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Supply network stress-testing of food security on the establishment-level

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ABSTRACT

Recent events exemplified the fragility of national and international supply networks (SNs), leading to significant supply shortages of essential goods, such as food and medicines. Severe disruptions propagating along complex SNs can expose entire regions or countries to these risks. A lack of data and quantitative methodology has hitherto prevented an empirical quantification of the vulnerabilities of populations created by SN disruptions. Here, we propose *supply network stress-testing* (SNST) as a new data-driven methodology to quantify product-level supply losses of administrative districts that result from cascading supply disruptions between establishments. We demonstrate SNST on a large fraction of the Austrian food SN – composed of the pork production network from farms to meat processors and the distribution network of large food retailers – containing 23,001 establishments, 44,730 supply links, and 116 administrative districts. We rank all establishments with respect to their systemic criticality for the population using a novel systemic risk index, $ESRI_i^{crit}$. We identify 28 facilities that – in case of failure – are expected to cause severe supply shortages to up to 20% of the population. SNST enables governments and industry to stress-test national supply networks of critical goods, to identify their weak spots and make them more resilient to future crises.

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Supply networks; food security; disruption propagation; systemic risk; supply chain resilience; ripple effect; establishment-level supply networks

SUSTAINABLE DEVELOPMENT GOALS
SDG 3: good health and well-being (particularly target 3.d)

1. Introduction

Recent crises and natural disasters (COVID-19, Ukraine war, tsunami in Japan 2011, flood in Thailand 2011) exemplified the vulnerability of corporate supply chains to (exogenous) shocks. Not only do these events cause large overall economic costs and substantial financial losses to firms (Carvalho et al. 2021), but can result in severe supply shortages of essential goods for populations of entire regions or countries (Sodhi, Tang, and Willenson 2023).

Stress testing supply chains of companies in critical industries – similar to stress-tests for systemically relevant financial institutions – was suggested as key tool to prevent severe supply shortages of essential goods (e.g. medicine, protective gear, food) during future crisis (Simchi-Levi and Simchi-Levi 2020). In this direction, Simchi-Levi and Simchi-Levi (2020) proposed two measures for supply chain stress testing *time to recover* and *time to survive* (Simchi-Levi 2015).[1] The two measures are akin to *microprudential stress testing* metrics (e.g. Liquidity Coverage Ratio[2]) computed by individual banks. In contrast *macroprudential or systemic stress testing* focuses on how stress scenarios for financial institutions can propagate along financial exposure networks, assessing which stress scenarios pose threats to financial stability, and finding policies to mitigate *systemic risks (SRs)* in the financial system (Breuer and Summer 2018; Farmer et al. 2022; Thurner 2022). Identifying *systemic risks* is a key aspect of stress testing (Thurner 2022), and being able to measure the systemic risk of individual institutions is a prerequisite for creating more resilient financial network topologies (Thurner and Poledna 2013; Poledna and Thurner 2016; Diem, Pichler, and Thurner 2020; Thurner 2022).

Analogously, firms are interconnected through complex supply networks (SNs) – webs of numerous tightly interwoven supply chains – enabling the production of essential goods for the population, but also the propagation of shocks and disruptions across firms. The propagation of disruptions that are alternatively also known as the snowball effect, supply chain contagion, the ripple effect, or cascading failures (Ivanov, Sokolov, and Dolgui

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2014) – exposes firms *and people* to supply chain shocks occurring in distant places or industries. The propagation of disruptions or other shocks along SNs has been identified as one of the main drivers of the severity of supply chain disruptions caused by COVID-19 and other crisis events (Dolgui and Invanov 2021). Understanding how disruptions propagate in SNs is key to assessing the vulnerability of firms to supply chain disruptions and has become a major concern in the production research literature (Xu et al. 2020; Dolgui and Ivanov 2021).

While financial systemic risk has been extensively studied by now, studies on systemic risk in SNs remain scarce, particularly, in the fields of Business, Management and Accounting and Decision Sciences (see Appendix A for a comparison of keyword searches in SCOPUS). Notable exceptions, e.g. Basole and Bellamy (2014), Brintrup, Ledwoch, and Barros (2016), Scheibe and Blackhurst (2018), or Colon and Hochrainer-Stigler (2023), show the relevance of systemic risk in production research, but lack shock propagation based quantitative methodologies applied to real-world SN data. Other studies utilise large-scale SN data and apply *financial systemic risk* measures like DebtRank (Fujiwara et al. 2016; Chakraborty et al. 2024). Recently, Diem et al. (2022) developed the *Economic Systemic Risk Index* (ESRI), which is *specifically tailored* to account for important economic shock propagation mechanisms of SNs, and calculated ESRI for all nodes in the backbone of the Hungarian SN (91,595 firms, 235,000 links). For a given firm, ESRI measures the *fraction of sales* across all firms in the SN that is at risk by the hypothetical failure of this firm. It has been used to identify high systemic risk nodes in other large-scale empirical SNs (Reisch et al. 2022), extended to measure financial systemic risk firms pose to the banking system (Tabachova et al. 2024), to identify firms that are particularly relevant to managing the green transition (Stangl et al. 2024), or to simulate revenue losses caused by the propagation of COVID-19 shocks in Hungary in 2020 (Diem et al. 2024).

Despite the recent progress in measuring systemic risk in SNs, existing models are not well suited to assess the supply shortages of critical goods suffered *by people*. The problem is that these models focus only on firms' disruption levels, ignoring how disruptions translate into reduced supply levels for *the population for specific goods in specific geographic regions*. While models for quantifying food supply shortages of countries exist, they are based on highly aggregated trade data of countries or provinces and do not consider the underlying granular SNs (Naqvi, Gaupp, and Hochrainer-Stigler 2020; Laber et al. 2023; Kuhla, Otto, and Kubiczek 2024). Hence, new models are needed to identify systemic risks to the supply of essential goods to people and to perform appropriate stress tests.

Here, we propose *supply network stress-testing* (SNST) as an economically and mathematically grounded method that is based on a SN disruption simulation model, which explicitly integrates the population of a country in a fine-grained geographically resolved way. We model administrative districts as population nodes and connect them to spatially close nodes of the final tier of the respective good's SN (e.g. supermarkets, or pharmacies). This allows us to simulate the propagation of supply chain disruptions, starting from any given node in the SN downstream to the final consumer. The simulation model can quantify how strongly the supply level of a specific administrative district declines in response to an upstream disruption. To find the most critical establishments in the SN, we propose a new systemic risk index, $ESRI_i^{crit}$, that measures the criticality of each establishment, for the population's supply. Criticality here means that an establishment's failure causes supply losses exceeding a threshold where wellbeing or health of the local population are severely affected. We showcase the real-world applicability of our model on a unique country-wide food SN dataset containing 23,001 individual facilities or establishments – covering pork production from farms to meat processors and the distribution network of large food retailers including warehouses and supermarkets – and their respective supply links. Hence, we cover the entire pork production process up to the local supermarkets in the respective administrative districts – including almost all actors relevant for the pork meat supply for Austria. By simulating the consequences of a hypothetical failure of each of the 23,001 establishments, we effectively stress-test the supply security for the population in all individual administrative districts by identifying the establishments posing the largest risks.

Our SNST framework allows for a systematic quantification of the effects of SN nodes failing on the supply of essential goods to the population and enables decision makers to identify the systemically critical players in essential goods SNs. As a decision aid model, it suggests SN nodes for which disruption backup plans should be implemented.[3] Such *targeted* backup plans can help making SNs more resilient by enabling faster adaptation to failures of critical nodes, resulting in higher supply security. Our study contributes to the literature focused on increasing the viability of critical supply chains during crisis – a goal called for during COVID-19 (Ivanov and Dolgui 2020, 2022) – by identifying nodes with high systemic risk and enabling decision makers to develop backup plans for their failures. It further contributes to the goal of treating the population as an integral part of supply chains, as recently emphasised by Mollenkopf, Ozanne, and Stolze (2020) and Ivanov and Dolgui (2022). Even though we apply the model to estimate the systemic risk of individual establishments, it can be used also for stress-testing SNs with more general and specifically generated hypothetical stress scenarios including many heterogenous disruptions across establishments, as explored for firms in Diem et al. (2024). Due to limitations of data availability, most literature analysing large-scale empirical SNs focusses on firm-level data (Shao et al. 2018; Wiedmer and Griffis 2021; Diem et al. 2022). Here, we are able to use establishment level data on the product level (to our knowledge, this is the first study using a multi-tier *large-scale establishment-level SN*[4]). Lastly, this work adds to the literature studying disruption propagation in empirical SNs by quantifying systemic risks.

2. Literature review

Our study builds on and extends three streams of literature: SNs, supply chain disruption propagation through networks, and measuring systemic risk.

2.1. Supply networks

A network is generally defined as a set of nodes (e.g. firms or establishments) and the links between them (e.g. product flows, or loans). Accordingly, a SN refers to the '"exchange relationships" between suppliers, customers, and their partner firms that are necessary for manufacturing and providing goods and services to the market.' (Wiedmer and Griffis 2021)[5] SNs are critical for firms to achieve competitive advantage (Basole and Bellamy 2014), because they affect the production of goods and services (Borgatti and Foster 2003), financial and operational performance (Kim et al. 2011; Lu and Shang 2017), innovation (Sharma et al. 2020; Potter and Wilhelm 2020), as well as resilience to disruptions (Nair and Vidal 2011; Kim, Chen, and Linderman 2015; Wiedmer et al. 2021).

