found that the complexity of global supply chains would amplify losses beyond the direct effects of COVID-19 regardless of the strategy adopted. The key takeaway from these studies is that understanding how shocks spread through supply chain networks is crucial for assessing their overall impact on the economy. In fact, second-round shockwaves may be more serious than the initial impact, but this varies based on productive techniques, operational models, market conditions, and the overall structure of networks.

For the automotive sector, which is the primary focus of this article, Muhammad et al. [2022] suggest that the industry may be significantly impacted by lockdowns due to the ripple effect across its closely interconnected global supply chain. Furthermore, Kaitwade [2021] claims that the global slowdown in automotive sector activities following the pandemic was heavily affected by disruptions in the supply chain caused by lockdowns in China, a key global hub for both production and consumption. Although this perspective may be somewhat extreme, it is undeniable that the shocks had worldwide repercussions. Indeed, Coffin [2019] and Lazarov [2020], for example, highlight the strong dependence of the USA automobile industry on Chinese-made components. Irsyadillah and Dadang [2020] contend that competitive advantage in the automotive sector relies not only on the quality of products or services but also on the ability to implement effective supply chain risk management (SCRM) systems to withstand disruptions like those caused by the pandemic[3].

The importance of understanding the SCN structures to assess the spread of shocks along supply relationships was also highlighted by Chakraborty et al. [2024]. They quantified differences in the countries' risk exposures to determine how the systemic risk is distributed across the globe. With this study, we aim to provide evidence that ABMs may be informative about the consequences of perturbations under different scenarios and help devise policies to prevent or counteract the effects of critical events, both at the business management and government intervention levels.

[3] Other scholars share this perspective. For instance, Belhadi et al. [2021] conducted an empirical study using interviews to identify strategies for mitigating pandemic-related risks. They concluded that adopting digital technologies across the automotive industry enhances supply chain resilience (see also Balakrishnan and Ramanathan [2021], Soares et al. [2021]). Similarly, Shin and Shin [2021] analyzed the global automotive supply chain, advocating for reshoring and diversifying production bases as key risk management approaches.

## 3 Data collection and network description

The automotive supply chain network dataset consists of 3,323 companies (nodes) connected by 11,182 trade relations (edges) collected from the Bloomberg platform. We collected information on all the companies within our dataset, including their size measured by the average annual sales (in USD millions) over the 2018-2020 fiscal years, the region where they are legally established, and their economic activity sector as classified by Morgan Stanley Capital International and Standard & Poor's GICS® taxonomy[4].

Our data collection procedure started by identifying and retrieving all automobile, motorcycle, truck, and heavy-duty vehicle manufacturers worldwide available on Bloomberg. We call them "focal companies" and obtained 165 of them. Then, we built the final dataset as follows: (1) identify and select the main suppliers and customers of the focal companies; (2) identify and select the main suppliers and customers of the latter[5]; (3) drop all companies with any variable of interest missing[6]. This implies that our dataset represents the automotive supply chain network up to the second order; it includes all focal companies in the network, as well as their suppliers, customers, and the suppliers and customers of those companies, provided we were able to obtain all the relevant variables for each company. Appendix B contains five tables of supply chain statistics.

Besides nodes, a network is defined by edges. In our case, an "edge" is a directed trade connection, from supplier to customer, between two companies; that is, if a company sells goods or services to another, then there is an edge stemming from it and pointing towards the other. Figure 1 provides a schematic representation of such a structure, where circles are nodes and arrows are directed edges connecting them; the direction of any edge follows the flow of goods and services from a company to another.

[4]The Global Industry Classification System® consists of 11 sectors, 24 industry groups, 69 industries and 158 sub-industries, where each level is more granular than its predecessors so that, for example, an industry is a more specific definition of economic activity that an industry group (`link`. Retrieved 7 June 2021). We collected data on sub-industries.

[5]Bloomberg defines "main" as top-ranking suppliers and customers according to revenues or cost of goods sold. The number of main suppliers and customers is not the same for every company, and typically is in the range of few to twenty units. Since not all connections necessarily contribute to production (e.g., consulting or food supply to feed employees), we have applied a restriction concerning supplier selection. We consider only suppliers operating in strategic business segments (e.g., steel, electrical components, etc.). Conversely, we do not apply such a constraint to consumers.

[6]Before step (3), we had 5,211 nodes and 14,062 edges: therefore, the final network we used in our research consists of 64% of raw nodes and 80% raw edges. It is known that ignoring nodes with incomplete information can significantly reduce the database and potentially lead to survivorship bias. However, we have chosen not to use imputation techniques, as they can introduce an arbitrary noise and bias. Nevertheless, we performed a robustness check (see Appendix A) with the larger sample and confirmed that the network morphology remains essentially unchanged and results are consistent.

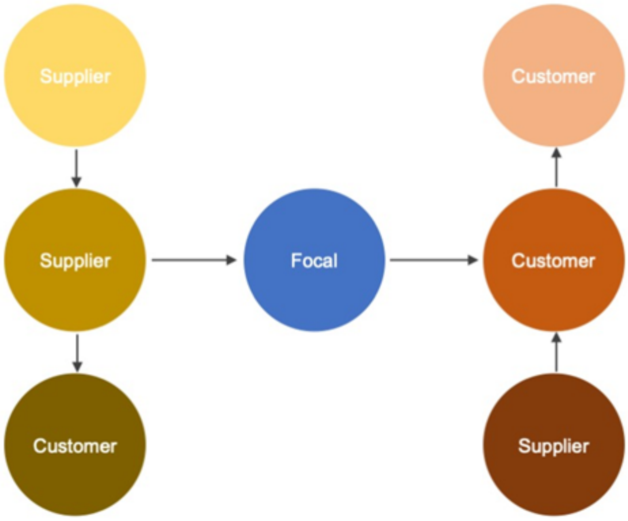


**Figure 1:** Exemplification of the focal companies, suppliers, and customers of the first and second levels.

It is worth noting that some companies in our dataset are both suppliers and customers, with both incoming and outgoing edges, while others only act as suppliers without any incoming edges, and some only as customers without any outgoing edges. Table 1 provides a detailed description of the different types of companies in the network, including the number and percentage of companies that serve as both suppliers and customers, the number and percentage of companies that only act as suppliers, and the number and percentage of companies that only act as customers.

| **Type of node** | **Absolute frequency** | **Relative frequency (%)** |
|---|---|---|
| Supplier and customer | 1,192 | 35.87 |
| *of which: Focal firms* | *92* | *2.77* |
| Only supplier | 1,201 | 36.14 |
| *of which: Focal firms* | *25* | *0.75* |
| Only customer | 930 | 27.99 |
| *of which: Focal firms* | *48* | *1.44* |
| **Total** | **3,323** | **100.00** |

**Table 1:** Distribution of network nodes by role.

Our procedure for constructing the network resulted in 11,182 directed edges. A visualization of the distribution of these edges is provided in Figure 2.

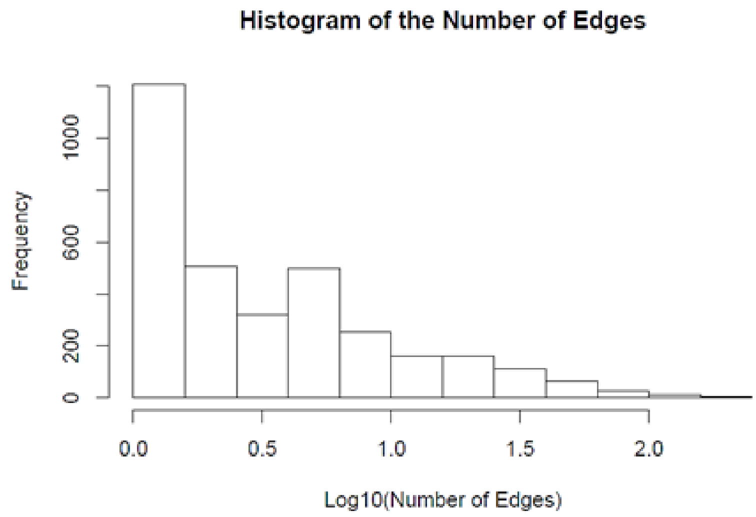


**Figure 2:** Distribution of total edges for network firms. The x-axis shows the logarithm of the sum of incoming and outgoing edges. The y-axis indicates the absolute frequency.

Most companies in the network have only a small number of edges, with a median value of two. The distribution is right-skewed, with a mean of 6.73 edges and extending to a maximum of 158 edges for a single company, with a third quartile of 6. Larger companies are likely to have more connections, according to the principle of "rich-get-richer" [Bernard et al., 2019, Krichene et al., 2019]. Thus, firm sales are an essential characteristic to be also considered. This evidence is coherent with the findings of Chakraborty et al. [2019], who examine the community structure of the Japanese production network.

When we look at the activity of companies, considering their economic sector and geographical location, some important differences emerge. In Appendix B, Tables B1 and B2 show the number of companies, outbound edges (from suppliers to customers), inbound edges (from customers to suppliers) and average edges by business sector and geographical area. Overall, 16 geographical regions have been identified, some of which are formed by single countries owing to their significance in the global supply network[7]. Table B3 focuses on the 165 focal companies. Almost all of them belong to the automobile and construction machinery and heavy equipment sectors (88%), with only a marginal proportion belonging to the motorcycle sector (12%). Asian countries and North America are confirmed to be the most significant regions. Besides the number of nodes and edges in the network, its size based on the average of 2018-2020 total sales is about 27 billion USD, out of which 2.890 billion USD (11%) are generated by focal companies[8]. Tables B4 and B5 present the total and average sales by company for all

[7] Appendix C shows the correspondence of each country to its geographical area.

[8] According to IBISWorld, the average annual sales of the global automotive market over the 2018-2020 period were 3,690 billion USD. Therefore, we estimate that focal companies in our dataset cover about 79% of the world market.

sectors and geographical areas, respectively. Automobile manufacturers have the largest share in terms of revenues, but Energy producers and Finance are also very relevant. Over 70% of the automotive network by sales consists of Asian companies, but an important role is also played by North America, with a share of about 15%.

Figure 3 depicts a map of our network, focusing on the geographical areas with the largest number of nodes (China) and the highest revenues (North America). Descriptive statistics for the network are provided in Table 2.

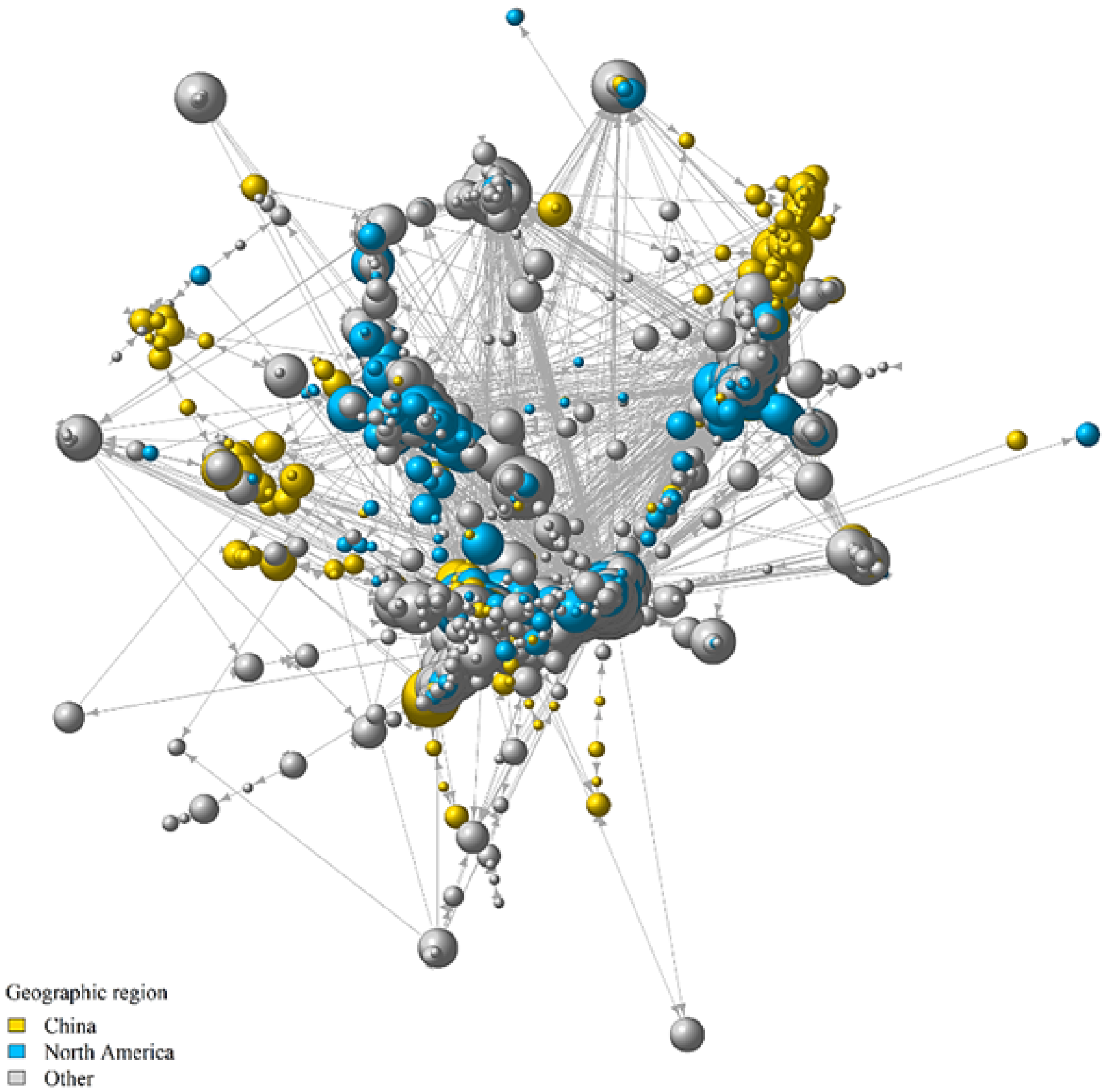


**Figure 3:** Visualization of the Chinese, American and other nodes in the global automotive network. The size of each node is proportional to its degree centrality. The plot was generated using the R package "igraph".

| **Statistics** | **Values** |
|---|---|
| Nodes | 3,323 |
| Edges | 11,182 |
| Average neighbors | 6.586 |
| Diameter | 20 |
| Radius | 8 |
| Average shortest path length | 6.306 |
| Clustering coefficient | 0.100 |
| Density | 0.001 |

**Table 2:** Global network descriptive statistics. Measures follow the definitions of Barabási [2017]; see Appendix D.

It is apparent that the automotive network has a significantly lower number of actual relationships compared to the number of all possible connections between its 3,323 nodes; indeed, the global network density is 0.001. At the local level, many companies are quite connected because they have, on average, six to seven neighbors. However, these connections are mainly bilateral, as indicated by the low clustering coefficient; this means that it is seldom the case that companies connected to a given company are themselves connected one another. Furthermore, most connections are a few steps away as the radius measure is eight. The diameter of the network —i.e., the longest path from any two nodes— is twenty; this is significant, because it means that while most relationships between companies are local there are few connections extending far away and involving many companies. The average shortest path length of about six is typical of a small world network and is relevant for how shocks may propagate through the network, as we will discuss in Section 4. Finally, as Figure 2 also suggests, the network statistics hint at the presence of "hubs"; these are nodes with many incoming and outgoing connections, from and to nodes that would otherwise be separated if it were not for their intermediary role.

As a further step, we qualify companies according to their position in the network, considering the bow-tie decomposition. Previous studies have analyzed supply chains from the same perspective [Chakraborty et al., 2018, Kichikawa et al., 2019, Chakraborty and Ikeda, 2020], which has also been widely used to understand the flow structure of various complex networks, including the worldwide web and metabolic networks. We employ this technique to explain how perturbations spread within the network systems depending on the bow-tie decomposition [Flori et al., 2022]. The bow-tie taxonomy comprises five major areas, as described in Broder et al. [2000] and Fujita et al. [2019].

As shown in Figure 4, the "strongly connected component" (Scc) is the largest area where from each node it is possible to reach any other node belonging to it through directed edges. The "in component" (In) is the set of nodes that cannot be reached from the Scc but point to it. Nodes that belong to the "out component" (Out) can be reached from the Scc but do not point to it. The in- and out-component nodes may be connected through "tube" nodes (Tubes), bypassing the Scc. Also, some marginal nodes called "tendrils" (Tendrils) are connected to in- and out-component nodes, with outgoing and incoming edges, respectively.