That supply chains are not linear chains, but truly complex networks has been long argued (Choi, Dooley, and Rungtusanatham 2001; Gerschberger et al. 2012). Yet, due to data constraints, the analysis of SNs has been often limited to simulated data or small subsets of actual SN structures (Brintrup and Ledwoch 2018; Wiedmer and Griffis 2021). For example, Choi and Hong (2002) used interview and archival data to map three SNs that pertain to one component in the automotive industry, whereas Potter and Wilhelm (2020) study a data set of 219 first-tier suppliers within the Toyota SN.

By now the availability of large scale SN datasets empirically confirms the complex network topology hypothesis across different types of SNs, e.g. for specific industries, like the aerospace and automotive SN (Brintrup, Wang, and Tiwari 2015; Brintrup, Ledwoch, and Barros 2016; Fessina et al. 2024), international SNs between multi-national firms (Shao et al. 2018; Mungo et al. 2023; Chakraborty et al. 2024), or nationwide SNs consisting of almost all firms and their supply links within a country, e.g. for Japan, Belgium, Hungary, and Ecuador (Fujiwara and Aoyama 2010; Diem et al. 2022; Dhyne et al. 2021; Bacilieri et al. 2023; Pichler et al. 2023). These networks are characterised by, e.g. power-law degree-, strength- and link-weight distributions, short average path lengths (i.e. SNs are scale-free small worlds), and large strongly connected components (i.e. a direct supplier can also be an indirect customer and vice versa). Yet overall, the extant empirical evidence remains sparse (Wiedmer and Griffis 2021) and needs to be extended (Choi et al. 2021). In particular establishment-level SN data sets – where the network nodes represent individual establishments of firms – are almost unchartered. To date we are only aware of large-scale establishment level data sets covering parts of the US opioid distribution network (Amico, Verginer, and Schweitzer 2024), the global automotive supply chains network (Fessina et al. 2024), and a part of the Japanse supply network (Inoue and Todo 2024). Leveraging large scale SN data sets is pointed out as highly promising for the development of a new generation SN models that can better inform policy and decision makers (Pichler et al. 2023).

2.2. Disruption propagation in supply networks

Given their frequency and severity, supply (chain) disruptions are a significant managerial concern (Bode and Macdonald 2017; Polyviou, Croxton, and Knemeyer 2020). Supply disruptions have been defined as 'unplanned and unanticipated events that disrupt the normal flow of goods and materials within a supply chain [...] and, as a consequence, expose firms within the supply chain to operational and financial risks' (Craighead et al. 2007). Supply disruptions may decrease performance related to operations (e.g. stockouts, production shutdowns), finance (lost sales, premium freight charges), and relationships (Hendricks and Singhal 2005; Wu, Blackhurst, and O'Grady 2007; Hendricks, Singhal, and Zhang 2009; Bode and Macdonald 2017). Yet, as illustrated by many empirical incidents, disruptions or failures of firms and establishments – e.g. due to fires, natural disasters, or lock downs – can affect customers and suppliers across multiple tiers of the SN (Yan et al. 2015; Carvalho et al. 2021).

The extant literature uses different approaches to better understand how disruptions of firms affect the performance of other firms in the wider SN (Dolgui, Ivanov, and Sokolov 2018), and what role the network structure plays for the extent of shock propagation.[6] Here we focus on computer simulation-based models. A popular choice are susceptible infected recovered (SIR) type simulation models. They have been applied to various types of simulated *small-scale networks* (scale-free, small world, Erdös-Reny random network) with below 1000 nodes (Basole and Belamy 2014; Li and Zobel 2020), and on small scale data derived from Bloomberg SPLC database with 121 suppliers and 193 links (unweighted) of Toyota and Honda (Li et al. 2021). The findings consistently indicate that network structure matters for the robustness of SNs to shock propagation. A second group of studies tests the effect of network topology with more detailed simulations conducted with agent-based models, where nodes and their interactions have richer representations. For example, they include different types of SN nodes (factory, distributors, warehouses, retailers, logistics providers), inventories, order processes with lead times, or 'first-come first-serve' type behavioural rules (Nair and Vidal 2011; Ledwoch, Yasarcan, and Brintrup 2018). Again, these studies use simulated small-scale networks, and again find that network topology matters substantially. Interestingly, Ledwoch, Yasarcan, and Brintrup (2018) find that also the effectiveness of different disruption mitigation strategies varies across network types. Recently, digital twins (agent-based models that aim to mimic reality especially close) have become popular tools in this stream of literature. E.g. Burgos and Ivanov (2021) investigate the effects of the Covid-19 pandemic on the food supply chain with 28 supermarket locations, 3 distribution centres and 10 different product categories that are supplied by a sample of 30 suppliers (3 per product). Other recent papers also consider shock propagation models on larger scale empirical SNs, e.g. the automative SN with 16,642 suppliers and 2,470 buyers based on Marklines data and study how product *nestedness* affects supply chain resilience (Chauhan, Perera, and Brintrup 2021). Inoue and Todo (2019) use the large-scale firm-level SN data of Japan to simulate the shock propagation effects of the Tsunami in 2011. Diem et al. (2022) develops a shock propagation model that takes important economic mechanisms of SNs, such as a distinction between firms' essential and non-essential inputs, a heuristic replaceability of failed suppliers based on market shares, and difference between down- and upstream contagion into account. It was applied to the Hungarian SN data in 2017 with 91,595 nodes (Diem et al. 2022) and in 2019 with 243,399 nodes (Diem et al. 2024).

While studies analysing large real-world SN topologies are scarce in general (Wiedmer and Griffis 2021; Choi et al. 2021), studies on disruption propagation in such networks are even rarer. Overall, the evidence shows that the SN structure strongly matters for firms' resilience to shocks and disruptions propagation. Hence, it is key to assess the effect of SN disruptions on the supply of the population on the *real world* network data, as we do in the present study. Further, disruption propagation models traditionally focus on how firm performance is affected and not how the supply of the population is affected by disruptions. This is also reflected in the literature surveyed by Wiedmer et al. (2021). Another stream of literature using trade data considers the effects of shocks on the food supply of the population explicitly (Naqvi, Gaupp, and Hochrainer-Stigler 2020; Laber et al. 2023; Kuhla, Otto, and Kubiczek 2024), but the nodes in these trade networks are either countries, or regions within countries that are modelled as single representative consumers and producers. Schuster, Polleres, and Wachs (2024) study how the access of the geographically resolved population of Austria to medical services depends on the road network, but they do not consider the upstream SN of medical goods. Pinior et al. (2015) analysed how consumers would be affected when pathogens are introduced by terrorists into the German milk supply chain (Pinior et al. 2012) and developed contingency plans for this scenario. Our study fills an important gap in the literature by connecting SN disruption propagation simulation on real world large scale SNs with a granular assessment of food supply security of the population.

2.3. Systemic risk (indicators) for socio-economic networks

The concept of disruption propagation is closely related to the stream of literature on systemic risk in complex networks. A key aspect of systemic risk is how initial shocks to the system are *amplified by the propagation of shocks* along exposure networks of banks and other institutions (de Bandt and Hartmann 2000). The term *systemic risk* refers to the risk that the failure of a single node – or a small set of nodes – exposes a large part of the network (system) failing to perform its regular function. 'Failing to perform its regular function' can have different meanings in different types of networks (systems). Consequently, a node is systemically risky when its failure threatens the functioning of a large part of the system. For example, the functioning of the communication network was studied by removing network nodes – in a random or targeted way – and the effect on the network's functioning was measured by the impact on network characteristics such as the network diameter and the size of the largest connected component (Albert, Jeong, and Barabási 2000). Similarly, the functioning of power grids in response to the failure of single nodes has been examined by simulating cascading failures in the network (Crucitti, Latora, and Marchiori 2004). The systemic risk in financial networks has been investigated, e.g. by simulating the propagation of financial losses via interbank loan contracts between banks (Eisenberg and Noe 2001; Boss, Summer, and Thurner 2004).

Especially since the great turmoil of the 2008 financial crisis, being able to measure the systemic risk of individual banks became increasingly relevant to better inform decisions of regulators and governments (Glasserman and Young 2016). One way to do so is to simulate – based on economically meaningful shock propagation mechanisms – how the financial losses – triggered by an initial failure of a bank – propagates via the financial connections between banks and then aggregate the losses suffered by all banks to a single number, i.e. the systemic risk index of the bank is proportional to the financial losses its hypothetical failure would cause. Examples for such systemic risk indices are the Contagion Index (Cont, Moussa, and Santos 2013) and DebtRank (Battiston et al. 2012; Diem, Pichler, and Thurner 2020). The quantification of systemic risk is a particular type of systemic stress testing where instead of a general shock affecting multiple agents, a specific type of shock – failure of an individual bank – is applied.

To date there are only very few studies measuring systemic risk of individual firms in SNs, yet understanding systemic risk is essential for maintaining the stability of SNs (Scheibe and Blackhurst 2018). One approach uses standard network centrality measures to assess the systemic risks of firms in SNs (Ledwoch et al. 2016) Shao et al. (2018) calculate the nexus supplier index – assessing the topological importance of direct and indirect suppliers to a focal firm (Honda), while taking their SN relations into account – up to fourth tier suppliers. In contrast to financial networks, studies that quantify systemic risk based on an economically motivated mechanisms describing how shocks propagate from one firm to another in large scale supply and production networks are still rare. Notable exceptions are the application of DebtRank to a large-scale SN data set of Japan (Fujiwara et al. 2016), and a large-scale SN of international firms (Chakraborty et al. 2024). The economic systemic risk index (ESRI) of Diem et al. (2022) is to our knowledge the first systemic risk index based on a shock propagation model specifically developed for SNs and was recently extended to assess the effect of SN contagion on the banking system (Tabachova et al. 2024). So far, the SCM literature analyses systemic risk mostly with conceptual and non-quantitative frameworks (Scheibe and Blackhurst 2019). Studies quantifying the systemic risks that the propagation supply chain disruption poses for the supply of the population with basic goods are still grossly missing (see Appendix A). Yet, recently, Mollenkopf, Ozanne, and Stolze (2020) and Ivanov and Dolgui (2022) emphasised the importance of treating the population as an integral part of supply chains, calling for more research on the effects of supply chains on individual and community well-being (Mollenkopf, Ozanne, and Stolze 2020).

To summarise, the literature unambiguously shows that the topological details of SNs not only matter but play a crucial role for the propagation of disruptions and thus the resilience of SN. This implies that a reliable and useful assessment of systemic risks in SNs require real world data sets, ideally in real time. However, studies using real-world large-scale SNs remain few, particularly establishment-level network data-based studies are missing. Further, disruption propagation models and systemic risk measures for SNs traditionally focus on firm performance or overall SN metrics, but do not consider how the supply of the population is affected by disruptions and their propagation. In the present study we fill this gap by developing a way to quantify the systemic risks for the *supply of the population* with essential goods based on a disruption propagation simulation model and apply the method to a real-world large-scale establishment-level SN. Closing this research gap will lead to a better understanding of the prevailing systemic risks for the supply security of the population and, hence, improve the resilience of essential goods SNs in future crisis.

3. Methods and data

3.1. Network representation

We model the SN of a particular type of good, α, (e.g. pork, other food products, hygiene article, medicines) as a directed and weighted complex network, and represent it with the adjacency matrix, W^{α}. The network consists of n nodes representing establishments (e.g. farms, production site, warehouse, supermarket).

A directed link (or edge), W^{α}_{ij}, represents the volume of good of type, α, a supplier node, i, sells to a buyer node, j, within an observed time period.[7] Additionally, the network contains, m, population nodes, where a particular population node, k, has a number of e_k inhabitants, and the total number of inhabitants is $e^{tot} = \sum_{k=1}^{m} e_k$.[8] Here we choose the m nodes to be the administrative districts of Austria, which allows for a granular geographical representation of the country, while keeping the number of nodes tractable.[9] The population nodes, e_k, are connected to the respective SN, W^{α}, by a supply link, W^{α}_{ik}, denoting the volume of product, α, the population node k buys from node i. Typically, node i is a final-tier node in the SN of a product, α, e.g. a supermarket for food, or a pharmacy for medicine. We use the simplifying heuristic that the population of a district only buys

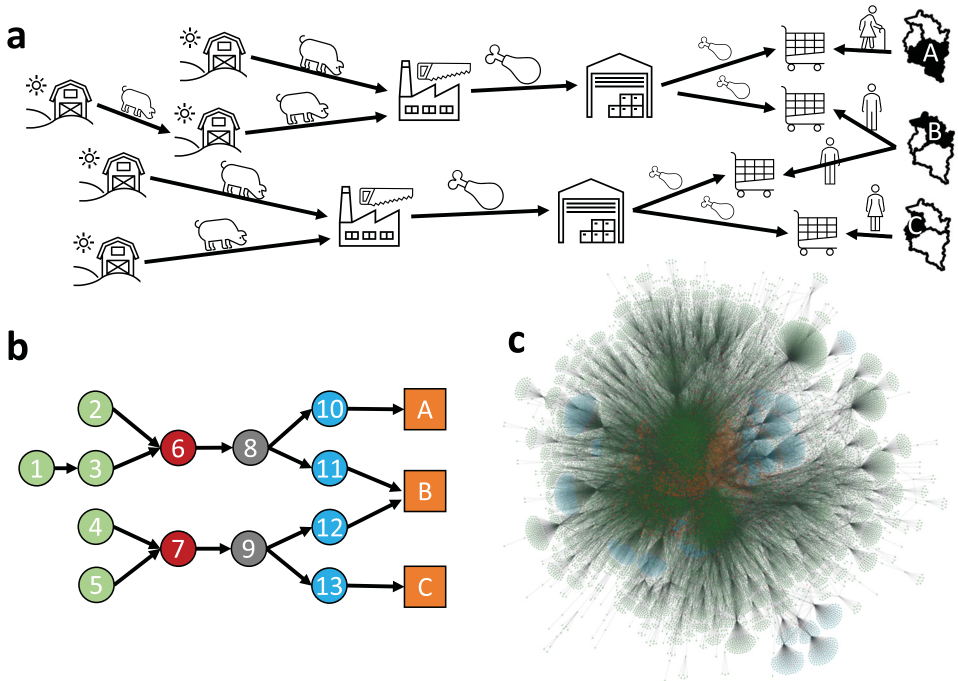

Figure 1. Visualisation of the Austrian pork supply network on the establishment (facility level): farms (green), slaughterhouses and meat processors (red), distribution centres (blue), and supermarkets (orange). (a) Schematic representation of the considered types of actors and how they are connected. Different types of primary production, slaughterhouses and meat processors, distribution centres of food retailers, local supermarkets, and administrative districts (population nodes). Goods flow downstream to stores where the local population buys them. (b) Network abstraction of the schematic example in panel a. Node colour indicates establishment types, edges indicate flows of products between the nodes; round symbols represent supply network nodes, square symbols represent population nodes. The actual network model considers node sizes and edge weights; they are omitted here for the clarity of presentation. (c) Visualisation of the reconstructed Austrian pork supply network from the collected data, containing approximately 23,000 nodes. Note that only the weakly connected component is displayed. A core periphery structure is visible, where farms and supermarkets are located at the periphery; slaughterhouses, meat processors, and distribution centres are close to the centre of the network.

from final-tier nodes located in their own district and no other. In this way the local population in every district is exposed to supply disruptions that occur anywhere in the SN upstream of the supermarkets it contains.[10]

The SN we consider here is organised in tiers that correspond to specific node types. This means that nodes of a given type are only supplied by nodes of one particular type, e.g. supermarkets are only supplied by warehouses, warehouses only by slaughterhouses, and slaughterhouses only by primary production nodes. This specific structure arises as the data only encompasses flows of one product type (pork meat) and the tiers correspond to different stages of its production and distribution process. Data on support materials like packaging are not available. We can therefore represent the data with a single network layer, W, and a vector, p, representing the node type for all n nodes, i.e. the element, p_i, specifies whether i is a primary production, slaughterhouse, meat processor, distribution centre, supermarket, or district. From the weighted adjacency matrix, W, we calculate the *in-strength* of node i, as $s_i^{in} = \sum_{j=1}^{n} W_{ji}$, representing the volume node i is buying from its suppliers. The out-strength of node i, $s_i^{out} = \sum_{j=1}^{n} W_{ji}$, represents the volume of products, i, is supplying to all its customers. For each node i we define the 'regular' *absolute* production level when the SN, W, is undisrupted as $x_i(0) = s_i^{out}$. The value, $x_i(0)$, is the production (or distribution) volume of node i recorded in the data.