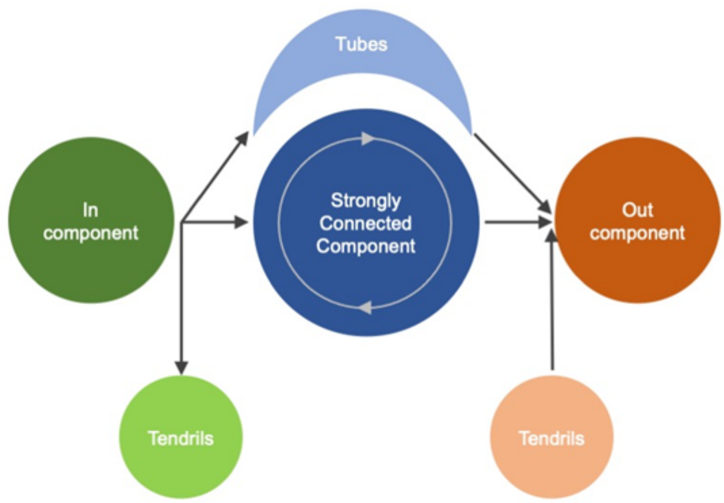


**Figure 4:** Taxonomy of network components according to the bow-tie model.

The first columns of Table 3 show the dimension of the bow-tie areas in the actual automotive network. Tubes are a residual component (21 nodes or 0.63% of the total), which means that most connections are intermediated by nodes belonging to the Scc. This component sums up to 755 nodes (22.72% of the total) with 58 focal companies in it. Also, In- and Out-components are important, together with Tendrils (2,547 nodes or 76.65% of the total). Figure 5 provides a graphical representation of the global network, highlighting the bow-tie zone of each node.

| **Components** | **Actual network** | | **Rnd network** | **Rid network** |
|---|---|---|---|---|
| | Count | Frequency (%) | Frequency (%) | Frequency (%) |
| Scc | 755 | 22.72 | 92.4 ± 0.2 | 29.0 ± 0.9 |
| *of which: Focal firms* | *58* | *1.75* | −− | −− |
| In | 1,071 | 32.23 | 3.9 ± 0.5 | 35.0 ± 0.9 |
| *of which: Focal firms* | *18* | *0.54* | −− | −− |
| Out | 883 | 26.57 | 3.7 ± 0.4 | 25.0 ± 0.9 |
| *of which: Focal firms* | *72* | *2.17* | −− | −− |
| Tubes | 21 | 0.63 | 0 ± 0 | 0.36 ± 0.3 |
| *of which: Focal firms* | *1* | *0.03* | −− | −− |
| Tendrils | 593 | 17.85 | 0.03 ± 0.02 | 10.5 ± 0.9 |
| *of which: Focal firms* | *16* | 0.*48* | −− | −− |

**Table 3:** Count and relative frequency of nodes by bow-tie zone. The first columns show count and relative frequencies for the automotive network. The last two columns show the average frequencies ± the standard deviation across ten simulated ensembles.

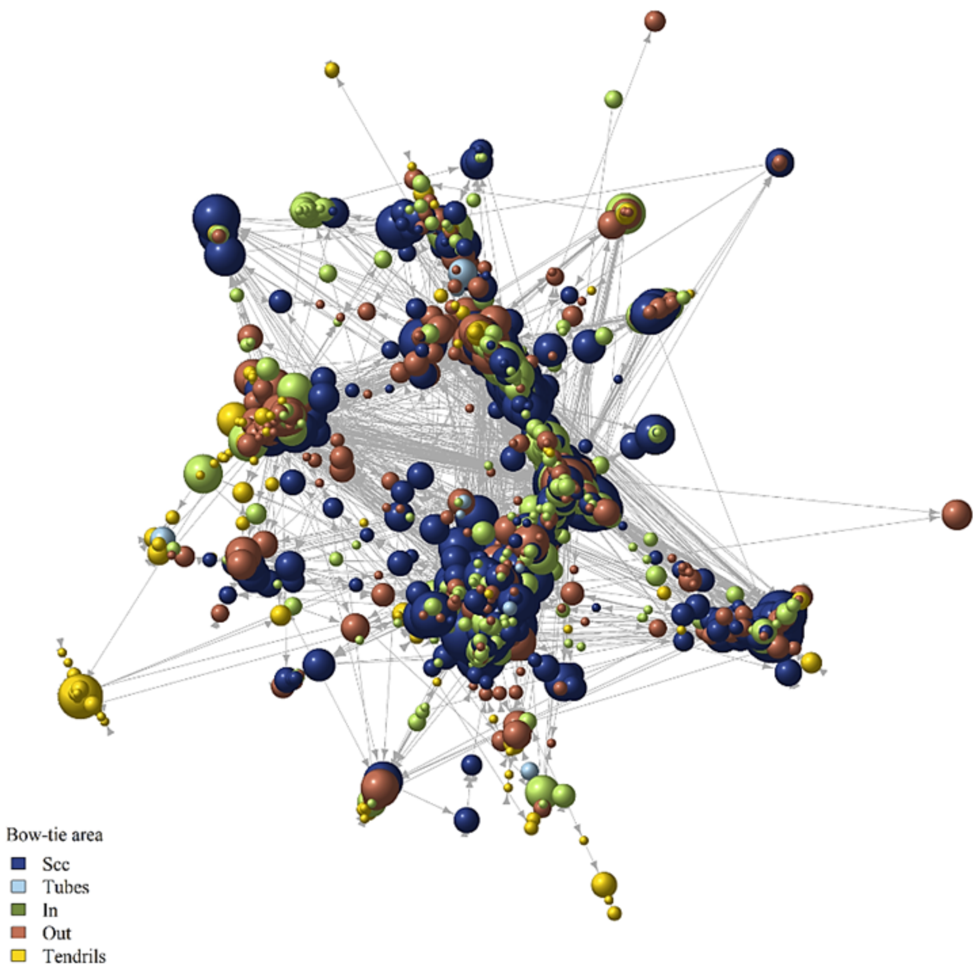


**Figure 5:** Visualization of the bow-tie areas within the global network. The size of each node is proportional to its degree centrality. The plot was generated using the R package "igraph".

To determine whether the identified areas are large or small, we compare the bow-tie organization of the automotive system with two artificial benchmarks; these are simulated ensembles, each consisting of ten networks which have the same number of nodes and connections as the automotive's, but:

- in the first ensemble, connections are uniformly distributed, as in the Erdős–Rényi random network ("Random", or "Rnd" in the following);
- in the second ensemble, the original degrees of each node are preserved, but each link is randomly redirected ("Redirected", or "Rid" in the following).

As depicted in Table 3, while the networks within both ensembles are random, they exhibit a highly homogeneous bow-tie organization. This expected behavior demonstrates that, at least concerning this characteristic, local details do not significantly influence the global structure. Compared to Random ensembles, the actual automotive network has a smaller Scc area and larger In and Out areas; also, it has more nodes in Tubes and, especially Tendrils. The system under examination does not exhibit characteristics akin to entirely random systems, indicating that its construction rules, as anticipated, are not random. Conversely, the automotive network showcases bow-tie regions remarkably akin to redirected networks. Consequently, delving into the topics associated with the identified connectivity distribution becomes an intriguing avenue for exploration.

Hence, our focus lies in exploring the in-degree and out-degree distributions. The in-degree distribution of a network is a description of the probability of any node having some incoming connections and is typically investigated by fitting a probability law to the empirical distribution of incoming edges across a sub-sample of nodes. The sample for estimation is determined by excluding nodes with an incoming edge count below a specified threshold, allowing for an examination of the tail distribution of nodes, as outlined by Clauset et al. [2009][9]. In network theory, tail distributions are associated with models of network formation. For example, random networks, whereby connections between nodes are random, are best described by a Poisson probability law. On the other hand, networks where the probability of connections depends on the number of incoming and outgoing edges or on other features of a node (also known as "preferential attachment") are characterized by Power- or Log-normal laws [Barabási, 2017, Sheridan and Onodera, 2018]. The same applies to the analysis of the out-degree distribution. Preferential attachment mechanisms typically generate situations where some nodes play a key

[9]We define "tail nodes" according to their in- and out-degrees; all nodes that have a degree higher than the first quartile of the overall distribution are tail nodes. For in-degree, this means that a tail node has at least five incoming edges, while for out degree the threshold of outgoing edges is four.

role in intermediating connections across the network because they act as hubs.

A way of assessing whether a network topology is consistent with some hypothetical formation process is to compare its empirical and theoretical tail degree distributions. To do this, some theoretical distributions of interest are fitted to the empirical one and compared with each other. Our fitting procedure relies on Maximum-Likelihood, as suggested by Clauset et al. [2009]. We consider two probability distributions to in- and out-degrees: Poisson and Power law. Comparisons are commonly done in three ways: eye-balling the log-log scale cumulative degree distributions to see if any law fits well to the empirical distribution; computing the Kolmogorov-Smirnov distance (KS) between the fitted and empirical distributions and seeing what their differences are; statistically testing such differences, to see if they are significant beyond sampling errors [Gillespie, 2024]. We made all such comparisons for in- and out-degrees. First, Figure 6 plots the fitted and empirical degree distributions, and then Table 4 shows the KS distance statistic.

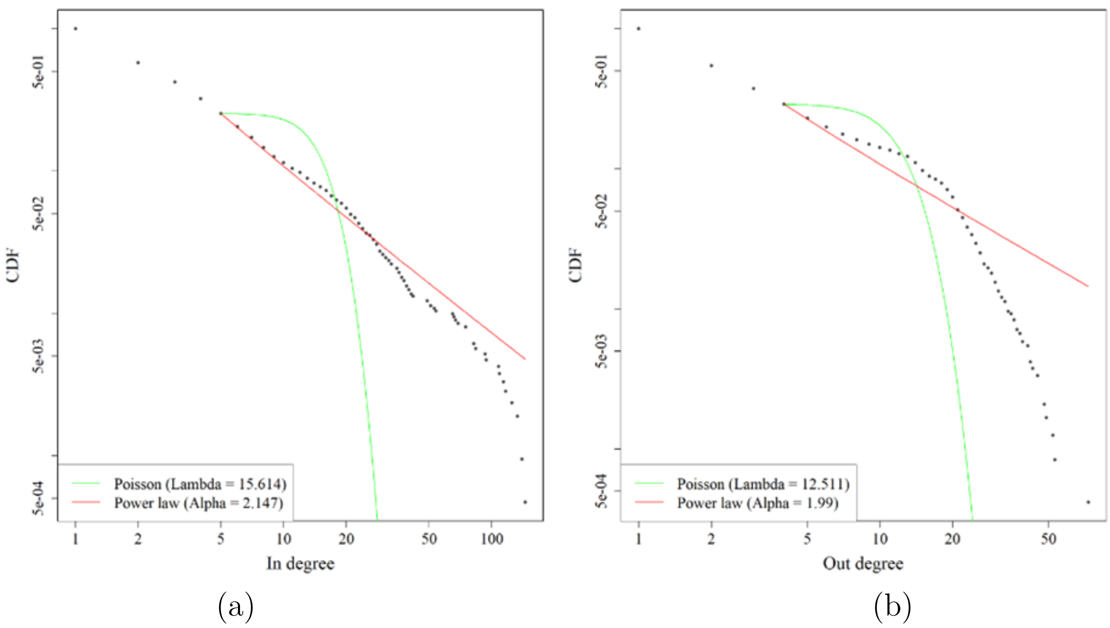


**Figure 6:** Empirical and fitted degree distributions on log-log scale. On the left, in degree, while on the right, out degree.

| Theoretical distribution | In-degree | Out-degree |
|---|---|---|
| Poisson | 0.4982 | 0.3742 |
| Power law | 0.0451 | 0.1397 |

**Table 4:** KS fit measures by theoretical probability laws and degree distributions. The lowest is the measure, the better the fit.

Considering both in- and out-degree distributions, all tests suggest that the Poisson distribution is unsuitable, confirming that the global supply-chain network does not adhere to a random structure. This result is in line with the findings of Chakraborty and Ikeda [2020], which state that the network in which a power law characterizes the degree distribution includes hub companies.

It is important to remark two features of the network. First, many companies have only upstream or downstream connections (2,131, or about 64% of all nodes; see Table 1), and focal companies may relate to one another. Second, the network is weakly connected, because there is necessarily at least one (undirected) path connecting any two nodes; this stems from our sampling and network construction strategies.

The final network we obtained provides a description of the supply links that characterize the automotive sector at a global level, albeit with a certain degree of approximation, since most of the companies in the sample are listed and large, thus excluding many smaller ones which are underrepresented. Nonetheless, available data allow us to significantly assess the technological and market relationships that connect companies along the supply chain. Therefore, it is reasonable to use the topology of the sampled network to examine the propagation of pandemic-related shocks that may affect companies across the automotive supply chain. For this, we envisioned some network perturbation scenarios and applied them under some assumptions about companies input elasticity of substitution. Benchmark perturbations are defined referring to lockdown policies adopted in Italy[10] during spring 2020, which had been in force for some months[11].

# 4 Simulation results

To test the impact of the lockdown measures adopted by governments to curb the spread of the pandemic, we develop several agent simulation scenarios following Watts [2002]. We intend to describe the propagation of shocks along the automotive supply chain given different initial conditions (S) and reactions of companies (R). Our analysis concentrates on a short-term time horizon. Consequently, when we mention a firm affected by the disruption, we imply that it has temporarily suspended its production activity. In this context, companies might opt to

[10] We choose Italy as it was the first country to be hit after China and it implemented very strict lockdown policies.

[11] To this end, Istat data relating to the lockdown of the NACE sectors were matched with the GICS® industries. Istat is the Italian statistical agency. Appendix E illustrates the 48 industries of the GICS® classification that were locked down. The correspondence table between NACE and GICS® sectors is available from the authors upon request.

implement policies that incur costs surpassing their revenues to protect their market share. Additionally, they may encounter challenges in replacing suppliers within the designated time frame. It is crucial to emphasize that our paper does not aim to examine the consequences of the COVID-19 crisis specifically in terms of business failures.

We model how companies respond to supply shocks, which we assume depend on the degree of substitution of their production factors in the short term, and the effects of demand shocks, to which companies can voluntarily react by suspending their business if customers cease requesting the goods or services they produce. Thus, our assumptions are:

**S1.** Companies do not have any elasticity of substitution for their inputs in the short term; therefore, they stop operating when they lose any of their suppliers.

**S2.** Companies have some elasticity of substitution in the short term, so they cease operating when one-third of their suppliers are lost.

**S3.** Companies have strong elasticity of substitution in the short term, so they stop operating if they lose two-thirds of their suppliers.

**R1.** Any company belonging to one of the sectors subject to lockdown stops operations.

**R2.** A company belonging to sectors subject to lockdown stops operations if it has fewer connections than the third quartile of the whole network.

**R3.** A company belonging to one of the sectors subject to lockdown stops operations if it has fewer connections than the median of the whole network.

Therefore, we develop nine scenarios based on different combinations of such assumptions. The first three scenarios assume an initial shock originating from the halting of all companies belonging to the sectors subject to lockdowns in Italy during Spring 2020. The other six scenarios assume, hypothetically, an initial shock from the closure of some companies belonging to the same sectors but having a limited number of connections; that is, only companies whose degree of connectivity is lower than the median or the first quartile of the overall network are considered as locked down. In any case, if a company loses all its customers, it shuts down. All scenarios are reported in Table 5.

| Scenarios | Assumptions | Elasticity of substitution | Lockdown policy |
|---|---|---|---|
| 1 | S1 + R1 | None | All businesses shut down |
| 2 | S2 + R1 | Weak | |
| 3 | S3 + R1 | Strong | |
| 4 | S1 + R2 | None | Very connected businesses do not shut down |
| 5 | S2 + R2 | Weak | |
| 6 | S3 + R2 | Strong | |
| 7 | S1 + R3 | None | Less connected businesses shut down |
| 8 | S2 + R3 | Weak | |
| 9 | S3 + R3 | Strong | |

**Table 5:** Synopsis of agent simulation scenarios.

In the first three cases, production inputs are perfect complements; therefore, if any supplier fails, a firm ceases to operate. In the other cases, from four to nine, this constraint is gradually eased as the input elasticity of substitution grows. For each scenario, the final outcomes are evaluated when the network becomes stable after the shock; that is, when the ripple effects of it peter out and the morphology of the network does not change any further. The results of the nine simulations are in Table 6.

The outcomes in terms of lost nodes, edges, and revenues are evidently influenced by the selection of companies for lockdown measures and the assumed elasticity of input substitution. Consistently across shocks, all facets of the network undergo changes in the same direction: as nodes fail, so do edges and revenues. The elasticity of substitution plays a pivotal role in delineating the magnitude of these effects. Companies with the ability to swiftly replace their inputs in the short term undergo less adversity. However, the resilience of the system to shocks also relies on the type of lockdown implemented. When lockdowns target less essential companies, the effects are less severe, making the elasticity of substitution more effective in preserving the system. Conversely, when there is a rigid input technology in place, the type of lockdowns has minimal impact on short-term outcomes.

| | | Scenarios | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** |
| | **Lockdowns** | 1,938 | 1,938 | 1,938 | 1,295 | 1,295 | 1,295 | 572 | 572 | 572 |
| **Nodes** | $T_0$ | 1,385 | 1,385 | 1,385 | 2,028 | 2,028 | 2,028 | 2,751 | 2,751 | 2,751 |
| | $T_1$ | 144 | 205 | 408 | 165 | 292 | 1,667 | 308 | 1,953 | 2,615 |
| | $\Delta$ | 89.60% | 85.20% | 70.54% | 91.86% | 85.60% | 17.80% | 88.80% | 29.01% | 4.94% |
| **Edges** | $T_0$ | 1,034 | 1,034 | 1,034 | 8,589 | 8,589 | 8,589 | 10,607 | 10,607 | 10,607 |
| | $T_1$ | 127 | 209 | 537 | 142 | 306 | 7,529 | 273 | 7,518 | 10,240 |
| | $\Delta$ | 87.72% | 79.79% | 48.07% | 98.35% | 96.44% | 12.34% | 97.43% | 29.12% | 3.46% |
| **Revenues** | $T_0$ | 16,185,663 | 16,185,663 | 16,185,663 | 23,436,935 | 23,436,935 | 23,436,935 | 25,730,922 | 25,730,922 | 25,730,922 |
| | $T_1$ | 2,650,419 | 2,940,643 | 5,939,233 | 2,671,391 | 3,272,494 | 19,906,247 | 3,321,597 | 16,513,345 | 23,083,545 |
| | $\Delta$ | 83.62% | 81.83% | 63.31% | 88.60% | 86.04% | 15.06% | 87.09% | 35.82% | 10.29% |

**Table 6:** Results of simulations: $T_0$ are initial conditions, $T_1$ are final, $\Delta$ are percent variations.

It is apparent that policymakers should take into account company connections and network topology when formulating lockdown decisions. Notably, stringent and extensive lockdown policies, designed to safeguard public health (i.e., scenarios 1-2-3), result in more pronounced adverse effects on the operations of the global automotive sector. Conversely, limited lockdown policies (i.e., scenarios 4-5-6 and, notably, scenarios 7-8-9) mitigate the costs associated with supply chain disruptions. We also analyze the results of the simulations according to the features of nodes that survive a shock. Table 7 shows the average size of these nodes in terms of number of links and sales in the different scenarios. Nodes characterized by the highest average revenues survive in the simulations where the lowest elasticity of substitution was assumed (i.e., scenarios 1-4-7), while nodes characterized by the highest average number of links survive in the simulations in which the highest elasticity of substitution was assumed (i.e., scenarios 3-6-9).