We illustrate the network model in Figure 1. Figure 1(a) shows a schematic representation of the network structure, starting from primary production of pigs at farms and fatteners (houses) that are then sold to slaughterhouses (factory symbol), which, in turn, deliver processed meat to the distribution centres of large food retailers (warehouse). The processed meat finally is shipped to the supermarkets (shopping carts). The population is split into three different districts (A, B and C) whose inhabitants buy meat at the supermarkets located within the respective district. Figure 1(b) shows the abstraction of the supply chain as a network, where colour corresponds to the different types of establishments in the SN (for ease of illustration we omitted link weights). Round nodes correspond to establishments, square ones represent districts (i.e. the

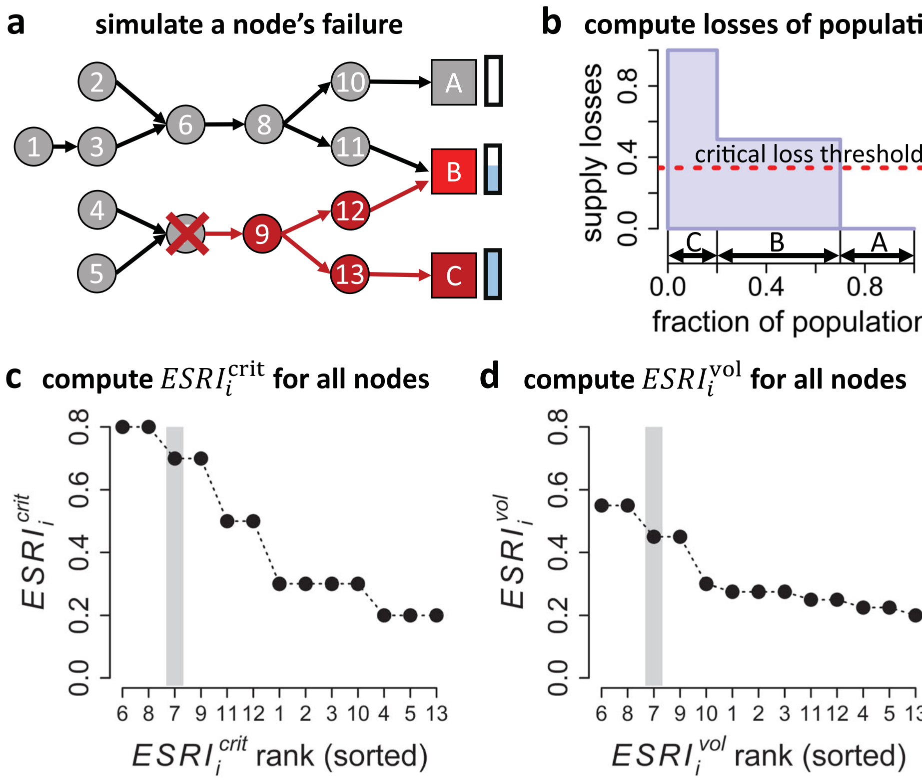

Figure 2. Illustration of the steps for computing the systemic risk of individual establishments. (a) Simulation of the temporary failure (e.g. fire, forced closure by authorities) of *node 7* and its downstream propagation in the example supply network. The failing *node 7* is marked with a red cross; red supply links indicate downstream shock propagation. The population in districts C and B suffer a supply loss of 1 (100%) and 0.5 (50%), respectively, whereas district A is not affected. The supply loss is indicated by the height of the blue bars next to districts (squares). (b) Line chart visualising the supply losses of the population after the failure of *node 7*. The x-axis shows the fraction of the population affected; the y-axis shows the size of the supply loss of each district. The most affected district, C, is on the very left; arrow length indicates districts' population sizes. The dashed red line indicates the *critical supply loss threshold* of 34% (0.34). We see that the initial failure of *node 7* affects 70% of the population criticaly ($ESRI_7^{crit} = 0.7$) and reduces the total volume of the pork meat supply to the population by 45% ($ESRI_7^{vol} = 0.45$). (c) Ranking of all 13 supply network nodes according to their systemic risk index, $ESRI_i^{crit}$. The x-axis shows the node IDs sorted according to their, $ESRI_i^{crit}$ values – the most risky premises are on the very left. The y-axis denotes the $ESRI_i^{crit}$ of each node (fraction of population that is critically affected). The initially failing *node 7* has rank 3 (grey shading). (d) Ranking of all 13 nodes according to the volume-based systemic risk index, $ESRI_i^{vol}$. Again, node *7* has rank 3, highlighted by grey shading. Note the differences between the two rankings.

population). Figure 1(c) shows of the empirical pork SN of Austria including approx. 23,000 nodes (without the population nodes). Only the weakly connected component is displayed. The network visualisation shows that the pork SN is of substantial size and complexity. The underlying data set is described in more detail in the data section and Appendix C, the economic importance of the pork SN is discussed in Appendix D.

3.2. SNST: quantifying the impacts of SN disruptions on the supply for the population

Our simulation study comprises five steps (as illustrated in Figure 2):

(1) observe the *undisrupted* supply network, W,
(2) assume a (temporary) *disruption* of a specific node, i,
(3) simulate how this *node's disruption propagates* downstream,
(4) calculate for each population node, k, its supply losses, $h_k(T)$
(5) calculate the fraction of the population surpassing the *critical supply loss threshold*.

First, we consider the undisrupted SN, W, where each node in the network can deliver to its buyers the amount of products that was originally recorded in the data. At time $t = 0$ before any shock occurs, for each node i the *initial absolute production* (or regular operational level) corresponds to its out-strength $x_i(0) = s_i^{out}$, i.e. the amount recorded in the data. We denote the relative production level of node i at iteration t as $h_i(t) \in [0, 1]$, where $h_i(t) = 1$ means 100% production and 0% disruption, while $h_i(t) = 0$ means no production and

100% disruption. The *relative production level*, $h_i(t)$, is the *absolute production*, $x_i(t)$, that i can maintain at simulation time step, t, as fraction of the initial state, $x_i(0)$, i.e. $h_i(t) = \frac{x_i(t)}{x_i(0)}$. For the undisrupted SN, we initially have $h_i(0) = 1$, for all nodes i.

Second, we assume an initial stress scenario, represented by the vector, ψ, where ψ_i, corresponds to the remaining production level of node i after the disruption occurs at time $t = 1$. To initialise the shock propagation simulation, we set the production level of each node to the shocked level, i.e. $h_i(1) = \psi_i$. As we are interested in the systemic risk of a particular node, we set $\psi_i = 0$ for the specific firm we want to compute the systemic risk for, and $\psi_j = 1$ for all other nodes $j \neq i$. In this framework a more general shock is generated by assigning a value between 0% and 100% to each node. Figure 2(a) illustrates a 100% operational disruption (initial failure) of *node 7*, a slaughterhouse, by a red cross.

Third, we simulate how the disruption of the failed node i propagates downstream to its customers, and from the customers to the customers of the customers etc. The simulation is based on a recursive equation that links the production level of a buying node to the production level of all its suppliers. The absolute production level of the node i at iteration $t + 1$ of the algorithm is denoted as $x_j(t + 1) = a_j \sum_{i=1}^{n} W_{ij} h_i(t)$, i.e. the sum of the original deliveries received weighted by the production level of the respective suppliers at t. Note that $a_j = s_j^{out}/s_j^{in}$ is the input conversion factor for j, e.g. in a slaughter house one pig is converted into 70 kg of meat, whereas for nodes that only distribute goods (e.g. warehouses and supermarkets) $a_i = 1$.[11] The recursion implies that the disruption size received by node j from its supplier i depends on the importance of the supply link, W_{ij}, for buyer j (the product volume provided by i, divided by the overall product volume node j buys) and the disruption level of supplier i.[12] We iterate the recursion equation until convergence (when no additional disruptions occur) at time step T (see Appendix D, for the full algorithm). In Figure 2(a) the failure of *node 7* propagates downstream to *node 9* (a distribution centre) directly and *nodes 12* and *13* (supermarkets) indirectly.

Fourth, we assess how the population nodes are impacted by the propagation of the initial shock. For each population node, k, the relative supply level, $h_k(T)$, corresponds to the fraction of the original supply remaining after the shock propagated. The in-strength, ${s_k}^{in}$, of a population node k corresponds to its original supply volume in the undisrupted state, i.e. $h_k(T){s_k}^{in}$, correctly displays the absolute remaining supply of district k after the failure of a specific node i (or a more general shock).

Note that we are interested in finding establishments that pose a high systemic risk to the (food) *supply security of the population*. When assessing food supply security we need to focus on stress scenarios (here node failures) leading to a critical undersupply of the population, causing a serious loss in well-being or a deterioration of its health. We take this into account by introducing a *critical supply threshold*, λ. A supply level, $h_k(T)$, of population node k below this threshold ($h_k(T) < \lambda$) indicates a severe loss of well-being or health risks for people living in district k. Nodes causing large parts of the population falling below this threshold pose high systemic risk to supply security. As we deal in our application with food products, a critical supply threshold can be formulated in terms of a minimum level of calories per day that are deemed medically necessary.[13] We use medical guidance on healthy weight loss to arrive at a reasonable critical supply threshold that should not be undercut in the medium term. The medical suggestion for healthy weight loss is to reduce calorie intake by 22% to 43% to lose between one and two pounds of weight per week.[14] For the remainder we set the threshold to $\lambda = 0.66$ (a 34% loss of calories), but provide a detailed sensitivity analysis with respect to λ in Appendix E. Applying the idea of the general calory based threshold to a single product layer will overestimate the supply security impacts for nodes upstream of the distribution centres, but should provide realistic estimates for the establishments of distribution centres and warehouses, see also Section 5.3. Note that for other types of essential products such a threshold could be very different, e.g. for medical drugs, where a fixed dosage is needed a reduction of the supply level by a few percent can mean that some patients will no longer receive necessary treatment.

In Figure 2(a) the population nodes, district B and district C, suffer from a reduction in their basic supply because the supermarkets (they are connected to) have been disrupted. The population in district A is not affected, as its upstream supply chain was not affected. Figure 2(b) shows that district A is not affected and remains with 100% (0% loss) of its original supply, whereas districts B and C received a supply loss of 50% and 100%, respectively. In Figure 2(b) the loss threshold ($1 - \lambda = 0.34$) is illustrated by the red horizontal line. In our example the supply losses of districts C and B, surpass the critical threshold due to the failure of node 7.