We exposed the Rnd and Rid ensembles to the same shock scenarios: again, despite the randomness, the networks belonging to the same ensemble showed very homogeneous behaviours. The case of Rnd networks is striking: none of the first six scenarios presents a single surviving node, while only the last scenario (limited initial perturbation and maximum flexibility) shows a number of surviving nodes comparable - although still much lower - to the number of surviving nodes in the automotive network. The cause of this behaviour lies in the large size of the Scc zone of these networks, capable of making the initial perturbation rapidly propagate to most nodes.

| | Scenarios | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** |
| **Lockdowns** | 1,938 | 1,938 | 1,938 | 1,295 | 1,295 | 1,295 | 572 | 572 | 572 |
| **Surviving nodes** | 144 | 205 | 408 | 165 | 292 | 1,667 | 308 | 1,953 | 2,615 |
| **Mean edges** | 0.88 | 1.02 | 1.32 | 0.86 | 1.05 | 4.52 | 0.89 | 3.85 | 3.92 |
| **Mean revenues (USD Mln)** | 18,405.69 | 14,344.60 | 14,556.94 | 16,190.25 | 11,207.17 | 11,941.36 | 10,784.41 | 8,455.37 | 8,827.36 |
| *Surviving nodes (Rnd network)* | *0.0±0.0* | *0.0±0.0* | *0.0±0.0* | *0.0±0.0* | *0.0±0.0* | *0.0±0.0* | *0.7±0.7** | *0.7±0.7** | *2,270±40** |
| *Surviving nodes (Rid network)* | *58±4* | *58±4* | *78±14* | *140±10* | *180±70* | *1,820±90* | *220±50* | *2,400±300* | *2,680±40* |

**Table 7:** Results of simulations: focus on surviving nodes. *It should be noted that in the case of the Random ensemble, the decision to eliminate all the nodes with a number of connections lower than the median would have led to identifying an average of over 970 nodes to be eliminated, i.e., a number much higher than the perturbation effected on the original automotive network. In this case, therefore, we limited ourselves to eliminating the 572 nodes having the lowest number of connections, imposing on the systems a perturbation like that carried out on the original network. By eliminating 970 nodes, we would have had no surviving nodes even in these cases.

The great similarity of the bow-tie organization between the original network and the Rid networks is reflected in a comparable dimension of the final size of the avalanches of perturbations. Interestingly, in six scenarios the automotive network still has resistance characteristics higher than those of the Rnd networks, which reveals that this system most likely also has supplementary reasons for resistance. Future works will analyze this aspect, especially present in scenarios of large perturbations and low flexibility. The only real exceptions are the scenarios number 6 and number 8 (where in any case the automotive network is not far from the confidence interval), while in the lighter scenario (i.e., the ninth) the automotive network and the Rid networks are substantially similar. Summing up, the bow-tie organization is confirmed as a major driver of the propagation of perturbations in network systems. Specifically, Flori et al. [2022] demonstrate that the consequences of disturbances depend strongly on the different bow-tie zones where they originate. The authors identified the Scc and In nodes as producing the most significant shocks[12] with cascading effects on both Scc and Out zones. Table 8 corroborates these findings, highlighting the vulnerability of Scc and Out areas. Interestingly, in case of simultaneous presence of slight restrictions and high elasticity, the Scc region instead turns out to be a high resistance zone.

| | **Scenarios** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Surviving nodes (%)** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** |
| **Scc** | ***0.0*** | ***0.1*** | ***2.6*** | ***0.0*** | ***0.5*** | 65.2 | ***0.0*** | 63.7 | 96.8 |
| **In** | 31.2 | 4.7 | 10.2 | 4.0 | 10.1 | 50.0 | 10.9 | 65.7 | 76.3 |
| **Out** | ***0.0*** | 0.6 | 8.8 | ***0.0*** | 1.8 | 42.0 | ***0.0*** | 47.8 | 74.9 |
| **Tubes** | 24.0 | 9.5 | 23.8 | 9.5 | 9.5 | 28.6 | 14.3 | 61.9 | 76.2 |
| **Tendrils** | 38.2 | 24.8 | 33.1 | 20.2 | 27.3 | 44.4 | 31.7 | 56.2 | ***65.8*** |

**Table 8:** Fraction of surviving nodes in each bow-tie region of the automotive system. For each scenario, the region with the lowest percentage of survivors is highlighted in bold italic. It can be noted that belonging to the Scc zone is extremely risky (similarly, belonging to the Out zone).

Our results are consistent if we consider smaller units than quartiles for company reaction assumptions. In Appendix F, we repeat the simulations identifying scenarios given by the initial conditions S1, S2 and S3 combined with the response of firms varying by five percentile (from 5 to 95) of linkages instead of quartiles.

[12] Shocks stemming from minor perturbations in the In and Scc zones of systems akin to the ones under current consideration typically exhibit effects—quantified in terms of the number of involved nodes and/or terminated relationships—several orders of magnitude greater than shocks originating in the Out, Tubes, or Tendrils zones [Flori et al., 2022].

# 5 Conclusions

In 2020, global supply chains experienced severe disruptions due to government-imposed restrictions to control the spread of COVID-19. These measures were often broadly applied without accounting for the specific roles of individual companies within the production system and supply chain. We show that future lockdown policies, if necessary, should be tailored to the structure of supply chains. To support this claim, we focus on the automotive industry, a globally significant sector in revenue generation, and the heterogeneity of companies it encompasses.

We employ network analysis tools and conduct ABMs to investigate the impact of lockdown restrictions, taking into account the ability of companies to substitute their inputs in the short term. Our study reveals two significant findings. Firstly, a firm is more likely to withstand the impact of closure measures if it has a flexible input substitution in the short run (i.e., a high degree of elasticity). Conversely, firms relying on production technologies or market situations that render specific inputs essential tend to become more vulnerable when restrictions are imposed. Second, companies have different positions in the network, and their positioning within the bow-tie organization is crucial regarding the progression of the perturbations. Failures of large companies immersed in the Out zone have a decidedly lower impact than failures of companies in the Scc or In zones. Therefore, lockdown policies should consider a company's position in its supply chain; shutting down important network intermediaries (hubs) or companies in the Scc or In zones results in more significant economic losses than restricting the activities of marginal businesses in other areas.

The contribution of this study to the extant literature is twofold. First, reconstructing the global automotive SCN at the level of individual companies extends much of the prior research, which has focused mainly on aggregated data at the level of economic sectors across countries. Our analysis examines the connections of individual companies within the automotive industry, offering insights into its core technological features, market relationships, and structural dynamics. The granularity of the data —encompassing the global supply chain network up to the second tier of customers and suppliers— represents a notable innovation, as no previous study, to our knowledge, has provided such detailed coverage. Second, this research advances beyond existing studies by assessing cross-border connections at the micro level. Moreover, our analyses provide additional insights into global supply chains and their potential policy implications. Policymakers may need to assess the effects of lockdowns on industries and companies, as broad lockdown measures tend to have higher economic costs than more targeted approaches. Similarly, companies may benefit from diversifying their suppliers and enhancing inventory management, reducing dependence on a limited number of sources and increasing stock reserves. While just-in-time and lean processes are typically efficient, supply shocks can impose significant costs due to shortages. Companies might find it worthwhile to consider maintaining higher inventory levels as a precaution against unexpected disruptions in the supply chain. Finally, understanding a company's position within the broader global automotive network could be crucial for its resilience during crises.

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# Appendix A

## Robustness tests with the extended network

To assess the effects arising from the presence of undetected nodes in the system, we chose to rely directly on our knowledge of the system instead of employing imputation techniques, which can introduce bias and noise. Consequently, we utilized a more extensive set of nodes and links (5,211 nodes and 14,683 links), acknowledging that the information about these entities was incomplete factors that are not crucial when restricting the analysis solely to graph-based approaches. Specifically, Table A1 shows that:

1. All areas experienced an increase in the number of nodes, albeit in varying proportions. Notably, the fraction of nodes in the Scc region is smaller, while the proportion of nodes in the Tendril region has seen a significant expansion. From this observation, two key considerations can be made: Nodes originally belonging to the Scc region in the original network continue to be part of the Scc region in the extended network. Nodes in the original In region may either remain in the In region or be incorporated into the Scc region in the extended network. Their status as a “trigger danger” has therefore not changed.

2. The majority of the “new” nodes now fall within the Tendril region, characterized by limited perturbation diffusion properties. This region propagates the signal solely from the In region to the Out region without influencing the Scc region.

| Components | Count | Frequency (%) |
|---|---:|---:|
| Scc | 875 | 16.79 |
| In | 1,704 | 32.70 |
| Out | 1,422 | 27.29 |
| Tubes | 26 | 0.50 |
| Tendrils | 1,184 | 22.72 |

**Table A1:** Count and relative frequency of nodes by bow-tie zone. It can be noted that the percentage of each zone in the extended network is close to the same as the original one (see Table 3), confirming a similar topology.

The situation of the nodes of the original network has therefore not changed significantly. Moreover, Tables A2 and A3 highlight that in the extended network, failures of the same nodes in the original network led to behaviors similar to those already observed. Therefore, we validate that the morphology of the network examined in the article remains substantially unaltered from the extended sample and does not lead to different simulation outcomes.

| | | **Scenarios** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** |
| | **Lockdowns** | 1,938 | 1,938 | 1,938 | 1,295 | 1,295 | 1,295 | 572 | 572 | 572 |
| **Nodes** | $T_0$ | 3,273 | 3,273 | 3,273 | 3,916 | 3,916 | 3,916 | 4,639 | 4,639 | 4,639 |
| | $T_1$ | 375 | 489 | 875 | 495 | 730 | 3,017 | 794 | 4,027 | 4,470 |
| | $\Delta$ | 88.54% | 85.06% | 73.27% | 87.36% | 81.36% | 22.96% | 82.88% | 13.19% | 3.64% |
| **Edges** | $T_0$ | 1,730 | 1,730 | 1,730 | 11,129 | 11,129 | 11,129 | 13,531 | 13,531 | 13,531 |
| | $T_1$ | 312 | 453 | 956 | 420 | 712 | 9,668 | 692 | 11,653 | 13,084 |
| | $\Delta$ | 81.97% | 73.82% | 44.74% | 96.23% | 93.60% | 13.13% | 94.89% | 13.88% | 3.30% |

**Table A2:** Results of simulations. The trend of percentage changes remains consistent with that reported about the original network in Table 6. We do not show the value of revenues due to the high number of missing values in the extended network.

| | **Scenarios** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Surviving nodes (%)** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** |
| **Scc** | ***0.2*** | ***0.3*** | ***3.5*** | ***0.1*** | ***1.0*** | 68.0 | 0.3 | 84.6 | 98.3 |
| **In** | 39.9 | 7.5 | 13.0 | 9.1 | 14.3 | 59.0 | 17.7 | 78.0 | 84.4 |
| **Out** | 0.5 | 1.8 | 12.0 | ***0.1*** | 4.1 | 54.0 | ***0.2*** | ***73.8*** | 84.4 |
| **Tubes** | 19.4 | 3.8 | 15.4 | 3.8 | 7.7 | ***26.9*** | 15.4 | 76.9 | 84.6 |
| **Tendrils** | 45.2 | 28.0 | 37.8 | 28.4 | 35.1 | 54.2 | 40.8 | 75.1 | ***80.2*** |

**Table A3:** Fraction of surviving nodes in each bow-tie region. For each scenario, the region with the lowest percentage of survivors is highlighted in bold italic. The Scc and Out zones are confirmed as the most vulnerable; see Table 8.

# Appendix B

## Supply chain statistics

| Sector | Companies | Outbound edges | Inbound edges | Average edges |
|---|---|---|---|---|
| Electronic Components | 406 | 1,730 | 1,359 | 7.61 |
| Auto Parts & Equipment | 304 | 3,406 | 1,550 | 16.30 |
| Steel | 300 | 1,330 | 1,266 | 8.65 |
| Application Software | 276 | 1,077 | 396 | 5.34 |
| Industrial Machinery | 122 | 304 | 134 | 3.59 |
| Semiconductors | 109 | 300 | 86 | 3.54 |
| Automobile Manufacturers | 76 | 350 | 2,650 | 39.47 |
| Semiconductor Equipment | 75 | 134 | 18 | 2.03 |
| Distributors | 73 | 103 | 275 | 5.18 |
| Technology Hardware, Storage & Peripherals | 71 | 95 | 305 | 5.63 |
| Construction Machinery & Heavy Trucks | 70 | 101 | 357 | 6.54 |
| Construction & Engineering | 68 | 73 | 97 | 2.50 |
| Electrical Components & Equipment | 68 | 134 | 84 | 3.21 |
| Commodity Chemicals | 55 | 151 | 34 | 3.36 |
| Trucking | 55 | 60 | 166 | 4.11 |
| Electronic Equipment & Instruments | 53 | 105 | 49 | 2.91 |
| Technology Distributors | 52 | 97 | 206 | 5.83 |
| Trading Companies & Distributors | 51 | 78 | 110 | 3.69 |
| IT Consulting & Other Services | 47 | 72 | 75 | 3.13 |
| Communications Equipment | 43 | 38 | 65 | 2.40 |
| Others | 949 | 1,444 | 1,900 | 3.52 |

**Table B1:** Number of companies and edges by business sector. The outbound edges follow the flow of goods and services from suppliers to customers, and the inbound edges from customers to suppliers.

| Geographical area | Companies | Outbound edges | Inbound edges | Average edges |
|---|---|---|---|---|
| China | 598 | 1,381 | 1,501 | 4.82 |
| Japan | 593 | 3,095 | 2,585 | 9.58 |
| Other Asia | 545 | 932 | 1,141 | 3.80 |
| North America | 512 | 2,201 | 2,232 | 8.66 |
| South Korea | 510 | 1,250 | 1,384 | 5.16 |
| Northern Europe | 126 | 420 | 509 | 7.37 |
| India | 114 | 335 | 376 | 6.24 |
| Germany | 66 | 412 | 601 | 15.35 |
| France | 54 | 328 | 354 | 12.63 |
| Oceania | 37 | 80 | 55 | 3.65 |
| Center Europe | 36 | 352 | 142 | 13.72 |
| East Europe and Russia | 32 | 82 | 85 | 5.22 |
| South and West Europe | 31 | 164 | 97 | 8.42 |
| South America | 30 | 77 | 71 | 4.93 |
| Middle East | 28 | 63 | 34 | 3.46 |
| Africa | 11 | 10 | 15 | 2.27 |

**Table B2:** Number of companies and edges by geographical area. The regional groupings of individual countries are shown in Appendix C.

| Geographical area | Automobile Manufacturers | Construction Machinery & Heavy Trucks | Motorcycle Manufacturers | Total |
|---|---|---|---|---|
| North America | 6 | 16 | 2 | 24 |
| South America | - | 1 | - | 1 |
| Germany | 5 | 6 | - | 11 |
| France | 3 | 2 | - | 5 |
| Northern Europe | 2 | 3 | - | 5 |
| Center Europe | - | - | 1 | 1 |
| South and West Europe | 3 | - | 1 | 4 |
| East Europe and Russia | 3 | 5 | - | 8 |
| Africa | - | - | - | - |
| Middle East | 3 | - | - | 3 |
| India | 4 | 2 | 5 | 11 |
| China | 25 | 15 | 4 | 44 |
| Japan | 9 | 5 | 1 | 15 |
| South Korea | 3 | 13 | 1 | 17 |
| Other Asia | 10 | 2 | 4 | 16 |
| Oceania | - | - | - | - |
| Total | 76 | 70 | 19 | 165 |

**Table B3:** Number of focal companies by business sector and geographical area.

| Sector | Revenues (USD Mln) | Revenues (%) | Mean Revenues (USD Mln) |
|---|---|---|---|
| Automobile Manufacturers | 2,407,128 | 8.93 | 31,672.74 |
| Integrated Oil & Gas | 2,359,588 | 8.75 | 181,506.77 |
| Diversified Banks | 1,795,307 | 6.66 | 61,907.14 |
| Technology Hardware, Storage & Peripherals | 1,109,192 | 4.11 | 15,622.42 |
| Steel | 1,010,530 | 3.75 | 3,368.43 |
| Integrated Telecommunication Services | 871,851 | 3.23 | 45,886.89 |
| Hypermarkets & Super Centers | 865,820 | 0.32 | 144,303.33 |
| Construction & Engineering | 851,541 | 3.16 | 12,522.66 |
| Auto Parts & Equipment | 815,556 | 3.02 | 2,682.75 |
| Industrial Conglomerates | 735,889 | 2.73 | 23,738.35 |
| Trading Companies & Distributors | 685,386 | 2.54 | 13,438.94 |
| Internet & Direct Marketing Retail | 490,437 | 1.82 | 40,869.75 |
| Wireless Telecommunication Services | 478,745 | 1.78 | 43,522.27 |
| Construction Machinery & Heavy Trucks | 444,236 | 1.65 | 6,346.23 |
| Aerospace & Defense | 427,154 | 1.58 | 12,944.06 |
| Health Care Distributors | 412,913 | 1.53 | 103,228.25 |
| Electronic Components | 396,599 | 1.47 | 976.84 |
| Diversified Metals & Mining | 382,125 | 1.42 | 10,055.92 |
| Semiconductors | 374,819 | 1.39 | 3,438.71 |
| IT Consulting & Other Services | 374,306 | 1.39 | 7,963.96 |
| Others | 10,457,580 | 38.78 | 5,955.90 |

**Table B4:** Revenues by business sector. Revenues are reported in absolute terms (column 2), relative to the network as a whole (column 3) and as an average per sector (column 4).

| Geographical area | Revenues (USD Mln) | Revenues (%) | Mean Revenues (USD Mln) |
|---|---|---|---|
| North America | 8,465,809 | 31.39 | 16,534.78 |
| China | 4,912,127 | 18.22 | 8,214.26 |
| Japan | 3,986,988 | 14.78 | 6,723.42 |
| Northern Europe | 2,148,042 | 7.97 | 17,047.95 |
| Germany | 1,501,269 | 5.57 | 22,746.50 |
| South Korea | 1,457,592 | 5.41 | 2,858.02 |
| Other Asia | 1,179,050 | 4.37 | 2,163.39 |
| France | 1,090,127 | 4.04 | 20,187.54 |
| Center Europe | 523,776 | 1.94 | 14,549.33 |
| South and West Europe | 431,097 | 1.60 | 13,906.35 |
| Middle East | 391,897 | 1.45 | 13,996.32 |
| India | 274,042 | 1.02 | 2,403.88 |
| South America | 250,793 | 0.93 | 8,359.77 |
| East Europe and Russia | 176,201 | 0.65 | 5,506.28 |
| Oceania | 161,277 | 0.60 | 4,358.84 |
| Africa | 17,377 | 0.06 | 1,579.73 |

**Table B5:** Revenues by geographical area. Revenues are reported in absolute terms (column 2), relative to the network as a whole (column 3) and as an average per region (column 4).

# Appendix C

## Definition of geographical regions

| Region | Countries |
|---|---|
| *North America* | Canada, United States |
| *South America* | Argentina, Brazil, Chile, Colombia, Mexico, Peru |
| *Germany* | Germany |
| *France* | France |
| *Northern Europe* | Britain, Denmark, Finland, Ireland, Netherlands, Norway, Sweden |
| *Center Europe* | Austria, Belgium, Luxembourg, Switzerland |
| *South and West Europe* | Cyprus, Greece, Italy, Portugal, Spain |
| *East Europe and Russia* | Croatia, Hungary, Poland, Romania, Russia, Serbia, Slovenia, Ukraine |
| *Africa* | Angola, Egypt, Mauritius, South Africa, Tunisia |
| *Middle East* | Israel, Jordan, Saudi Arabia, Turkey |
| *India* | Bangladesh, India, Pakistan |
| *China* | China |
| *Japan* | Japan |
| *South Korea* | South Korea |
| *Other Asia* | Hong Kong, Indonesia, Malaysia, Philippines, Singapore, Sri Lanka, Taiwan, Thailand, Vietnam |
| *Oceania* | Australia, New Zealand |

# Appendix D

## Equations and definitions of network statistics

| Statistic | Equation | Definition |
|---|---|---|
| Nodes | $N = \sum_{i=1}^{N} n_i$ | Number of nodes in the network, where $n_i$ denotes the i-th node |
| Edges | $L = \sum_{i=1}^{L} l_i$ | Number of connections between nodes, where $l_i$ denotes i-th link |
| Average neighbors | $Avg\ neighbors = \sum_{i=1}^{K} k_i/N$ | Average number of neighboring connected nodes over the count of all nodes, where $k_i$ denotes i-th neighbor |
| Diameter | $Diameter = max(d_{ij}) \quad \forall_i, j$ | Maximum distance between any pair of nodes |
| Radius | $Radius = min[max(d_{ij})] \quad \forall_i, j$ | The minimum among all the maximum distances between any pair of nodes |
| Average shortest path length | $Avg\ shortest\ path\ length = 1/[n(n-1)] \sum_{i \neq j} d_{ij}$ | Average shortest distance between two nodes |
| Clustering coefficient | $C_i = 2L_i/[k_i(k_i - 1)]$ | Average of the clustering coefficients of all nodes. The clustering coefficient of a single node is the ratio of the count of actual links between it and all its neighbors and the number of all potential links that may directly connect any pair of them |
| Density | $Density = L/L_{max}$ | Proportion of actual edges to the maximum of all possible edges between all pairs of nodes. The value is in [0, 1]. The lower limit corresponds to (unproper) networks without relationships and the upper limit networks where all nodes are pairwise connected. The closer the value is to one, the denser is the network and the more cohesive are its nodes |
| Connected components | $Connected\ components \subset G\ where\ Density = 1$ | Number of network subsets in which all nodes are connected |

# Appendix E

## Industries assumed to be locked down

| | |
|---|---|
| Aerospace & Defense | Heavy Electrical Equipment |
| Agricultural & Farm Machinery | Home Furnishings |
| Aluminum | Home Improvement Retail |
| Apparel Retail | Homebuilding |
| Apparel, Accessories & Luxury | Hotels, Resorts & Cruise Lines |
| Auto Parts & Equipment | Household Appliances |
| Automobile Manufacturers | Human Resource & Employment Services |
| Automotive Retail | Industrial Machinery |
| Building Products | Interactive Home Entertainment |
| Construction & Engineering | Leisure Products |
| Construction Machinery & Heavy Trucks | Motorcycle Manufacturers |
| Construction Materials | Movies & Entertainment |
| Consumer Electronics | Office Services & Supplies |
| Copper | Real Estate Development |
| Department Stores | Real Estate Operating Companies |
| Diversified Metals & Mining | Restaurants |
| Diversified Real Estate Activities | Retail REITs |
| Diversified Support Services | Specialty Stores |
| Electrical Components & Equipment | Steel |
| Electronic Components | Technology Hardware, Storage & Peripherals |
| Electronic Manufacturing Services | Textiles |
| Footwear | Tires & Rubber |
| General Merchandise Stores | Tobacco |
| Gold | Trucking |

# Appendix F

## Simulation results by varying the initial perturbation

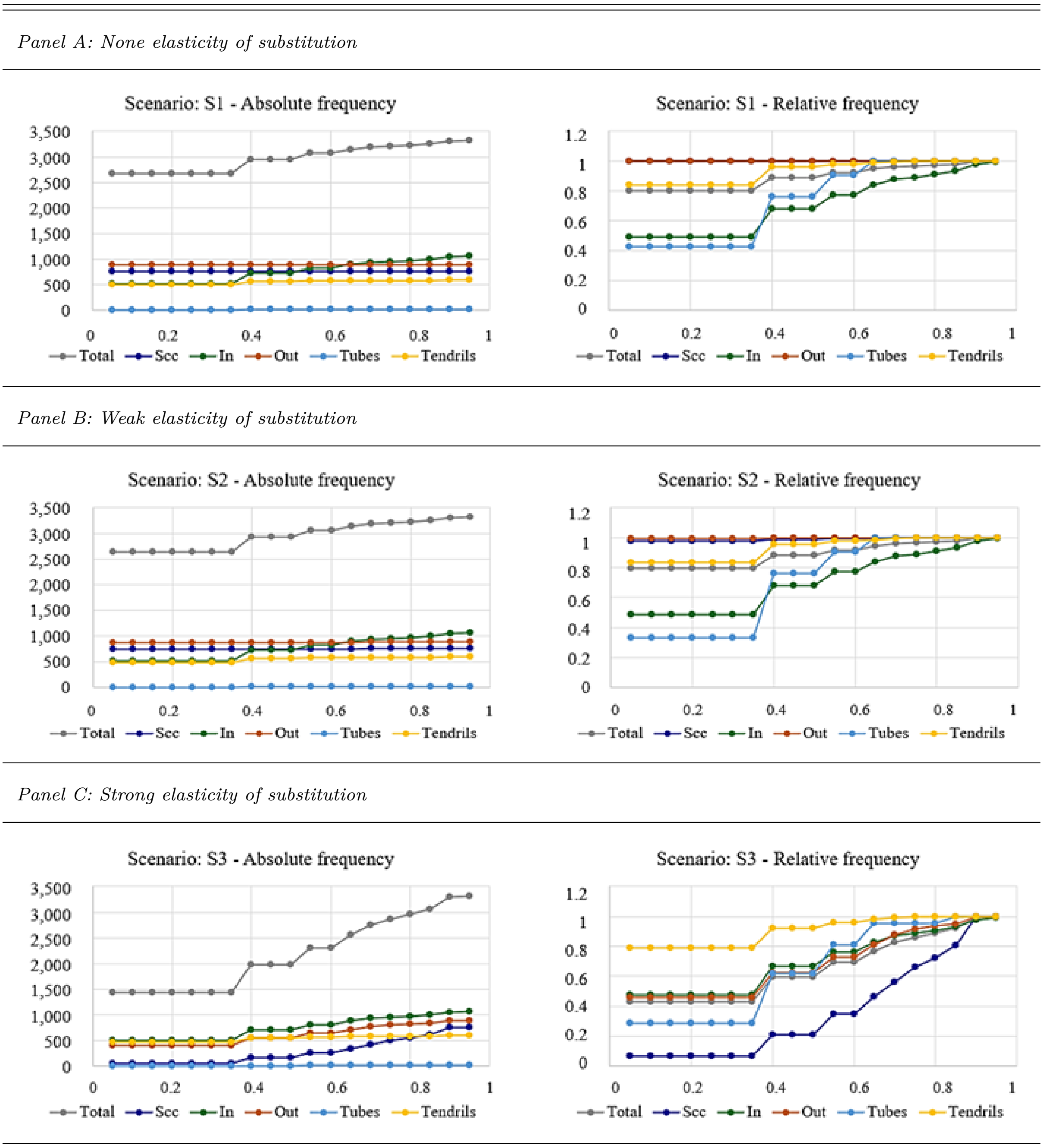


**Figure F1:** Number of failed nodes at the end of the avalanche of the perturbation for each bow-tie region (left side of each panel) and the fraction of failed nodes in each region (right side). The flat zones in the graphs correspond to areas where the percentile change did not imply a change in the initially deleted nodes. The results confirm the riskiness of nodes belonging to the Scc and Out zones, which maintain a nonzero survival probability only in the case of extensive flexibility of inputs (Panel C).

# Chapter 3

## A Network Perspective on the DAX 30 Supply Chain: Stylized Facts and Resilience*

with Sandra Paterlini[1], Maria Luigia Segnana[1] and Nadia von Jacobi[1]

[1]Department of Economics and Management, University of Trento

### Abstract

This paper employs network analysis techniques to investigate the tier 1 supplier and customer relationships of companies listed in the previous German DAX 30 index. We build a specific dataset and establish a series of key observations that shed light on the nature of the German economy in terms of prevalent structural network characteristics typically found in supply chain networks. Based on stylized facts in the buyer-seller matching literature, we identify four facts that allow for link heterogeneity (with skewness), the centrality of larger companies, the complementarity between large and smaller companies, and a multi-faceted hierarchy of the German system. These empirical regularities are consistent with some features of international production and can be used for testing the resilience of German focal companies to recent shocks. We find that highly central companies experienced prolonged post-shock recovery times, while those with a broader customer base rebounded faster.

*Keywords:* supply chain networks, social network analysis, stylized facts, DAX 30 index

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# 1 Introduction

Supply chains and the role they play in the economy are increasingly in the news. Recent shortages of critical components, concerns about the global supply of raw materials, and doubts about the current system's resilience and security are increasing. Many of these concerns give rise to the need for mapping supply chains to manage the emerging challenge of climate change [Feng et al., 2024, Pankratz and Schiller, 2024]. Therefore, firm-to-firm connections in production networks are increasingly viewed as playing a key role in shaping economic outcomes, ranging from trade patterns and the transmission of economic shocks to the spread of innovative ideas. Recognizing this, economists have started to pay explicit attention to firm network structures with investigations that have tied features of firm growth to issues of broader economic importance, such as the ability (or inability) of the macroeconomy to absorb idiosyncratic shocks and have tested the predictive power of network measures (e.g., centrality) to identify firms, which are most at risk during systemic events.

Different strands of research have studied a wide array of topics with a robust overall finding: the network structure matters for firm-level and aggregate outcomes. Firm connections are used in order to look at the sources of heterogeneity in firm size and performance, at the propagation of microeconomic shocks into the aggregate economy, at the formation and duration of supplier networks, at the features of domestic and international trade networks, at the matching of exporting firms and importing firms, with close links to the literature on granularity and shock propagation in macroeconomics. The evolution of these interactions[1], e.g. why connections survive and how they evolve over time, are just beginning to be considered in this emerging literature.

Research has taken advantage of the massive data collection of longitudinal plant and firm-level data sets, customs transaction data, and, in some cases, information about the identities of buyers, sellers, and products. It has established a set of common empirical regularities on these relationships and has further enabled researchers to focus on the relational and organizational nature of firm interactions. At the same time, some problems in mapping firm-level and country or sector-level data arise and remain a key challenge to the field of investigation.

[1] Carvalho and Tahbaz-Salehi [2019] provides a review of the literature on production networks in macroeconomics by looking at the theoretical foundations of input–output linkages as shock propagation channel and as a mechanism for transforming microeconomic shocks into macroeconomic fluctuations. Microeconomic shocks have been shown to be an important source of aggregate fluctuations in the granularity literature initiated by Gabaix [2011] and Acemoglu et al. [2012]. Some papers utilize micro-level firm-to-firm data [Lim et al., 2017, Carvalho et al., 2021], while others do not.

A growing body of evidence from domestic and international transaction data has drawn empirical regularities that have inspired new theories that emphasize firm heterogeneity among buyers and suppliers in production networks. For instance, Bernard and Moxnes [2018] give an initial comprehensive account of the heterogeneity of buyer-supplier matches where the distributions of the number of buyers per seller and the number of sellers per buyer are very skewed. Only a tiny subset of sellers successfully matches and trades with many buyers – and similarly, only a tiny fraction of buyers are linked with many sellers – even though these links account for the bulk of transacted values. Furthermore, the authors detect a pattern of "negative degree assortativity" as sellers that have few links - and are thus presumably smaller and less productive firms - tend, on average, to sell to buyers that have many connections and are therefore probably larger and more productive. Conversely, sellers who have many connections sell to buyers exhibiting a smaller number of links. Empirically, the model supports similar predictions in international trade relationships and domestic production networks of many countries [Lim et al., 2017, Bernard et al., 2018a, 2022a][2].

This paper proposes an investigation into the global network that emerges from the supply chains of the leading German financial index constituents. DeutscheBundesbank [2014] assessed the success of German exports as increasingly shared with foreign suppliers of inputs and intermediates. Given such high integration in the global supply chain and the marked presence of superstar firms, the empirical regularities gathered so far on skewness and assortativity are likely to be consistent with the part of the German economy we investigate.

Both domestic as well as international markets are matching environments, dominated by many-to-many matches. Links between buyers and sellers, the relationship-specificity of their investments and a limited contractual security are part of production networks. Hence, the part of the German system we investigate could be viewed as GVCs within international production as networked activity and a matching environment. We therefore propose that a network approach is a promising technique to study multiple firm-to-firm connections, as they can visualize the GVC structure [Ohnishi et al., 2010] and could further qualify its importance for firm-level and aggregate level results, as well as for patterns of adjustment in the presence of shocks[3]. The links between buyers and suppliers and the fixed costs in link formation are not

[2] Country-specific studies have so far been implemented for Norway [Bernard et al., 2018b], Colombia [Eaton et al., 2021, Bernard et al., 2018a], Costa Rica, Ecuador, and Uruguay [Carballo et al., 2018], France [Kramarz et al., 2020], and the U.S. [Heise et al., 2019].

[3] We use GVC as synonymous of network structure when the economic viewpoint is considered even though the methodologies applied are not necessarily related to network analysis. We also borrow from the operational management literature on supply chain and supply network, here used interchangeably since we argue that individual supply chains cannot be generally understood and examined in isolation from the extended network

only central to firm's production decisions but also to its responses to shocks (as in Calzolari et al. [2021], Macchiavello and Morjaria [2015], Monarch and Schmidt-Eisenlohr [2017]) and as shown by the patterns of adjustment in buyer-supplier matches that follow, for instance, economic or transport shocks [Bernard et al., 2019, Benguria, 2021, Sugita et al., 2023].

We use data on tier 1 customer-supplier connections, not as dyads or short chains of interfirm connections where the impact of a broader network is disregarded, but instead focus on the network that all dyads jointly add up to. Thus, supply chains are examined from a network perspective, in which the system is a set of nodes (companies) and links (connection between companies). Network analysis tools allow us concentrating on both network structure and firm performance. This mapping exercise[4] is applied to the most important German companies[5]. We carefully reconstruct the supply chain networks of 26 focal companies listed in the previous German DAX 30 using the Thomson Reuters Refinitiv platform[6]. Examples of focal firms included in the DAX 30 supply chain network are: Adidas AG, Allianz SE, BASF SE, Bayer AG, BMW AG, Daimler AG, Deutsche Bank AG, Infineon Technologies AG, SAP SE, Siemens AG, Volkstwage AG. In 2020, the sum of the revenues of these companies was just under 40% of the German GDP (1.47 out of 3.89 trillion USD). Our analysis can therefore not be considered comprehensive of the German economic system, but digs deeper into an important chunk of it.

This study shows how network tools can help gain insights into trade patterns whose granularity and heterogeneity matter for the propagation of systemic shocks. Our results confirm the presence of four stylized facts for the DAX 30 supply chain network (SCN) that corroborate economic literature findings regarding heterogeneity, centrality, assortativity, and hierarchy [Bernard et al., 2019]. First, it is essential to note that only a subset of firms within the DAX 30 SCN exhibits multiple links, while the vast majority either act as suppliers to a single firm or possess fewer than two connections. Within our supply chain network, Germany resembles the global economy: We find that companies with higher revenues tend to occupy more central positions within the network and frequently function as customers rather than suppliers. Our analysis suggests that companies with higher revenue volumes have a greater propensity to both

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in which they are embedded.

[4]A discussion of the many challenges in mapping supply chains is in MacCarthy et al. [2022] that position mapping studies with respect to their focus and scope.

[5]While DAX 40 has now been introduced, our dataset is antecedent to that change, and we maintain our focus on DAX 30 to investigate the firms that are most at the core of the German economy. Nevertheless, we must point out that our analysis does not include several companies that play a significant role in the German economy, as they are not listed on the German stock exchange. Some examples are Robert Bosch GmbH, ALDI, Boehringer Ingelheim, Carl Zeiss AG, Haniel Schaeffler Group, and Wuerth Group.