Fifth, we want to summarise the systemic risk that a SN node poses for the supply of the population with essential goods by a single number. Based on the supply threshold and the population shares we can assess how large the fraction of the population is that suffers from seriously reduced well-being in response to the initial shock. For each population node k we define the indicator variable δ_k indicating whether the supply level of that population node (district) fell below the critical threshold

λ (i.e., $\delta_k = 1$ if $h_k(T) < \lambda$ and $\delta_k = 0$ if $h_k(T) \geq \lambda$). We define the systemic risk index with respect to the critical supply level of the population for node i as

$$ESRI_i^{crit} = \sum_{k=1}^{m} \frac{e_k}{e^{tot}}(1 - h_k(T))\delta_k. \quad (1)$$

Note the differences to the definition of the classical economic systemic risk index (ESRI) in Diem et al. (2022) that focuses on the overall production level in the SN, but where the supply to the population and critical supply levels are not considered. To illustrate the importance of the critical supply threshold we also consider a volume based systemic risk index measuring the overall reduction in the supply volume due to the failure of node i as $ESRI_i^{vol} = \sum_{k=1}^{m} \frac{e_k}{e^{tot}}(1 - h_k(T))$. The critical supply threshold captures the population well-being in the systemic risk index, $ESRI_i^{crit}$. In contrast, the volume-based index, $ESRI_i^{vol}$, ignores the fraction of the population, suffering from a serious SN disruption. For example, consider the disruption of a large supplier, accounting for 10% of the supply of a specific product type across all districts in the country. Then, this disruption is large in volume and affects every district, but since the supply loss is spread evenly across the country, arguably nobody's well-being will be critically affected. A simple volume-based measure cannot distinguish if 10% in volume is reflected in 10% of the population having no supply at all, or if 10% in volume means that 100% of the population face a mere 10% loss. The proposed systemic risk index, $ESRI_i^{crit}$, allows us to rank firms and establishments in the SN with respect to their likely impact on the essential product supply and thus well-being.

We compare the two indices for the example network in Figure 2(b). We assume population shares of *A*, *B* and *C* of 30, 50, and 20, respectively, (population shares are illustrated by arrow length). Hence, 70% of the population suffers a critical loss in their supply when *node 7* fails, i.e. the *systemic risk index with respect to the critical supply of the population* of *node 7*, is $ESRI_7^{crit} = 0.7$. Figure 2(c) shows the ranking of all 13 nodes computing the critical-threshold-based systemic risk index, $ESRI_i^{crit}$ for each node. The x-axis shows the riskiest nodes on the very left, the least risky nodes to the right, they y-axis the respective $ESRI_i^{crit}$. *Node 7* is ranked as the third most risky node and is highlighted by grey shading. The volume-based index, $ESRI_i^{vol}$, is calculated as the *total volume of essential supply to the population that is reduced when a node's operation is fully disrupted* – in Figure 2(c) this corresponds to the area (light blue shaded) under the supply loss curve, calculated as the sum of supply losses per district weighted by the districts' population share. In our example, *node 7* has an $ESRI_i^{vol} = 0.45$ that is calculated as $0.2 \times 1 + 0.5 \times 0.5 + 0.3 \times 0$. Figure 2(d) depicts the ranking of the 13 nodes based on $ESRI_i^{vol}$. *Node 7* is highlighted by grey shading. Note that the two rankings differ (x-axis).

This method can be extended to multiple essential goods (e.g. medicine or hygiene products) by using appropriate critical supply thresholds for each respective good. For the specific case of multiple food products there are two options. Option one is constructing for each food product category (with similar aggregation levels, e.g. meat, dairy, cereals) a single layer network (e.g. pork) and apply the methodology as is, yielding a systemic risk index specific to each product group. Option two is representing each establishment as *replica node* in each product layer, W^{α}, and use for each replica node the shock propagation mechanism of Diem et al. (2022) where nodes can take multiple inputs from all layers (including, e.g. packaging). The supply losses across layers can be compared by converting them into calories. The computational effort of multiple layers is proportional to the number of supply links across all product layers. The simulations for the current network take less than four minutes on 13 cores (AMD Ryzen 7 3700X).

3.3. Data

Assessing the food supply security of an entire country, requires a detailed SN data set that allows for a sufficiently realistic network reconstruction covering the majority of the relevant nodes in the investigated essential goods sector. Since the majority of the population satisfies its demand for basic supplies – essential food and hygiene products – primarily from local supermarkets, the upstream SNs of large food retailers are a suitable choice. For this study we could reconstruct the Austrian pork SN from farms to supermarkets, fulfilling the above criteria. Note that the parts of the SN corresponding to the distribution centres and stores of food retailers also applies for most other food products, making our results relevant beyond pork meat. Further, the collected data also contains imports of life pigs of farms and slaughterhouses and for the food retailer that cooperated with us for the project also processed meat imports. The data set provides almost full coverage and contains 23,001 establishments as SN nodes, 44,730 supply links between the establishments, as well as the population data of 116 administrative districts (population nodes). The data set includes real world and estimated trade volumes between the establishments, allowing for reliable estimates of disruption propagation. In comparison, commonly used data sets based on business intelligence databases (such as Bloomberg, CompuStat, etc.) only contain binary information about firm-level buyer-supplier links, i.e. if a link exists or not.

The data set is composed of several data sources and was created in the course of a project with the Austrian Ministry of Agriculture. It combines animal movement data, supermarket data and public records; almost all relevant nodes directly associated with the pork SN have been identified. These include a full coverage of the primary production nodes (breeding farms, fattening farms, wholesalers, and animal transport), food processing industry (slaughterhouses, meat processors) and the distribution network (distribution centres and supermarkets) of the four large food retailers operating in Austria (joint market share $> 90\%$). Thus, it almost fully covers the relevant establishments of the entire sector. In places where data was missing, we resorted to imputation algorithms based on Monte-Carlo simulations that make use of the empirical supply link volume distribution where data was available, overall production volumes of nodes and geographical distances between premises. For details of the individual data sets, the network construction, and the imputation procedure we refer to Appendix C. The economic relevance of the constructed data set is shown in Appendix D.

4. Results

SNST when applied to the above SN data allows us to discuss different aspects of how failures in the SN affect the basic supply of a country's population.

4.1. Supply losses due to failure of individual establishments

SNST allows for an in-depth analysis of the supply losses suffered by the population due to the disruption propagation triggered by the failure of an *individual* SN node (establishment). We show that it is crucial to know how supply losses are distributed across the population living in the 116 districts and therefore if and where critical supply shortages are likely to occur if no intervention action is taken. We exemplarily analyse the consequences of the hypothetical disruptions of a large slaughterhouse (Figure 3(a) and (c)) and a distribution centre of a large food retailer (Figure 3(b) and (d)). Due to anonymisation and data protection agreements, establishments cannot be named. Panels 3a-b show the supply losses of the districts' population in response to the disruption propagation on the map of Austria where every district is coloured according to the severity of its supply losses. Districts with low supply levels (strongly affected) are coloured in yellow, districts with high levels (mildly affected) in dark blue.

Figure 3(a) shows that the disruption of the slaughterhouse affects a wide range of districts across the east of the country (light blue tones), but no district suffers severe supply shortages. Widespread but low supply losses occur as large slaughterhouses often sell to various meat processors that, in turn, often supply various food retailers, while distribution centres of food retailers commonly receive meat from more than one supplier. Even though a sizable volume of pork meat is temporarily unavailable, the branching of the downstream network spreads this supply losses widely across the population.

Figure 3(b) shows that the supply losses due to the failure of the distribution centre are very localised, affecting the population of the capital of Austria, Vienna, drastically (yellow tones, inset). The geographical concentration arises as particular regions – often federal states – are supplied by a given food retailer only from one specific distribution centre. The food retail sector in Austria is highly concentrated, yielding high market shares for individual retailers that vary among regions. Therefore, a serve disruption of a single distribution centre with high market share and supplying a highly populated region can cause a critical supply loss to a considerable fraction of the population. Supply levels of individual districts within the affected province can differ. This is explained by varying market shares across districts for the food retailer of the failed distribution centre.

Figure 3(c, d) show the supply losses of the population of the respective districts after the node's failure as line graph (compare Figure 2(b)). The x-axis shows the cumulative fraction of people affected by sorting districts from highest to lowest supply loss, while the y-axis shows the supply losses in the respective district. Note that the supply losses correspond to the colouring of districts in Figure 3(a,b). The horizontal line (dashed, red) indicates the critical-supply-loss threshold of 0.34 (34%). The value on the x-axis where the supply loss curve (blue) intersects with the critical threshold (dashed red) indicates the number of people that suffer a supply loss beyond the critical threshold. This value determines the systemic risk index, $ESRI_i^{crit}$, for the respective establishment that failed. The volume-based systemic risk index, $ESRI_i^{vol}$, denoting the countrywide fraction of the supply volume lost after the node's failure, is represented by the area (blue shade) under the supply loss curve (solid blue).

Figure 3(c) shows that no district suffers supply losses above the critical threshold in case the slaughterhouse would fail. The most affected district suffers a supply loss of 13%, i.e. the slaughterhouse is deemed to pose no systemic risk to the supply of the population ($ESRI_i^{crit} = 0.00$). The value of $ESRI_i^{vol} = 0.06$ shows that the slaughterhouse is responsible for 6% of the overall population's pork supply. Figure 3(d) shows that the supply losses of the districts within Vienna vary between

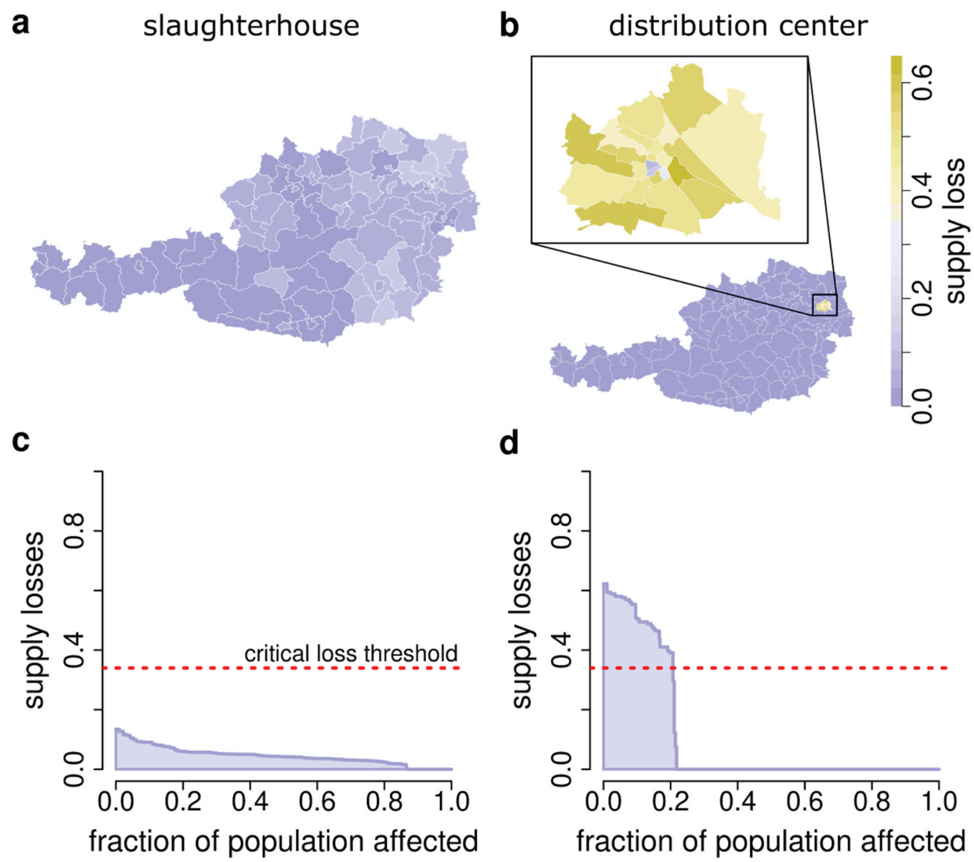

Figure 3. SNST results for two stress scenarios triggered by failure of two different establishments, respectively. Panels a-b show the pork supply losses for the population for each of the 116 districts on the Austrian map; yellow marks high supply losses, blue low supply losses. The x-axis in panels c-d show the cumulative fraction of the population affected by sorting districts from lowest to highest losses; the y-axis shows the districts' respective supply losses (compare Figure 2(b)). (a) Supply losses per district for the simulated failure of a large slaughterhouse. The supply losses are geographically widespread, but relatively small in size (blue, light blue). The maximum loss suffered by a district is 13.4%. (b) Supply losses per district for the simulated failure of a large distribution centre. The supply losses are highly localised affecting only the capital Vienna (inset), but large in size (yellow colour). (c) The failure of the slaughterhouse does not lead to supply losses above the critical supply loss threshold (34%) for any district, the most affected district suffers a supply loss of 13.4%. A majority of the districts suffer very small supply losses. The respective systemic risk indices of the slaughterhouse are $ESRI_i^{crit} = 0$, and $ESRI_i^{vol} = 0.045$. (d) The failure of the distribution centre leads to supply losses surpassing the critical loss threshold for 20.7% of the population (intersection of blue solid line with red dashed line), implying a high critical-threshold-based systemic risk index value, $ESRI_i^{crit} = 0.207$, while the volume weighted systemic risk index is comparatively low, $ESRI_i^{vol} = 0.108$.

0.62 and 0.08 (two districts are less severely affected due to low local market shares). This leaves approx. 1.9 million people (20.7%) suffering losses above the critical threshold of 34%, yielding a critical-threshold-based systemic risk index of $ESRI_i^{crit} = 0.207$. The distribution centre is responsible for 10.8% of the pork supply of the overall population, i.e. $ESRI_i^{vol} = 0.108$.

For the distribution centre the volume-based systemic risk index, $ESRI_i^{vol}$, is relatively low in comparison to the systemic risk index with respect to the critical-loss-threshold, $ESRI_i^{crit}$, whereas the opposite is true for the slaughterhouse. This indicates that the volume-based systemic risk measure, $ESRI_i^{vol}$, is by no means optimal for capturing the relevance of nodes in the SN when analysing food supply security, as it focuses more on overall economic importance as the original ESRI of Diem et al. (2022). We advocate for using both measures to obtain a more complete picture of the likely consequences of SN disruptions.

4.2. Systemic risk ranking of all establishments in the SN

We complement the detailed information of the simulation results presented in Figure 3 with a system-wide overview of prevailing systemic risks. Calculating the $ESRI_i^{crit}$ and $ESRI_i^{vol}$ for all nodes in the SN allows a pre-selection of critical nodes that must be analysed in-depth. This allows a targeted design of potential response strategies to failures of high systemic risk nodes and makes the introduced method a useful decision aid tool. Figure 4 illustrates the systemic risk rankings for five

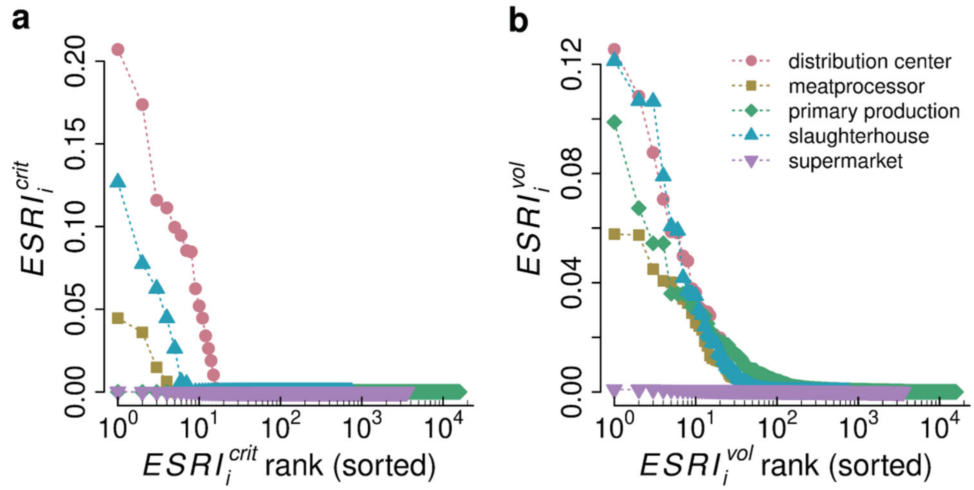

Figure 4. Systemic risk ranking for 23,001 nodes in the Austrian pork supply network wrt., $ESRI_i^{crit}$ and $ESRI_i^{vol}$ for each node type. The x-axis (log-scale) shows the nodes ranked with respect to $ESRI_i^{crit}$ or $ESRI_i^{vol}$ for each node type separately; most risky nodes are to the very left. The y-axis shows the nodes' respective systemic risk index. (a) Critical-supply-loss-threshold-based systemic risk index, $ESRI_i^{crit}$. Most establishments do *not* cause a critical supply reduction to the population. The most critical premises are distribution centres (16 nodes, highest $ESRI_i^{crit}$ value 20.7%) followed by slaughterhouses (7 nodes, highest $ESRI_i^{crit}$ value 12.7%) and meat processors (4 nodes, highest $ESRI_i^{crit}$ value 4.5%). No individual establishment from the primary production (farms, wholesalers, etc.) or supermarkets are critical for the supply of the population. (b) Volume-based systemic risk index, $ESRI_i^{vol}$. Distribution centres are the riskiest type of premises in terms of overall volume, closely followed by slaughterhouses. Few primary production nodes have high, $ESRI_i^{vol}$ values (the largest one represents alive pig imports from Germany). Meat processors show lower volume-based systemic risk.

different node types – primary production, slaughterhouse, meat processor, distribution centre and supermarket. Figure 4(a) shows the ranking for the critical-supply-loss-threshold-based systemic risk index, $ESRI_i^{crit}$. The x-axis shows the $ESRI_i^{crit}$-rank of nodes within their category, the y-axis shows $ESRI_i^{crit}$ values. The x-axis in log-scale shifts the focus on establishments with highest $ESRI_i^{crit}$ values. It is clearly visible that the distribution centres (red dots) constitute the riskiest category. The results suggest that 10 distribution centres can cause critical supply losses to more than 5% of the population and the riskiest affects 20.7% of the Austrian population. Overall, 16 distribution centres can cause critical losses. Slaughterhouses (upward triangles) and meat processors (squares) are the second and third most relevant categories, respectively. The riskiest slaughterhouse can affect 12.7% of the population with a critical supply loss in pork meat. However, just three slaughterhouses can cause critical supply losses larger than 5%. The riskiest meat processor can cause critical supply losses of around 4.5% of the population and three meat processors cause critical losses above 1%. Primary production nodes, e.g. farms, wholesalers, etc. (diamonds) and single supermarkets (downward pointing triangles) do not cause critical supply losses. A detailed sensitivity analysis for the critical threshold, λ, shows that these findings are robust; the ranking of individual nodes can change with varying λ, for details see Appendix E.