[6]For a literature review that utilizes curated databases in empirical operations management literature, see Demirel [2022].

attract a larger customer base and establish connections with multiple suppliers. Such increased connectivity is not limited to a specific group of firms or industries but extends across multiple regions and sectors. We observe assortativity patterns that underpin that revenues, more than network centrality, constitute the source of hierarchy in the German economy. Furthermore, with increasing revenues, sectoral diversification grows more than geographical diversification. The more powerful firms in the network have the highest revenues and are mostly connected to firms in a less powerful position, having lower revenues and fewer connections. We find that the hierarchy in the DAX 30 SCN is multifaceted, as it is not only reflected in the number of connections, revenues, or the regions and sectors a company connects to but also in a different resilience. Our results show that specific node characteristics influenced the recovery period from the COVID-19-induced shock. Highly central companies experienced longer recovery times, while those with a wider customer base rebounded more quickly. Thus, we provide evidence that a firm's position within the network affects its resilience to exogenous shocks.

The paper is structured as follows. Section 2 discusses data sources and describes the data generation process we chose. Section 3 provides descriptives of the DAX 30 network. Section 4 is devoted to detecting some stylized facts in the core of the German economy. Section 5 reports our findings on how network structure can affect firm resilience. Section 6 concludes. The appendix provides additional details on the sample under investigation.

# 2 Data

## 2.1 The appropriate data: an overview

The current empirical regularities produced in the literature result from research that used a variety of different data ranging from longitudinal plant and firm-level data sets to customs transaction data or information on the identities of buyers, sellers, and products. There is growing consensus on studying firm-to-firm relations within a broader network of connections: GVCs of international production become a networked activity and a matching environment. Considering both features, what is central is the relational nature of the firm-to-firm link within and between networks. However, properly mapping such data remains a key challenge to the field of investigation. In what follows, we frame measurement problems from two viewpoints: bottom-up and top-down.

Studies based on firm, establishment, or even transaction-level data have uncovered empirical regularities on GVC activity from a bottom-up viewpoint, which aligns with the practice that it is not countries or industries that trade but rather firms. Such investigations have contributed a more complete picture of the firm-level correlates of forward and backward participation in GVCs. Usually, global input-output databases compute these participation measures at the aggregate and sectoral level, highlighting salient patterns of countries' positioning along GVCs [Cigna et al., 2022, Mancini et al., 2024]. For a better connection between firm and sector-country level of analysis a different type of data that can be used is transaction-level custom datasets[7].

A precise mapping of backward and forward participation requires product-level information (for backward participation) and linking customs data across countries to develop firm-level measures of forward GVC participation. Computing intensive measures of GVC participation with firm-level data is challenging, however (especially if complementary census information is not available), because customs data do not cover firms' domestic purchases of inputs or domestic sales of goods. Thus, it is difficult to infer the ratio of foreign inputs used in production, and it is even more difficult to disentangle the foreign input content of exports from the foreign content of overall production.

The complex mapping between data at the firm and country level remains an issue when the macro measurement or the top-down viewpoint is used. In this case, variables at the aggregate country or country-industry level are used that rely on value-added accounting and measures of trade in value added. These analyses have led to the construction of global input-output databases, an extensive undertaking by many initiatives such as the GTAP, OECD-ICIO, Eora, WIOD, GTAP, etc. Firm-level information on import and export transactions could shed light on whether global input–output tables accurately describe value-added trade flows across countries. A key issue of such an approach is that the standard methods used to compute bilateral value-added trade flows assume that the same combination of inputs is used in production regardless of the sales destination of the output of a country or an industry. In other words, the global production structure is summarized by a single technology, with a single matrix of input-output coefficients with value-added accounting, ultimately, not free of modelling assumptions about the structure of production within GVCs [De Gortari, 2019].

[7] These can deliver firm measures of GVC participation and are similar to those based on the country-industry information, but precise mapping is very challenging and important data-breaks are very common especially between the country- sector and the firm level of analysis.

The difficulties with top-down and bottom-up mapping just outlined are amplified by the many types of data that have been used: primary and secondary data sources as well as international trade databases. The collection of diverse sources is resource-intensive and fails to guarantee the discovery of supply relationships systematically. Data on buyer-supplier relationships are therefore very valuable but hard to collect. Several data providers have developed curated databases specifically for supply chains but with different purposes and different accuracy (e.g., regarding ownership and location).

To date, the most accurate data for the investigation of GVCs seem to be importer-exporter trade transactions as they open a window into examining the characteristics of buyer-supplier matches, the intensity of their exchange and the forces that drive their formation[8]. Complementary insights come from data on buyer-supplier matches if they are accurately collected. First, several datasets report on links but have no or partial information on the values transacted. Databases of publicly listed firms such as Compustat often include disclosures of major customers or suppliers (which Atalay et al. [2011], for example, use to map out production networks). Second, in the presence of unlocked access to administrative value-added tax (VAT) records, there is a close to complete profile of buyer-supplier matches within the formal domestic economy[9].

This brief review shows that a full reconstruction of the supply chain network remains a challenge and that different datasets may provide differently detailed insights on some aspects of the system. The data we next describe are buyer-supplier matches.

## 2.2 Construction of the DAX 30 supply chain network

We compiled a comprehensive dataset focusing on the 30 constituents of the DAX 30 index, which served as our focal nodes[10]. We could access supply chain data for 26 out of the 30 companies in the German index. To construct the supply chain network, we identified and selected the primary (tier 1) suppliers and customers for each of these 26 focal companies. The selection criteria for establishing supply chain links were based on the companies reported by the Thomson Reuters Refinitiv platform as customers or suppliers on September 5, 2021.

[8]Such data have so far been explored for Norway [Bernard et al., 2018b], Colombia [Eaton et al., 2021, Bernard et al., 2018a], Costa Rica, Ecuador, and Uruguay [Carballo et al., 2018], France [Kramarz et al., 2020], and the U.S. [Heise et al., 2019].

[9]VAT data have been studied for Belgium [Bernard et al., 2022a, Dhyne et al., 2021], Chile [Huneeus, 2018], Costa Rica [Alfaro-Urena et al., 2022], Turkey [Demir et al., 2024], among others, and have yielded affluent insights when merged with other administrative data such as firm-level customs records.

[10]See footnote 5.

For most of the companies in the network, we can rely on additional information retrievable via the Refinitiv Business Classification. We therefore know a firm's size, which is measured by revenues (in USD Million) over the fiscal years 2018-2022, the region in which these companies are legally established and their economic activity sector. Noteworthy is that the sectoral classification used by Refinitiv does not neatly match the NACE classification (see Table A2 in the Appendix). The financial classification TRBC (The Refinitiv Business Classifications) is a market-based classification system (where companies are classified in 13 economic sectors, 32 business sectors, 61 industry groups, 153 industries, and 895 activities). Organizations are assigned to an industry based on the type of market they serve rather than the products or services they offer.

Market-based classification emphasizes the usage of a product rather than the materials used for the manufacturing process. This is done because the performance of an organization is tied to the market it serves, and market-based systems allow investors to group companies that share similar market characteristics. It distinguishes, for instance, between Consumer cyclicals and non-cyclicals, identifying how closely correlated a company's share price is to the overall economy's fluctuations. Cyclical stocks and their companies have a direct relationship with the economy, while non-cyclical stocks repeatedly outperform the market when economic growth slows. Consumer cyclicals are stocks that rely heavily on the business cycle and economic conditions. Consumer cyclicals include industries such as automotive, housing, entertainment, and retail.

Our network is directed, meaning that arcs connect starting nodes representing companies selling goods or services (i.e., suppliers) - to ending nodes (i.e., customers). It is important to note that the direction indicated by the arcs in the network is opposite to the direction of the monetary flow. The dataset employed in our study encompasses a total of 835 companies (nodes) interconnected by 1,088 trade relations (arcs). We refer to it as the DAX 30 supply chain network (SCN).

The network can be regarded as an aggregation of ego networks, as each link we record is detected because of a direct connection to one of the focal (DAX 30) companies. We are unable to detect links among secondary companies with the same certainty. Because some firms relate to different focal companies, our network has sufficient density, constituting a single component. However, our data are likely to underestimate connections. This is acceptable in as much as the full recognition of focal company ego-networks already captures a very relevant portion of the supply chain.

# 3 Description of the network

The DAX 30 network exhibits a diverse range of nodes in terms of geographical areas, sectors, and the number of connections. Table 1 and Figure 1 provide an overview of the regions and sectors to which the companies in the network belong.

In terms of geographical areas, we classified five distinct regions, separating Germany from the rest of Europe. Overall, we find that about 13% of all firms involved in the DAX 30 SCN are legally established in Germany, indicating a relevant role of the domestic market within the network. While 38.3% of firms are within Europe, it is noteworthy that the prevalence of links to North America is even more pronounced, mainly through supplying links within the technology sector. The focal companies of the German economy seem to be more dependent on the Atlantic alliance than on key emerging markets.

Regarding sectors, we analysed the macro-level "Economic Sector" classification provided by Refinitiv Business. This classification encompasses 13 categories, but we record only 12 among our data. We categorize the companies in the DAX 30 SCN accordingly. This categorization provides insights into the sectoral composition of the network and allows for further analysis based on sector-specific characteristics and dynamics.

| **Geographic area** | **Countries** | **Companies** | **%** |
|---|---|---|---|
| *Germany* | Germany | 108 | 12.93 |
| *Europe* | Austria, Belgium, Croatia, Cyprus, Czech Republic, Denmark, Finland, France, Greece, Hungary, Ireland, Jersey, Italy, Luxembourg, Malta, Netherlands, Norway, Poland, Spain, Sweden, Switzerland, United Kingdom | 212 | 25.39 |
| *North America* | Canada, United States of America | 358 | 42.87 |
| *Asia* | Bangladesh, Cambodia, China, Hong Kong, India, Japan, Malaysia, Singapore, South Korea, Taiwan, Thailand, Vietnam | 112 | 13.41 |
| *Other* | Argentina, Australia, Brazil, Israel, Kuwait, Mexico, New Zealand, Russia, Saudi Arabia, South Africa, Turkey, Ukraine, United Arab Emirates | 45 | 5.39 |

**Table 1:** Distribution of companies tied to the German focal firms, by geographic area.

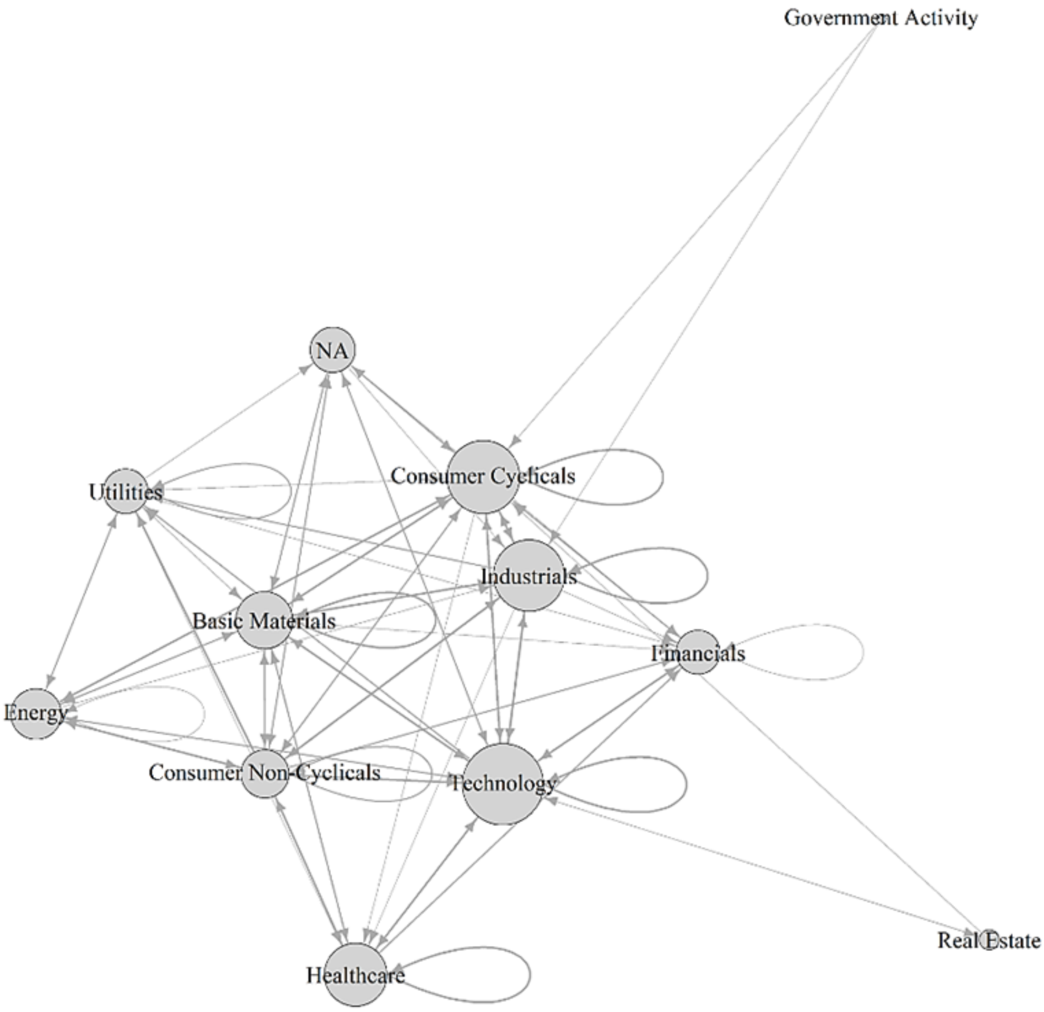



**Figure 1:** Graph of DAX 30 network by sector (the size of circles indicates the numerosity of firms).

Figure 1 shows that the DAX 30 SCN is specialized in technology, consumer cyclicals and industrials, the main sectors in which many firms are categorized. Healthcare and Basic Materials also absorb large numbers of firms. Firms categorized in the sector of consumer non-cyclicals (e.g., Siemens) are less common, but highly central to the network, as are firms belonging to the sectors of basic materials and financials. As typical in directed networks, nodes with higher out-degree than in-degree are located on the outskirts of the network, so Government Activity and Real Estate firms are relatively marginal but act as suppliers to other nodes[11]. On average, we find that utilities, cyclicals, non-cyclicals, healthcare, and financials are dominated by inward-facing arcs. In contrast, industrials, technology and energy are dominated by outward-facing arcs (see Table 5). The former are sectors where firms are more often customers rather than suppliers, whereas the opposite is true for the latter.

[11] For both sectors, there are a few links in which North American/European/German firms appear as suppliers to their German counterparts.

To provide a comprehensive overview of the network, Table 2 displays the frequency of each type of company included in the database. This allows for a clear understanding of the distribution of companies based on their role within the network, distinguishing between those that function as both suppliers and customers, those that only act as suppliers, and those that exclusively serve as customers.

| **Type of node** | **Absolute frequency** | **Relative frequency (%)** |
|---|---|---|
| Supplier and consumer | 112 | 13.41 |
| *of which: DAX 30 companies* | *20* | *2.40* |
| Only supplier | 494 | 59.16 |
| *of which: DAX 30 companies* | *1* | *0.12* |
| Only consumer | 229 | 27.43 |
| *of which: DAX 30 companies* | *5* | *0.60* |
| **Total** | **835** | **100.00** |

**Table 2:** Distribution of nodes by type.

Despite the initial expectation that all focal companies in the DAX 30 SCN would serve as both suppliers and customers, our observations reveal a noteworthy finding. Out of the 26 focal companies, a subset of them (6 companies, or 23% of the total) are exclusively categorized as either "pure suppliers" or "pure customers".

When considering the overall distribution of companies by type, the largest proportion consists of "pure suppliers", with 494 companies accounting for 59.16% of the total. However, only one of these is a focal company (i.e., Siemens Energy AG). The next significant group is "pure customers", with 229 companies representing 27.43% of the total (and 19% of our focal companies). Finally, the remaining companies (112 or 13.41%) are identified as both suppliers and customers – 77% of our focal companies assume this role. Figure 2 offers a visual representation of this network structure.

Summing up, the DAX 30 network is rather sparse, presenting a density of 0.002 and a reciprocity of 0.134. Such a feature is intrinsic in its construction as an aggregation of ego networks in which links between secondary firms are underestimated. Sparsity is however a typical feature of GVCs in the empirical literature covering many countries, and given our focus on DAX 30 focal companies, we expect our dataset to nevertheless provide valuable information on a driving segment of the German economy.