Figure 4(b) shows the ranking of all establishments for the systemic risk index with respect to the overall supply volume of pork meat, $ESRI_i^{vol}$. As in Figure 4(a), the distribution centres are ranked the riskiest, the highest risk distribution centre has an $ESRI_i^{vol}$ of 12.5%, six distribution centres have $ESRI_i^{vol}$ values above 5%, and 24 above 1%. The highest risk slaughterhouse has an $ESRI_i^{vol}$ of 12.1%, six slaughterhouses have $ESRI_i^{vol}$ values above 5%, 23 above 1%. The highest primary production node has an $ESRI_i^{vol}$ of around 9.9%, its high risk is explained by the node representing all aggregated alive pig imports from Germany.[15] Four primary production nodes have $ESRI_i^{vol}$ values above 5%, and 38 above 1%. The high values can arise as the primary production category includes not only farms, but also wholesalers and alive animal logistic providers that play an important role in supplying slaughterhouses with pigs and breeding farms supplying pigs to other large farms. These premises, however, do not cause individual districts to fall below the critical supply threshold, due to the downstream branching of the SN, hence, their negligible $ESRI_i^{crit}$. Single supermarkets are practically irrelevant with respect to $ESRI_i^{vol}$.

For all node types it is visible that more nodes have a $ESRI_i^{vol}$ visibly above zero than for $ESRI_i^{crit}$. This difference occurs by design, as for $ESRI_i^{vol}$ every node having a downstream connection to the population (districts) must have an $ESRI_i^{vol}$ that is numerically larger than zero, even though being very small for most nodes. In

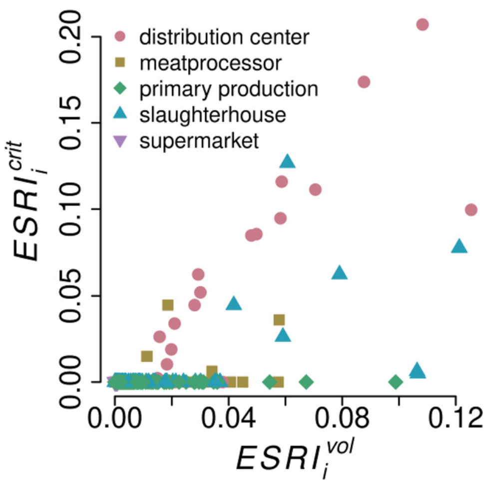

Figure 5. Comparison of the critical-supply-loss-threshold-based- and volume-based systemic risk index, $ESRI_i^{crit}$ (y-axis) and $ESRI_i^{vol}$ (x-axis). Symbols and colours correspond to the five establishment types. It is clearly visible that several nodes with high $ESRI_i^{vol}$-values have an $ESRI_i^{crit}$ of zero. On the opposite side there are a few nodes with relatively small $ESRI_i^{vol}$-values but noticeable $ESRI_i^{crit}$. For all distribution centres (red circles) the relationship between the two risk indices is relatively linear, but for one supplying a large population, but having a lower market share in several districts. For slaughterhouses (upward triangle) and meat processors (squares) the relationship is much less linear, e.g. the slaughterhouse with the second highest $ESRI_i^{vol}$ has only the sixth largest $ESRI_i^{crit}$-value – the network structure matters for these relatively upstream nodes more than for the downstream distribution centres.

contrast, $ESRI_i^{crit}$ identifies establishments causing supply levels below the critical threshold, hence, for non-critical establishments $ESRI_i^{crit}$ is zero, see Figure 4(a). This differentiated picture makes $ESRI_i^{crit}$ the suitable metric to quantify systemic risk to the supply of the population in the SNST framework.

4.3. Comparison of $ESRI_i^{crit}$ and $ESRI_i^{vol}$

To show that $ESRI_i^{crit}$ and $ESRI_i^{vol}$ really are different, Figure 4 compares their values for each establishment in a scatter plot. $ESRI_i^{crit}$-values are on the y-axis, $ESRI_i^{vol}$-values on the x-axis. Symbols and colours correspond to the five establishment types. Several nodes with high $ESRI_i^{vol}$-values have an $ESRI_i^{crit}$ of zero and a few nodes with relatively small $ESRI_i^{vol}$-values have a noticeable $ESRI_i^{crit}$. For all distribution centres (red circles) the relation between the two risk indices is relatively linear, apart from one; it is supplying a large population but has a lower market shares in several districts. For slaughterhouses (upward triangle) and meat processors (squares) the relationship is much less linear, e.g. the slaughterhouse with the second highest $ESRI_i^{vol}$ has only the sixth largest $ESRI_i^{crit}$-value, as the network structure matters for this relatively upstream node more than for the downstream distribution centres. The lack in correlation between $ESRI_i^{vol}$ and $ESRI_i^{crit}$ for important establishments shows the necessity of having a systemic risk index specifically tailored to basic supply security of the population. Further, since only a few nodes show a high $ESRI_i^{crit}$ it allows a much more targeted identification of high systemic risk nodes, for which backup plans should be put in place.

These results suggest that establishments with high supply volumes and a strong geographical concentration of supply losses should be the most critical. Those with large supply volumes and a widespread geographical impact are likely to be not critical, because they do affect a large part of the population, however, the impact is not strong enough to be true threat. Establishments with smaller supply volumes but a highly localised impact can critically affect small parts of the population but are not critical on a wider geographical scale. Low volume and low concentration nodes – constituting the majority of the 23,001 nodes – do not require systemic risk management actions.

5. Discussion

The threat of severe supply shortages of essential goods (e.g. medicine, protective gear, food) during the COVID-19 pandemic led to calls for *stress testing* supply chains of companies in critical industries to better prepare for future crisis (Simchi-Levi and Simchi-Levi 2020). Yet methodology to identify systemic risks for the supply to the *population* is grossly missing. Based on a simulation model for disruption propagation in supply networks (SNs), we propose the framework of supply network stress-testing (SNST). We use the SNST framework to conduct a systemic risk assessment for a large-scale establishment-level food SN that enables decision-makers to identify actors that are systemically critical for the food supply security of the population. To this end we introduced the systemic risk index, $ESRI_i^{crit}$, that allows decision makers to rank establishments with respect to their relevance for the supply of the population with basic goods. We demonstrated the applicability of the new systemic risk assessment method based on a nation-wide pork meat SN of approx. 23,000 establishments, 45,000 supply links, and 116 administrative districts. Even though, the SN structure of supermarkets and warehouses is derived from pork meat trade, this is likely similar for other product groups, hence, the systemic risk indices calculated for these establishments should be a good approximation across food products for these establishment types. Our results showcase that for Austria only very few nodes are likely to cause critical supply shortages in the pork supply the population, particularly distribution centres of food retailers, large slaughterhouses and meat processors. These are readily identified with the suggested systemic risk index, $ESRI_i^{crit}$. The methodology further allows for a detailed geographical resolution of where (in-)direct supply losses are likely to occur within the country following a stress scenario. Even though here we demonstrated the new method on one particular food product group, it can be readily applied to other product groups and combinations to arrive at a more complete picture of the systemic risks within the food SN.

5.1. Implications for the literature

The necessity to integrate people into SN models has been recently emphasised (Mollenkopf, Ozanne, and Stolze 2020; Ivanov and Dolgui 2022). Our SNST framework provides a first step in this direction by innovatively *integrating the whole population of a country explicitly* into our SN disruption propagation model in a geographically resolved way. Our method fills an important gap in the literature, as disruption propagation and systemic risk in SNs usually focuses on the overall economic effects, SN performance (Diem et al. 2022), or firm-performance (Shao et al. 2018) but not on the supply of the population. Our results show that $ESRI_i^{crit}$ adds a valuable dimension in the systemic risk assessment of SNs, the supply security of the population, and shows that conventional systemic risk indices similar to the original ESRI lack this dimension. Future work should focus on better modelling how the population of countries and regions is connected to the final tier nodes of essential goods SNs, e.g. based on travel distance, modes of transportation, number of reachable establishments. Incorporating these features is important as they can be crucial during crisis, e.g. to consider travel constraints during lockdowns. First steps could be in the direction of Schuster, Polleres, and Wachs (2024) who study peoples access to medical services by taking the road network into account. Further, future research should find ways to determine critical supply thresholds across a variety of essential goods and also consider the impacts of supply losses on population well-being and health. Even though, here we assess the systemic risk of individual facilities and establishments, our model is a general framework for stress testing supply chains; each of the five steps of the computational model of SNST can be (independently) extended and improved to increase realism.