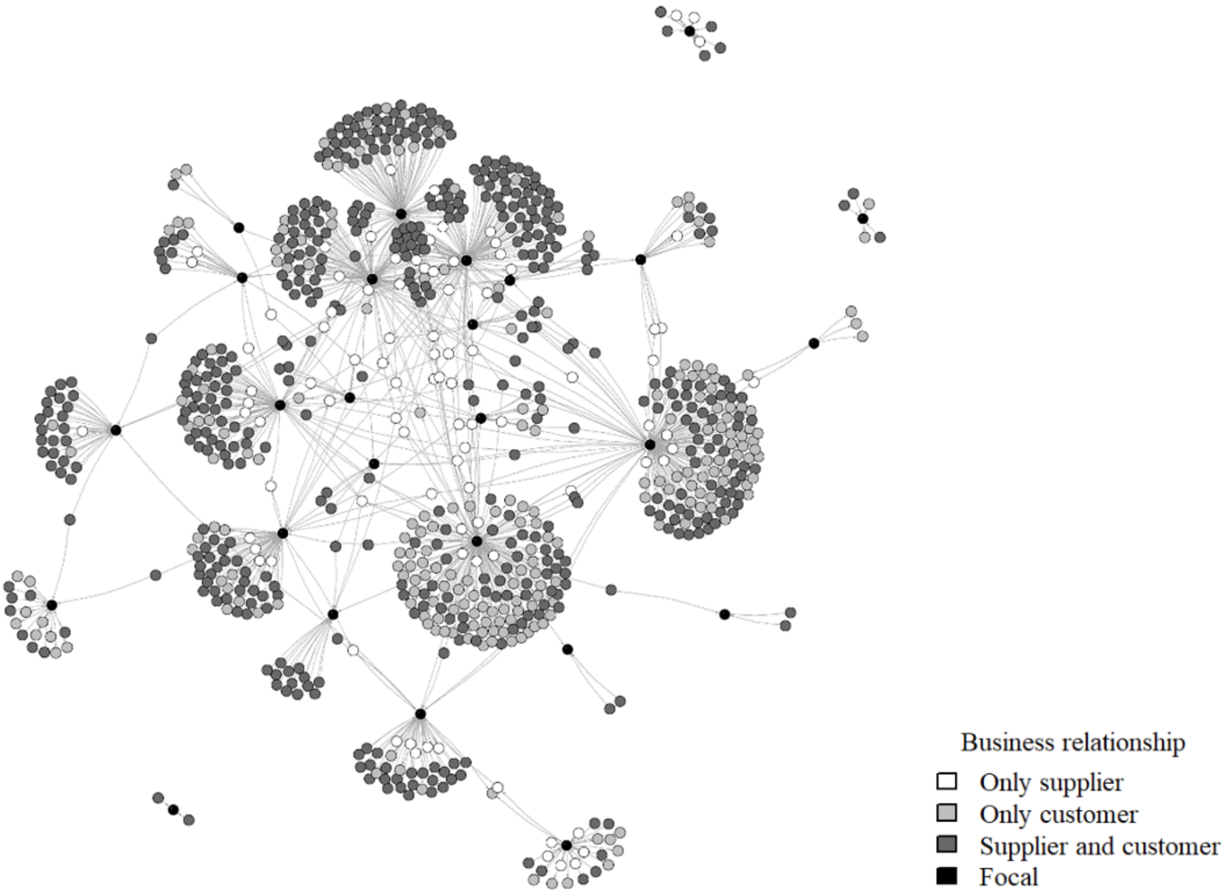



**Figure 2:** Graph of DAX 30 network by business relationship.

# 4 Firm-to-firm network stylized facts

To empirically analyze the DAX 30 SCN, we employ social network analysis tools. By leveraging these analytical techniques, we can gain insights into the structural properties of the network. We build upon commonly observed characteristics in supply chain networks, as documented, for instance, by empirical findings in domestic and foreign markets of the US, Norway, Colombia, or Belgium [Bernard et al., 2018a,b, 2019, 2022a, Bernard and Zi, 2022b]. Our aim is to characterize the DAX 30 network along these established patterns: heterogeneity, centrality, assortativity, and hierarchy.

## 4.1 Link heterogeneity

Fact I: Firms in the DAX 30 are heterogeneous in the number of links.

Firm heterogeneity and the sparse nature of firm-to-firm connections implicitly discipline network structure. Table 3 presents descriptive statistics on the number of links that nodes in the DAX 30 SCN have - categorized by their direction. The distribution of arcs is very skewed, with up to 75% of nodes having only one link and only the top quartile displaying a greater number of connections. Companies that serve as both suppliers and customers possess both incoming and outgoing arcs, pure suppliers only outgoing arcs, and pure customers only incoming arcs (see Table 2).

| | Number | Min | 1st Qu | Median | Mean | 3rd Qu | Max |
|---|---|---|---|---|---|---|---|
| Total | 835 | 1.00 | 1.00 | 1.00 | 2.61 | 1.00 | 164.00 |
| Out | 606 | 1.00 | 1.00 | 1.00 | 1.80 | 1.00 | 96.00 |
| In | 341 | 1.00 | 1.00 | 1.00 | 3.19 | 1.00 | 114.00 |

**Table 3:** Distribution of arcs among nodes in the network.

Table 3 illustrates that most nodes in the DAX 30 SCN have only a limited number of connections, while a few nodes exhibit a significantly larger number of connections (up to 164). This observation aligns with the principle of preferential attachment, which describes the tendency of nodes in a network to acquire new connections based on their existing degree or number of links [Barabási et al., 1999, Dorogovtsev et al., 2000, Sheridan and Onodera, 2018]. In other words, nodes that are already well-connected or have a higher degree are more likely to attract additional connections compared to nodes with fewer connections.

The phenomenon of preferential attachment often leads to the emergence of a power-law distribution in the networks, as opposed to a Poisson distribution, which characterizes random networks [Erdős and Rényi, 1959]. In power-law distributions, a small number of nodes, known as "hubs", accumulate a significant proportion of the total connections, while most nodes have relatively few links. This pattern has been extensively studied and documented in network science literature [Dorogovtsev and Mendes, 2002, Newman, 2003, Barabási, 2013].

Figure 3 plots incoming and outgoing degree distributions considering three different functional forms: (i) Poisson, (ii) log-normal, and (iii) power-law.

We notice a very poor relative fit of the green line, corresponding to the Poisson fitting. Therefore, as expected from our data collection, we exclude the hypothesis that it is a random network and confirm that firms in a more central position will likely acquire further links, thereby becoming even more central and powerful [Sheridan and Onodera, 2018]. To check the goodness of fit of the different functional forms, in Table 4, we rely on the Kolmogorov-Smirnov (KS) test statistics, a test based on the maximum difference between an empirical and a hypothetical cumulative distribution [Massey Jr, 1951].

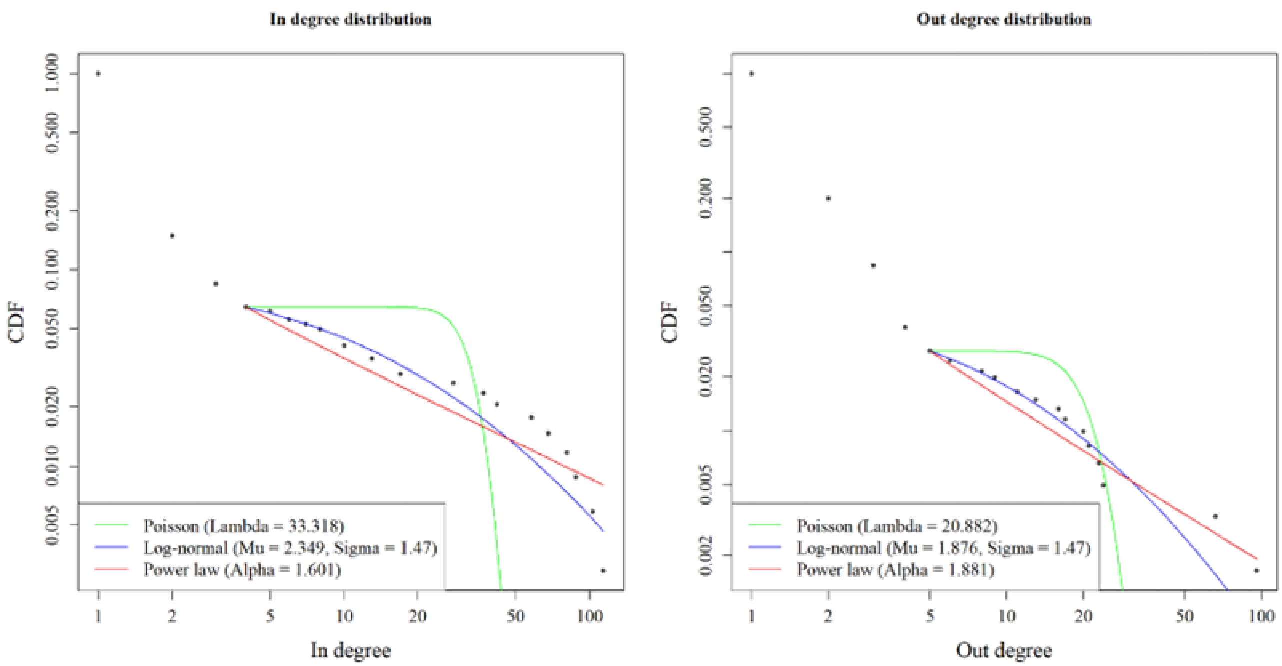



**Figure 3:** In and out degree distribution by functional form.

| Functional form | KS statistics for fitted in degree distribution | KS statistics for fitted out degree distribution |
|---|---|---|
| Log-normal | 0.1131 | 0.1145 |
| Poisson | 0.5895 | 0.4838 |
| Power law | 0.1384 | 0.1336 |

**Table 4:** Kolmogorov-Smirnov statistics for fitted degree distributions by functional form.

According to KS statistics, both the out- and in-degree distributions are best described by a log-normal probability law, confirming the real nature of our network. Several scholars observed that the log-normal distribution can arise, for example, in the branch of biology [Williams, 1964, Koch, 1966].

We also find heterogeneity in the number of arcs when looking at companies from a regional and sectoral perspective, as reported in Tables 5 and 6.

| Region | N Out | N In | N Tot | In/Out ratio |
|---|---|---|---|---|
| Germany | 435 | 778 | 1,213 | 1.79 |
| Europe | 188 | 92 | 280 | 0.49 |
| North America | 335 | 148 | 483 | 0.44 |
| Asia | 98 | 51 | 149 | 0.52 |
| Other | 32 | 19 | 51 | 0.59 |

**Table 5:** Number of links by geographic area.

| Sector | N Out | N In | N Tot | In/Out ratio |
|---|---|---|---|---|
| Basic Materials | 75 | 75 | 150 | 1.00 |
| Consumer Cyclicals | 225 | 407 | 632 | 1.81 |
| Consumer Non-Cyclicals | 73 | 111 | 184 | 1.52 |
| Energy | 31 | 21 | 52 | 0.68 |
| Financials | 5 | 43 | 48 | 8.60 |
| Government Activity | 2 | 0 | 2 | 0.00 |
| Healthcare | 82 | 101 | 183 | 1.23 |
| Industrials | 134 | 77 | 211 | 0.57 |
| Real Estate | 3 | 1 | 4 | 0.33 |
| Technology | 428 | 205 | 633 | 0.48 |
| Utilities | 15 | 38 | 53 | 2.53 |
| NA | 15 | 9 | 24 | 0.60 |

**Table 6:** Number of links by activity sector.

Table 5 shows that Germany stands out as the only region where the ratio between incoming and outgoing arcs exceeds unity. This observation suggests that Germany primarily functions as a customer region within the network we analyze.

Our focus on the DAX 30 focal firms confirms global perspectives, according to which Germany has a key role as an assembler. However, Table 6 shows that such a tendency differs across sectors. The other regions are mainly suppliers but also customers – the ratio between incoming and outgoing arcs being below one and roughly similar across geographical areas (see Table 5).

Table 6 displays that various sectors are involved in the DAX 30 supply chain, most acting as both suppliers and customers. We find firms categorized in the technology, energy, and industrials sector to be more often suppliers. In contrast, firms belonging to financials, utilities, consumer cyclicals and non-cyclicals, and healthcare are mostly customers.

Among our focal firms, we observe the same sectoral diversification and link heterogeneity, with some of them reporting as few as two (i.e., Heidelberg Cement) or three (i.e., Deutsche Börse) links and others reporting as many as 164 (i.e., SAP SE), 154 (i.e., Siemens AG) or 131 (i.e., Volkswagen AG). Table A1 in the Appendix shows the revenues and the number of links for each focal company. The five most connected firms are categorized as belonging to technology (i.e., SAP SE), consumer non-cyclicals (i.e., Siemens AG), and the key players of the German automotive industry, which of course, fall under consumer cyclicals (i.e., Volkswagen AG, BMW, Daimler AG). This is also the sector with the highest prevalence of incoming arcs, in line with the findings of Blázquez and González-Díaz [2016].

Given the conglomerate nature of the focal companies considered, we use both TSRB and NACE Rev. 2 classification, in which organizations are classified according to their business activity in the Manufacturing (C), Services (D, H, J, Q) and Financial (K) sectors (Table A2 in the Appendix). Such comparison highlights the central role of Manufacturing and Financial hubs, which emerge with an evident dominance of incoming links, while Services also have several outgoing links.

## 4.2 Centrality

Fact II. Revenues and centrality move together. The largest firms have the greatest number of connections and reach most of the markets.

To examine the connection between the size of revenues and their network connections, we categorized the companies into revenue classes based on tertiles, excluding those for which data was unavailable. So, nodes in our network belong to the low/high revenue class if their revenues are smaller than p(33)/larger than p(66) of our firms' revenue distribution, respectively. This analysis unfolds the relationship between the financial magnitude of companies and their network connectivity.

Table 7 provides information on the average revenue value for companies within each revenue class. For a focus on the revenues of our focal companies, see Table A1 in the Appendix.

| Revenue class | Revenues interval (USD Mln) | Mean revenues (USD Mln) | Companies |
|---|---|---|---|
| Low | [0; 321,858,020) | 81,519,095 | 233 |
| Medium | [321,858,020; 5,741,437,851) | 2,011,223,146 | 233 |
| High | [5,741,437,851; $+\infty$) | 40,478,261,673 | 241 |
| NA | NA | NA | 128 |

**Table 7:** Average revenues and number of companies by revenue class.

Furthermore, Tables 8 and 9 present the number of edges (both in absolute terms and relative to the total) for each revenue class. These tables allow for a comparison of the network connectivity of companies across different revenue categories, providing a clearer understanding of how the size of companies relates to their degree of connectivity within the network. The upper third of firms in terms of revenues detains 71% of all connections of the network (Table 8).

| Revenue class | N Out | N In | N Tot |
|---|---|---|---|
| Low | 205 | 58 | 263 |
| Medium | 207 | 111 | 318 |
| High | 581 | 872 | 1,453 |
| NA | 95 | 47 | 142 |

**Table 8:** Number of links by revenue class.

| Revenue class | Mean Out | | | Mean In | | |
|---|---|---|---|---|---|---|
| | Company | Region | Sector | Company | Region | Sector |
| Low | 0.88 | 1.00 | 1.05 | 0.25 | 1.07 | 1.09 |
| Medium | 0.89 | 1.07 | 1.16 | 0.48 | 1.28 | 1.47 |
| High | 2.41 | 1.67 | 2.28 | 3.62 | 2.08 | 2.85 |
| NA | 0.74 | 1.00 | NA | 0.37 | 1.00 | NA |

**Table 9:** Average number of companies, regions and sectors connected to, by revenue class.

We observe that as firms move up the revenue classes, their ratio between incoming and outgoing arcs flips, becoming more imprinted on connections in which they are customers. On the other hand, firms in the two lower revenue classes are more often suppliers than customers. The analysis findings suggest that companies with higher revenue volumes have a greater propensity to both attract a more extensive customer base and establish connections with multiple suppliers. This ability allows these companies to expand their market presence across various geographical regions and sectors.

Specifically, when examining the average number of both outgoing and incoming arcs, it becomes evident that as revenues increase, there is a corresponding increase in the number of connected companies, regions, and sectors. This indicates that companies with higher revenue levels tend to have a broader network of connections and a more complex production process, facilitating their engagement with diverse stakeholders. Table 9 shows that in such a process, connectivity across diverse firms and sectors grows more than across regions.

By leveraging their financial strength and market position, companies with higher revenue volumes are better positioned to establish and maintain relationships with a wide range of business partners. This enables them to explore opportunities in different markets, expand their reach, and potentially achieve economies of scale and scope in their operations in line with the results of the literature on superstar firms.

## 4.3 Negative degree assortativity

Fact III. Complementarities across the system prevail. Firms with many links trade with firms that are less well connected. High-revenue firms tend to associate with low-revenue firms.

Assortativity refers to the tendency of nodes within a network to form connections with other nodes with similar or dissimilar characteristics. This phenomenon captures the preference for nodes to connect with others that share similar attributes, resulting in a structure of either homophily (similar nodes connecting) or heterophily (dissimilar nodes connecting) within the network [Newman et al., 2011, Barabási, 2013].

Assortativity can be examined using various node attributes, such as node degree, node strength, or any other relevant characteristic specific to the network. Positive assortativity indicates a tendency for nodes to connect with others that possess similar features. Conversely, negative assortativity suggests a preference for connections between nodes with differing characteristics. A value close to zero suggests a lack of correlation or assortative mixing, indicating that connections are formed independently of the node attribute under investigation.

We find a negative assortativity of -0.5203. Thus, highly connected firms tend to associate with less connected firms within the network. In other words, companies that have a greater number of connections tend to form ties with companies that have fewer connections.

Negative assortativity is common in system networks in which complementarities tend to tie dissimilar nodes to each other, e.g., a customer to a supplier. Our results confirm that the German DAX 30 SCN resembles other economies: there is a tendency for highly connected firms to establish ties with less connected firms. Empirically, there is strong support for this prediction both in international trade relationships and domestic production networks [Bernard and Moxnes, 2018, Bernard et al., 2018a,b, 2022a, Lim et al., 2017].

We run additional assortativity analysis, focusing on categorical features of the nodes instead of degree assortativity. First, we use our revenue classes to test whether nodes tend to associate with firms belonging to the same revenue class or with firms belonging to different revenue classes. In case of negative assortativity, the DAX 30 SCN would be characterized by the complementarity between high-revenue and low-revenue firms. In contrast, positive assortativity would suggest that firms belonging to different revenue classes are more isolated (and independent) from other revenue categories, as they tend to associate more among themselves.

We estimate a negative assortativity of -0.1924. Therefore, in our network, firms belonging to higher revenue classes tend to form links with low- or medium-revenue firms, confirming complementarities across classes more than assortative matching.

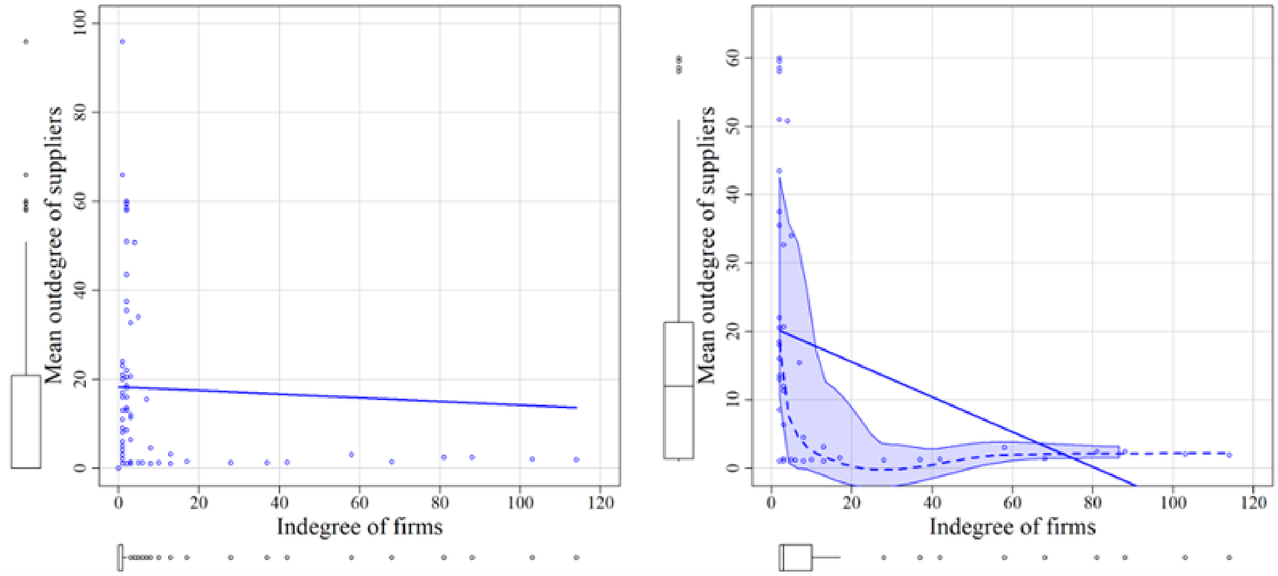
Furthermore, we analyzed the relationship between nodes and firms based on their location and industry. Our findings show a negative assortativity of -0.3501 regarding geographical regions, suggesting that firms prefer associating with companies from different areas. On the other hand, there is a positive assortativity of 0.3229 regarding sectors, indicating that firms tend to link with companies belonging to the same industry but in different locations.

## 4.4 Hierarchy

FACT IV. MULTIPLE LAYERS SHAPE THE ADVANTAGEOUS NETWORK POSITION OF SUPER-STAR FIRMS.

Hierarchy refers to the structural organization of a network where nodes are arranged in a ranked manner based on their level of influence. It represents the asymmetrical distribution of importance within the network, with some nodes occupying higher positions than others. Hierarchical networks exhibit a top-down structure, often resembling a pyramid or a tree-like organization [Ravasz and Barabási, 2003, Boccaletti et al., 2006]. Our assortativity results have already provided first insights on how more powerful firms (better connected in the network and belonging to the highest revenue class) tend to have more links, mostly with firms in a less powerful position in terms of both connectivity and revenues.

We next dig deeper into this relation by following Bernard et al. [2019], where the hierarchical nature of production networks is explicitly considered. Figure 4 plots the number of suppliers per company on the x-axis and the average number of customers of these suppliers on the y-axis. In the left Panel (a), we have retained all 835 network nodes. We then replicate the scatter-plot suppressing all nodes that have no incoming link or only one. In the right Panel (b), only 51 nodes are left after such restriction. In such a partial network, we detect a (non-linear) negative relationship between the indegree of a firm (the number of suppliers it relies upon) and the number of customers these same suppliers serve. The fact that so many firms go missing between Panel (a) and Panel (b) in Figure 4 could be due to the data construction process, which is likely to underestimate existing links. Indeed, many of these suppliers may have other customers (both small and large), but we do not know this because the network is composed of ego networks of the DAX 30 focal companies.




(a) (b)

**Figure 4:** Number of suppliers and their connectivity. Full network with 835 firms (Panel a) and partial network with 51 firms having at least 2 suppliers (Panel b).

We take a closer look at the firms excluded in Panel (b) and notice that the majority are North American firms (347), followed by European ones (204). As expected, the sectors excluded are those with a supplying prevalence, e.g., technology (269 firms) and industrials (133), but also consumer cyclicals (139). At the core of the DAX 30 SCN (Figure 4, Panel b), we notice that 29 out of 51 firms are German (57%), confirming a prominent role in the domestic economy. North American (11) and European (8) firms follow in terms of numerosity. The prevalent sectors in Panel (b) are consumer cyclicals (16), the rest spreading across other sectors, corroborating the central role of the automotive sector in the German economy and a commonly expected additional economic diversification.

In Panel (a), the distribution is highly skewed. In Panel (b), we observe a non-linear relation, with a threshold of around 40 links. Below that value, links are "many-to-few", as in Panel (a). Such a relation elucidates how well-connected firms link with less connected suppliers. A firm with more than 40 suppliers links up with slightly better-connected suppliers: These are suppliers that have at least some diversification of their customer base.

Undoubtedly, the sectoral characteristics matter, but it is interesting to observe that the least connected firms link up with non-specialized suppliers that serve various customers. Less and medium-connected companies (in terms of incoming links) have an almost exclusive link with their suppliers. In contrast, the most connected firms have more suppliers but not necessarily exclusive links.

Such findings support existing empirical evidence [Bernard et al., 2019] aaccording to which in a relational environment, matching is not frictionless, and the selection in the formation of buyer-supplier matches in domestic and GVCs could imply match-specific fixed costs [Bernard and Moxnes, 2018]. In this case, matches are subject to a relation-specific fixed cost so that only highly productive companies can reach many customers/sellers and their marginal customers/sellers. Our results suggest that for the biggest parts of the network (Figure 4, Panel a), customers tend to assume a pattern in which their suppliers are fully specialized for the specific link. However, as connectivity further increases – reaching superstar level – this pattern is overcome as suppliers are themselves better connected and therefore not exclusively specialized on one customer only.

# 5 Network position and firm resilience to shocks

As a final step, we use our network to investigate whether some features of a focal firm's position in the network are related to its ability to recover after a shock. Specifically, we consider the exogenous shock induced by the COVID-19 pandemic in 2020. Although there are noticeable variations across sectors regarding the extent to which the shock impacted firms' expectations and companies' performance, we are interested in observing differences in the recovery ability that can be explained by a firm's position in the network.

Since risk mitigation is typically tied to diversification strategies, we compute a diversification index using the complement to the Herfindahl concentration index (HI) to capture the degree of diversification of focal firms' linkages across geographical regions and productive sectors. Table 10 shows the average of this index obtained by dividing the DAX 30 firms considering the revenue classes as identified in Table 7[12]. Figures A1 and A2 in the Appendix focus on each focal firm.

| **Revenue class** | **Div Geo Out (%)** | **Div Geo In (%)** | **Div Sect Out (%)** | **Div Sect In (%)** |
|---|---|---|---|---|
| Low | - | - | - | - |
| Medium | 21.40 | 50.96 | 12.35 | 46.09 |
| High | 45.57 | 52.13 | 39.13 | 45.34 |

**Table 10:** Geographical and sectoral diversification indices of focal companies by revenue class.

[12] No focal companies belong to the lower revenue class.

We find that geographical and sectoral diversification is very pronounced among our focal firms. Furthermore, we observe that higher-revenue companies diversify more than medium ones, particularly regarding customer base. This aligns with the hierarchical nature of the diversification of customers/markets by the most prominent companies acting as hubs[13]. We build upon this perspective to examine the performance effects of diversifying focal firms' customer base across different sectors when they face and recover from a disruption.

We examine the market quotations of DAX 30 firms between 1 January 2019 and 31 December 2021, focusing on the number of days it took each firm to recover from the pandemic shock. Specifically, we calculate the days required for each firm to recoup its average quotation between 2019 and the date of its lowest value in 2020. Figures 5 and 6 depict the evolution of these firms' listings, distinguishing between "high", "medium", and "low" classes based on their degree centrality and customer diversification over the entire time span. Table 11 summarizes the average number of days to recovery for each class.

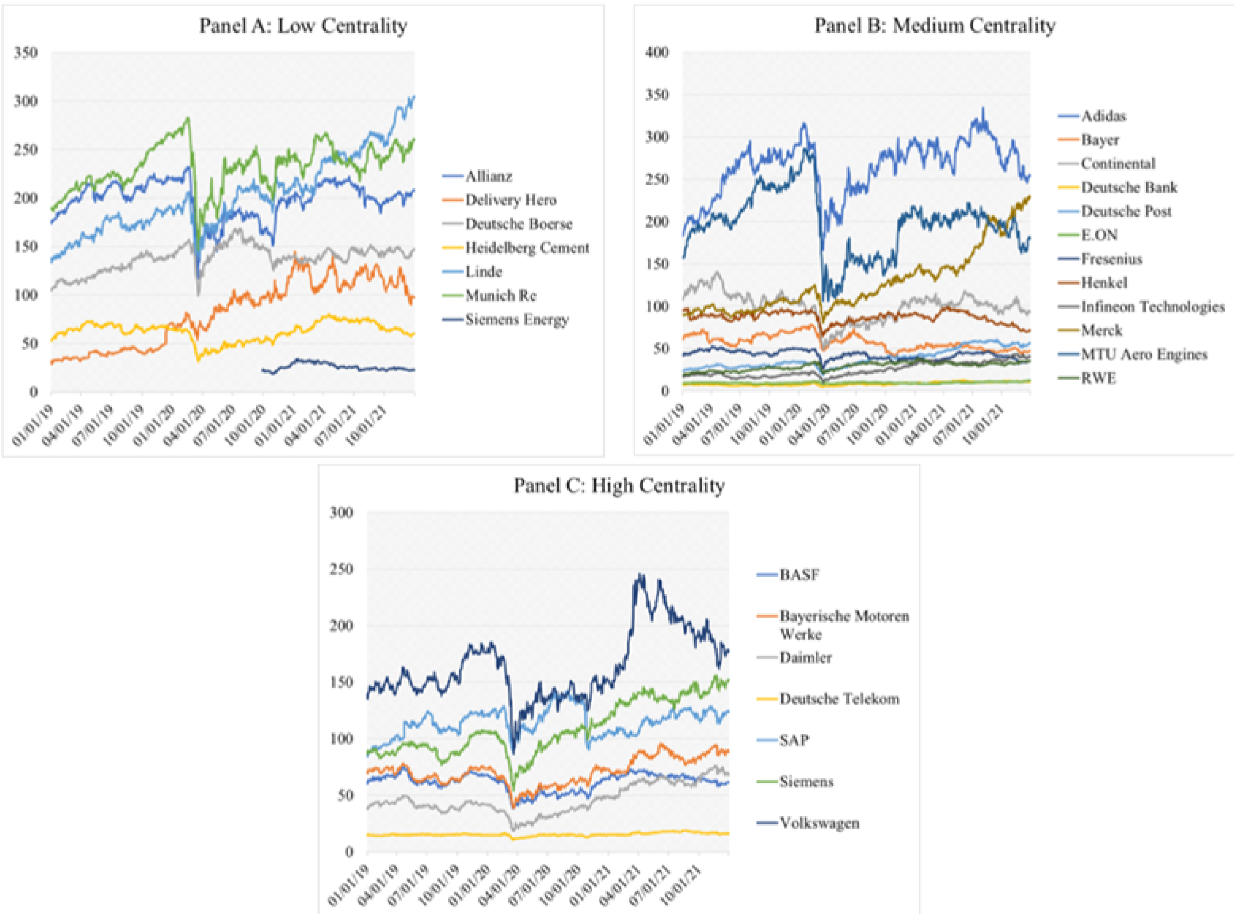



**Figure 5:** Listing evolution of focal companies by centrality classes.

[13] In the literature of international business, the international diversification-performance link has attracted considerable interest, but no convergent opinion has emerged: results have ranged from a U-shaped curve to an inverted U-shaped one and a horizontal S-shaped relationship, suggesting potentially conflicting effects of international diversification on performance and significant size-dependence [Benito-Osorio et al., 2016].

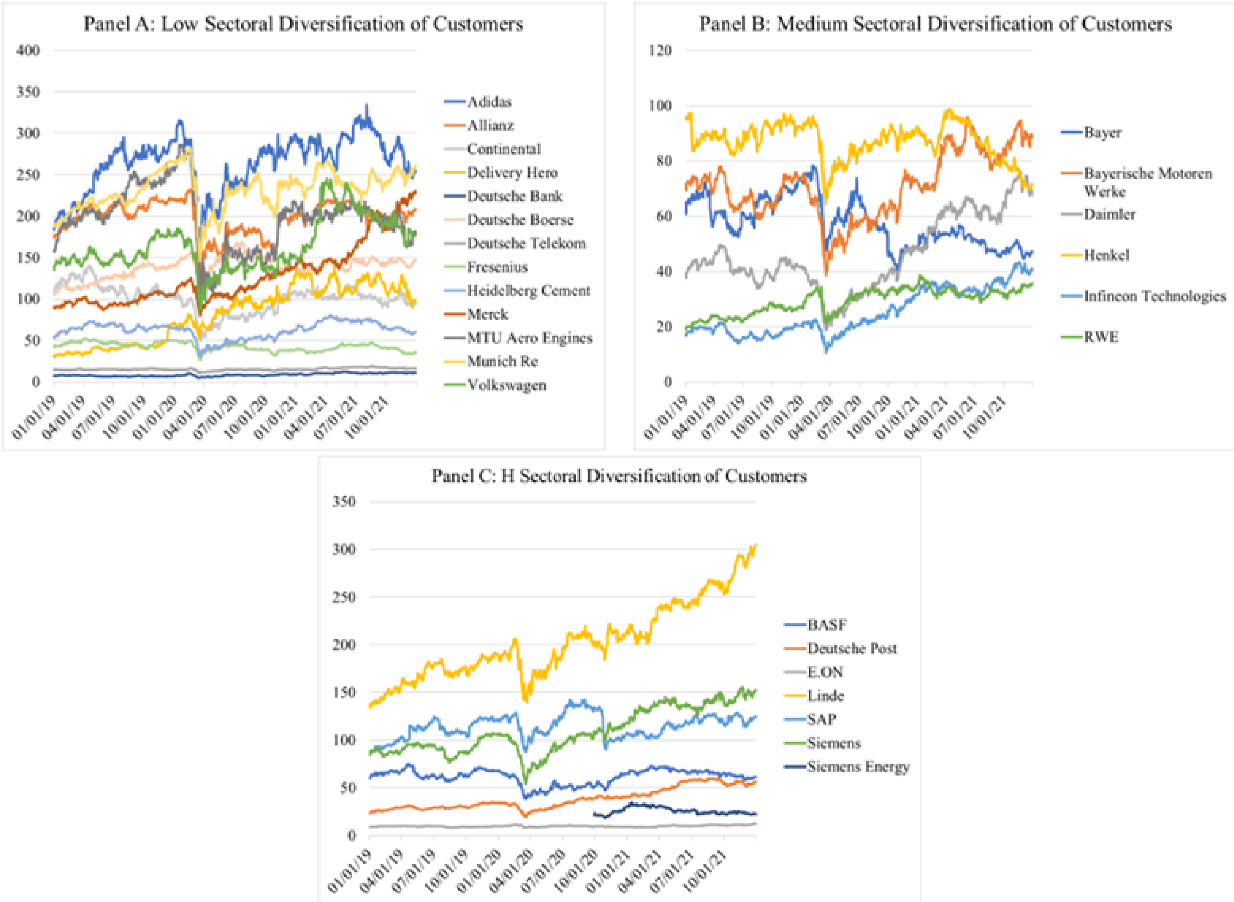



**Figure 6:** Listing evolution of focal companies by diversification classes.

| Centrality | Avg Days | Div Sect Out | Avg Days |
|---|---|---|---|
| High | 116 | High | 50 |
| Medium | 92 | Medium | 100 |
| Low | 73 | Low | 116 |

**Table 11:** Average number of days that focal firms required to recover from the COVID-19 outbreak. Focal firms are classified into three categories based first on degree centrality and then on customer base diversification.

The decreasing values in the second column provide evidence that firms in central positions exhibited prolonged recovery times compared to their less central counterparts. It aligns with established principles of network dynamics, wherein central nodes, characterized by a higher degree of connectivity, are inherently more susceptible to cascading effects. As Todorova [2019] emphasizes, the higher exposure of central nodes translates into increased market risk, as their vulnerability amplifies the impact of systemic disruptions. Conversely, our analysis reveals that firms with a more diversified portfolio of clients demonstrate a stronger capacity to rebound from network shocks. This finding suggests that diversification serves as a buffer, mitigating the dependency on any single sector and thus reducing the ripple effects of localized disruptions. Together, these insights underline the dual forces at play: while firm centrality increases its vulnerability, diversification enhances resilience by distributing risk across a broader spectrum of economic activities.

# 6 Conclusions

Supply chains are increasingly in the spotlight, not least after the COVID-19 pandemic and the war in Ukraine, which have channelled media interest in their design and operation, highlighting their global nature and complexity. The future of the global economy seems to be highly dependent on supply chain security, resilience, and sustainability - including the challenges that new digital frameworks for supply chain data and information governance imply. In this paper, we have briefly reviewed how different strands of the literature, different units of analysis, and different datasets have explored supply chain information and mapping. However, they exhibit great diversity in what is captured, what is depicted, and how it is depicted. Our focus has been on applying social network analysis tools to the DAX 30 SCN to uncover the supply chain network of the leading German companies, which means capturing important features of that economy.

Using a supplier-customer matching data collection, we departed from a description of the resulting networked system and have then investigated four stylized facts, namely link heterogeneity, centrality of a firm's position in the network, assortativity in the matching patterns and emerging patterns of hierarchy. We have noticed that the DAX 30 supply chain network is consistent with such facts, as it is characterized by heterogeneity (with skewness), centrality of larger companies, the complementarity between large and smaller companies and a multifaceted - likely self-reinforcing - hierarchy. Our analysis has suggested that firms that occupy a powerful position in the DAX 30 supply chain are very central, displaying high revenues and greater diversification across regions and sectors. We have found confirmation in existing research that more central firms are potentially susceptible to exogenous shocks. Nevertheless, we have observed that sectoral diversification of customer base, which is a common characteristic of high-revenue firms, is highly desirable as it is associated with a faster recovery from a shock like the outbreak of the COVID-19 crisis.

In the German context, the dominant role of superstar companies in terms of connectivity, centrality, and revenues is paralleled by the complementary between large buyers and medium to small suppliers. Behind this matching between buyers and suppliers there are relationship-specific investments, the exchanging of intangibles, and living with limited contractual security in the firm-to-firm links, especially in the international context. They reflect the costs of finding suitable suppliers of parts and components or suitable buyers of a seller's products, in line with selection, in forming buyer-supplier matches in domestic and global markets value chains [Benguria, 2021]. The presence of match-specific fixed costs could drive such selection: only the more productive sellers can burden these costs to create matches with a larger number of buyers; only the most productive buyers can burden these costs to form matches with a larger number of sellers. While theory suggests that relationship-specific investment could lead to sticky networks and, thus, high switching costs[14] in case of exogenous shocks, our analysis has suggested that the recovery of the most diversified firms from the COVID-19-induced downturn has been faster. We have found that investments in sectoral diversification of customer base play a key role in firms' resilience to the crisis.

Our application brings attention to the crucial role that firm-to-firm connections play, not only in enhancing firms' connectivity, but also in shaping the overall response of aggregate output to unexpected events. Future developments of the study aim to go beyond the analysis of DAX 30 companies that distinguish upstream and downstream linkages by examining supplier-focal-customer triads. Future developments of the study aim to go beyond the analysis of DAX 30 companies that distinguish upstream and downstream linkages by examining supplier-focal-customer triads. Moreover, further research could explore firms' make-or-buy decisions, as vertical integration has profound implications for firms' connectivity and resilience. Firms that internalize more stages of their production processes are expected to possess fewer external linkages. This reduced connectivity could be a disadvantage in networking but counterbalanced by increased control and stability. Such companies might exhibit greater resilience to external shocks as they rely less on external partners and are less exposed to disruptions in supply chains.

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# Appendix

| Focal firm | Revenues (USD Mln) | N Out | N In | N Tot |
|---|---|---|---|---|
| Adidas AG | 2,104,289,202 | 3 | 28 | 31 |
| Allianz SE | 13,749,755,740 | 0 | 8 | 8 |
| BASF SE | 7,223,864,191 | 21 | 42 | 63 |
| Bayer AG | 4,725,661,673 | 11 | 37 | 48 |
| Bayerische Motoren Werke AG | 12,089,643,381 | 20 | 103 | 123 |
| Continental AG | 4,607,022,472 | 6 | 6 | 12 |
| Daimler AG | 18,845,749,878 | 24 | 81 | 105 |
| Delivery Hero SE | 282,158,529 | 2 | 3 | 5 |
| Deutsche Bank AG | 3,015,869,806 | 0 | 17 | 17 |
| Deutsche Boerse AG | 458,768,930 | 0 | 3 | 3 |
| Deutsche Post AG | 8,159,013,190 | 8 | 13 | 21 |
| Deutsche Telekom AG | 12,335,002,443 | 23 | 58 | 81 |
| E.ON SE | 7,443,087,445 | 5 | 7 | 12 |
| Fresenius SE & Co KGaA | 4,140,889,578 | 3 | 8 | 11 |
| HeidelbergCement AG | 2,009,650,407 | 0 | 2 | 2 |
| Henkel AG & Co KgaA | 2,197,318,532 | 9 | 10 | 19 |
| Infineon Technologies AG | 1,003,878,649 | 13 | 5 | 18 |
| Linde PLC | 2,724,300,000 | 4 | 1 | 5 |
| Merck KGaA | 2,001,443,280 | 16 | 13 | 29 |
| MTU Aero Engines AG | 453,960,301 | 9 | 10 | 19 |
| Muenchener Rueckversicherungs Gesellschaft in Muenchen AG | 7,317,013,637 | 0 | 3 | 3 |
| RWE AG | 1,671,714,704 | 6 | 8 | 14 |
| SAP SE | 3,338,788,471 | 96 | 68 | 164 |
| Siemens AG | 6,695,531,937 | 66 | 88 | 154 |
| Siemens Energy AG | 3,404,214,060 | 5 | 0 | 5 |
| Volkswagen AG | 27,220,810,943 | 17 | 114 | 131 |

**Table A1:** Revenues and links by focal firm.

| Focal firm | Refinitive classification | NACE classification |
|---|---|---|
| Adidas AG | Consumer Cyclicals | C15.20 (Manufacturing) |
| Allianz SE | Financials | K65.11 (Financials) |
| BASF SE | Basic Materials | C20.30 (Manufacturing) |
| Bayer AG | Healthcare | C21.20 (Manufacturing) |
| Bayerische Motoren Werke AG | Consumer Cyclicals | C29.10 (Manufacturing) |
| Continental AG | Consumer Cyclicals | C22.11 (Manufacturing) |
| Daimler AG | Consumer Cyclicals | C29.10 (Manufacturing) |
| Delivery Hero SE | Technology | J63.12 (Services) |
| Deutsche Bank AG | Financials | K64.19 (Financials) |
| Deutsche Boerse AG | Financials | K66.11 (Financials) |
| Deutsche Post AG | Industrials | H53.10 (Services) |
| Deutsche Telekom AG | Technology | J61.20 (Services) |
| E.ON SE | Utilities | D35.13 (Services) |
| Fresenius SE & Co KGaA | Healthcare | Q86.90 (Services) |
| HeidelbergCement AG | Basic Materials | C23.51 (Manufacturing) |
| Henkel AG & Co KgaA | Basic Materials | C20.52 (Manufacturing) |
| Infineon Technologies AG | Technology | C26.11 (Manufacturing) |
| Linde PLC | Basic Materials | C20.11 (Manufacturing) |
| Merck KGaA | Healthcare | C21.20 (Manufacturing) |
| MTU Aero Engines AG | Industrials | C30.30 (Manufacturing) |
| Muenchener Rueckversicherungs Gesellschaft in Muenchen AG | Financials | K65.20 (Financials) |
| RWE AG | Utilities | D35.13 (Services) |
| SAP SE | Technology | J58.29 (Services) |
| Siemens AG | Consumer Non-Cyclicals | J62.02 (Services) |
| Siemens Energy AG | Energy | C28.11 (Manufacturing) |
| Volkswagen AG | Consumer Cyclicals | C29.10 (Manufacturing) |

**Table A2:** Activity sectors by focal firm.

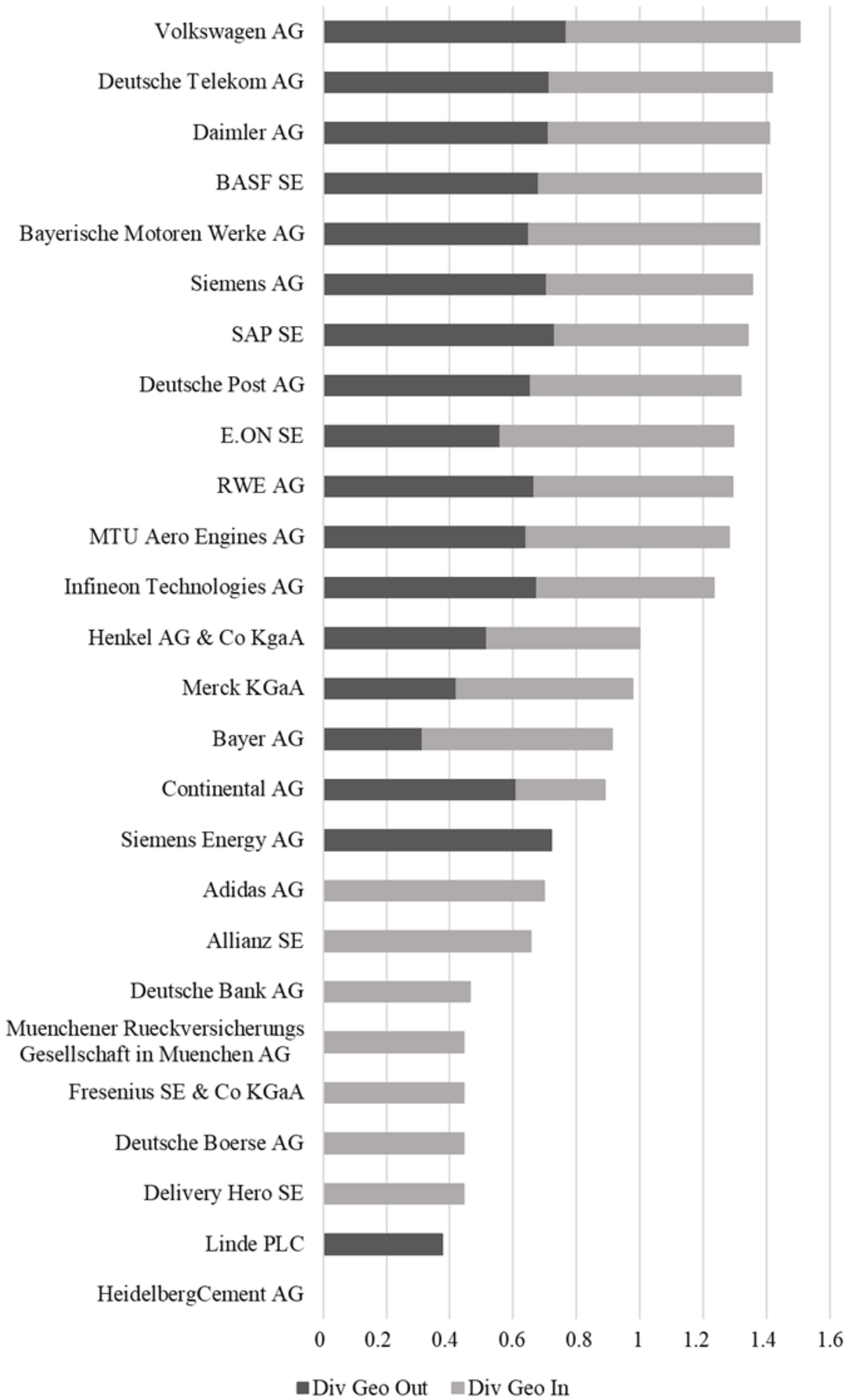


**Figure A1:** Geographical diversification of focal companies.

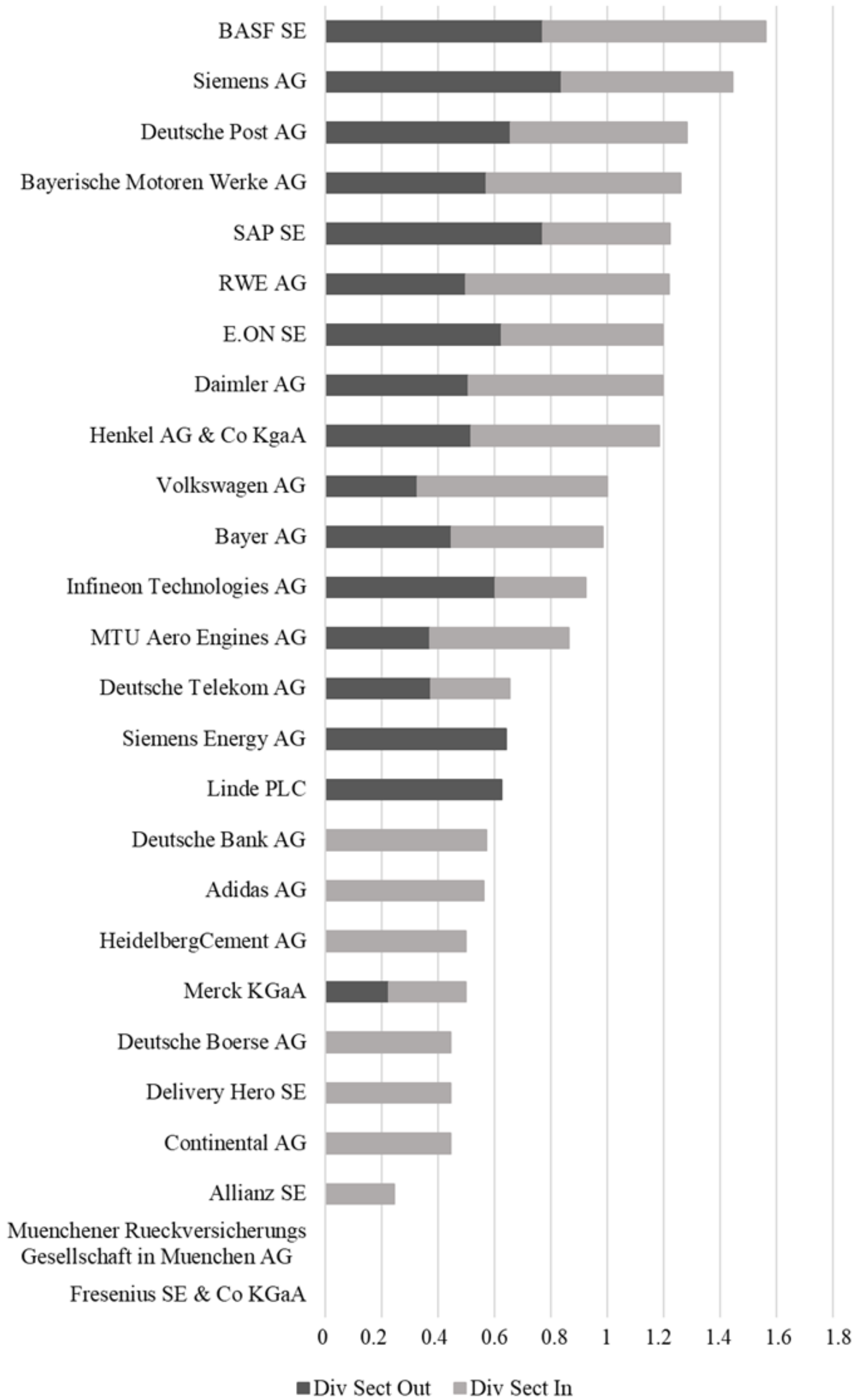


**Figure A2:** Sectoral diversification of focal companies.

# Final Remarks

This thesis underscores the profound potential of network analysis as a versatile and powerful tool for addressing pivotal issues in applied economics, with a particular focus on global value chains. The three chapters aim to offer insights into economic systems' structure, resilience, and dynamics by examining the intricate interconnections within supply chain networks and their susceptibility to external shocks.

Chapter 1 uses the bow-tie taxonomy to investigate the fragility of the automotive supply chain. The study leverages the directed relationships between suppliers and customers to dissect how shocks propagate across different zones of the bow-tie structure, such as the core, upstream, and downstream regions. The findings are particularly relevant to the automotive sector, given its global interdependencies and exposure to disruptions. However, they are widely enforceable to other systems that could be represented as directed graphs.

Chapter 2 continues the exploration of the automotive network but shifts the focus to the dynamic impacts of policy interventions during crises, specifically the short-term effects of lockdown measures imposed during the COVID-19 pandemic. The work reveals that the economic consequences of lockdowns are far from uniform along the supply chain. We find that firms' vulnerabilities depend heavily on their role within the network and ability to adapt their production factors. Firms with rigid production configurations faced more significant challenges than those with high elasticity in substituting inputs. These insights advocate for targeted lockdown measures that minimize economic damage by accounting for the specific network positions of affected firms. This chapter provides a framework for examining supply chains in different industries by bridging the gap between network topology and economic resilience. Thus, it offers actionable guidance for managers, emphasizing the importance of flexibility in supply chain management to mitigate the risks associated with policy-induced disruptions.

Chapter 3 shifts the focus from the automotive sector to the German economic system, analyzing the supply chain networks of firms listed on the DAX 30 index. This work identifies critical structural features of the German economy, including (i) the skewed distribution of linkages within the network, (ii) the centrality of large firms as pivotal nodes, (iii) complementarities between large and small enterprises, and (iv) the hierarchical, multilayered organization of the national production. Moreover, this study explores the financial response of focal firms (i.e., those occupying central positions in the network) to the COVID-19 pandemic. Our findings suggest that, while these firms were significantly affected due to their systemic importance, their ability to recover was strongly linked to their diversification strategies. Specifically, firms that diversified their industrial relationships by working with downstream customers across different industries demonstrated greater resilience. We contribute to the literature on the strategic importance of diversification as a resilience mechanism in highly interconnected economic systems.

The insight derived from this thesis is twofold. First, it provides a solid methodological framework for representing and examining interdependent economic interactions. Network analysis captures supply chains' structural and dynamic properties in a way that traditional economic models often fail to do. It also allows for a deeper understanding of systemic resilience and shock propagation pathways. The results in the various chapters emphasize how network topology, such as node heterogeneity and centrality, affects the ability of economic systems to survive or recover from disruptions. Secondly, our results lead to actionable recommendations for policymakers. By integrating knowledge of networks with agent-based simulations and empirical data, the thesis offers practical strategies to mitigate negative economic consequences through targeted policy interventions or flexible supply chain management strategies.

In conclusion, the investigation of network structures emerges as a critical avenue for comprehending the intricate interdependencies that underpin contemporary production systems. As global supply chains continue to grow in complexity, the capacity to map and analyze their potential vulnerabilities will prove ever more essential. Moreover, the application of network analysis to case studies such as the automotive sector and the German financial index highlights the versatility and broad relevance of this methodological approach across diverse contexts and scales. Future research could shed light on how technological innovation, regulatory shifts, or geopolitical dynamics influence network evolution, offering insights to policymakers and market leaders navigating an increasingly interconnected global economy.