Finding suitable initial shocks is key to financial stress testing (Breuer et al. 2009). Diem et al. (2024) made a step in this direction for firm-level SNs yet approaches to systematically generate shock scenarios to specific essential goods SNs are still missing, but required to assess which stress scenarios are particularly risky for which part of the SN. A more detailed shock propagation mechanism (see limitations section) with more general simulation rules (e.g. Ledwoch, Yasarcan, and Brintrup 2018; Diem et al. 2022) or digital twins (e.g. Burgos and Ivanov 2021), and data on multiple product groups can improve the realism of stress tests in the future.

Extant studies on real-world large-scale SNs are still scarce (Wiedmer and Griffis 2021); and Choi et al. (2021) recently emphasised that more empirical evidence is needed. So far, large-scale SNs are almost exclusively available on the firm-level (Wiedmer and Griffis 2021; Choi et al. 2021; Pichler et al. 2023) and not the establishment/facility-level. Note that, for example, food retailers have hundreds or thousands of stores even in small countries – they are represented as single node in firm-level SN data. While this might be sufficient to study firm-performance or economic effects, our study shows that individual establishments are likely to pose substantial systemic risks to the population's food supply. Without establishment level data it is hard to take geography into account and it seems impossible to model the detailed effects in a geographically resolved way. Hence, for identifying systemic risks and conducting realistic stress tests of the critical goods supply, large scale establishment-level SN data is required. Assembling establishment-level data sets is time consuming, costly and requires the cooperation of various key players (firms and supervisory bodies) of a particular SN, as typical SN data sources (VAT and payment records, business intelligence providers) only provide firm-level information (Pichler et al. 2023). Nonetheless, future research should seek to build such collaborations to enable better stress test models and gain a deeper understanding of systemic risks to the supply people.

5.2. Implications for policy makers and firms

The results presented suggest that individual establishments can be highly critical for the supply of large parts of the population and that the effects can be geographically very diverse. For decision makers in public administration and government agencies responsible for supply security this implies that in case of crisis exactly these establishments need be functional to avoid large supply problems. As a decision aid tool, SNST, when applied on regularly updated SN data can identify establishments that should be in the focus of decision makers. The information can be used to develop up-to-date backup plans for SN-disruption of highly critical establishments. Decision makers of public institutions and firms with critical establishments should jointly design these back-up plans. The output of the simulation model (Figure 3) can be used to play through how the failure of a specific distribution centre with high systemic risk affects a region. Based on these results it can be discussed whether the operational capacities of the retailer's other warehouses are sufficient to supply enough to the affected regions, or if other retailers need to react and increase their supply volumes to this region. Together they can evaluate how long this capacity adjustments would take. Another use case is simulating the effects of multiple warehouse failures occurring at the same time, firms could discuss strategies how to react in such a case. If the discussions suggest that firms alone cannot keep supply up, it can be planned if and how the public sector can provide support, e.g. additional logistics capacity provided by the military.[16] Simulations, such as those presented, can serve as baseline scenarios to work out such back up plans for future emergencies. Such *targeted* back-up plans can help to make SNs more resilient by adapting more swiftly to failures of critical nodes, resulting in higher supply security. The Covid-19 pandemic demonstrated the importance of coordinated responses in order to avoid adverse effects of the welfare of the population (Haug et al. 2020; Li et al., 2021, Chandra, & Kapucu, 2020). Accordingly, decision makers can simulate the effects of any specific stress scenario and draft countermeasures against their most likely effects.

Another way to improve SN resilience is – similar to financial stress-testing – to ask highly critical firms to report supply chain resilience metrics such as *time to recover* and *time to survive* (Simchi-Levi 2015), and set minimal thresholds of these metrics that need to be fulfilled. This additional resilience could increase costs in the production and distribution system and there needs to be a discussion who bears these costs and how much costs should be incurred for additional levels of resilience.

For financial networks the idea of communicating the systemic risk values of banks was put forward as a way of reducing systemic risks and increasing resilience (Thurner and Poledna 2013). Simulations of Thurner and Poledna (2013) showed that this solution is potentially effective in reducing systemic risks. Similarly communicating the systemic risk of establishments to firms could incentivise the rewiring to a saver SN topology.

Too often companies focus only on strategic, top-tier suppliers (Yan et al. 2015). Yet, a critical supplier 'can come from anywhere in a multitier SN' (Yan et al. 2015). The establishment-level SN data paired with the simulation model can show, for each facility to which up- and downstream establishments it is exposed to (a directly available result from the simulation model). If the SN data presented here is collected in real-time, sudden drops in product outflows of specific nodes can be automatically detected and the likely impacts simulated and communicated to firms that are likely affected before they will be actually affected. This information could improve the reaction time of firms when they know in advance about an upcoming supply disruption. Yet, such an early-warning system for disruptions would need to be agreed on by firms and antitrust (competition) authorities.

5.3. Limitations and future research

The proposed method suffers several limitations due to model assumptions and data availability. We discuss six of them. First, although we demonstrated our framework to work on a data set that covers almost the entire nation-wide pork supply chain, for parts of the network actual flow data could not be collected. We had to impute the missing data between slaughterhouses and meat processors, and for the retailers that did not cooperate with us imputed their link weights and links to meat processors with Monte Carlo simulations (see Appendix C for details). Second, due to data unavailability, we could not include supporting materials, such as packaging in the production process. Obviously, suppliers of supporting materials potentially carry significant systemic risk and should be included as data becomes available. For example, a single packaging manufacturer supplying several large production plants might be highly critical for the overall system. The SNST framework methodology is of course able to include these actors. Third, we do not consider product inventories, which results in an overestimation of the disruption impact of a supplier. However, goods like fresh meat are not durable and inventories are relatively small, and in general distributions centres and supermarkets only have limited inventories for many product categories. As data becomes available, the framework should be extended to include inventories, e.g. in the fashion of Henriet, Hallegatte, and Tabourier (2012). Fourth, the shock propagation recursion equation implies the so called 'proportional rationing' mechanism that gives all customer nodes equal priority. The remaining production is distributed pro rata to customers proportional to their original order weights. Note that in practice customers with more market power might be rationed less, and we might overestimate disruption propagation for larger nodes. Fifth, by applying an exogeneous critical supply threshold, $\lambda = 0.66$, designed to model overall calory intake to a single product group, we overestimate the impacts on the population for primary production nodes, as (pork) meat can be substituted. Note however that for the establishments of food retailers (distribution centres, supermarkets) the estimates are meaningful since most food products in Austria are supplied by a few big food retailers. This is to be confirmed by future work when the SN layers of the most relevant food products are available. Sixth, in the proposed framework we did not specify the duration of how long a failing node is not operational; we implicitly assume that it lasts until nodes do not receive additional shocks anymore and the disruption propagates downstream the population level. Since meat products are fast moving goods from slaughtering to reaching the supermarket a disruption takes at maximum a few weeks to reach consumers, whereas for primary production nodes the disruption takes much longer to reach the final consumer. An obvious extension to the framework is to introduce a time dimension together with the inventory-reach information. Then, SNST can be used to calculate how long a disruption needs to last such that it critically affects the supply of the population. These limitations should be addressed in future research, in particular it is necessary to extend and test the methodology to a multi-product SN, where all major food and supporting supplies are integrated.

A number of further analyses can be conducted within the framework of SNST. For example, for each district one could calculate how many nodes pose a critical threat to the district and one could define a resilience index for every district. Here, rather coarse-grained administrative districts were chosen for the analysis. Future extensions could include estimations of driving times from smaller population nodes represented by more fine-grained administrative districts (for example electoral districts) to supermarkets. This would take the fact into account that people will drive to other districts when local supply depletes. Further, the primary production sector could be decomposed into separate categories as in Puspitarani et al. (2023). Our SNST framework can be used to assess the impacts of animal disease outbreaks when paired with animal disease contagion model (Puspitarani et al. 2023; Conrady et al. 2024). Finally, we mention that in several exposed countries the presented framework could be used to estimate the exposure of the population to draughts, floods, and other natural or man-made catastrophes affecting primary production. From a sustainable development goals perspective, increased efforts in building similar data sets for the most vulnerable parts of the global population would be essential.

6. Conclusion

Supplying the population with essential goods depends on the functioning of an intricate production system with complex SNs at its core. Quantitative stress-testing and systemic risk assessment models tailored to food supply security and using large-scale establishment level SN data have hitherto been missing. We show how data-driven realistic SN stress-testing is possible and provide a methodological framework for this task. We show that SN data with establishment-level resolution is an essential requirement for such a task. Establishing such data sets that eventually are available on a daily basis needs cooperative efforts of the public and the private sector. Without such data, an effective stress-testing of supply security of critical goods remains unattainable. To complete the picture, considering the geographic distribution of a population, how it is connected to the local supply outlets, and the employment of suitable disruption propagation models are then necessary. Our results show that only a few nodes carry high systemic risk and are critical for the food supply security of the population. However, public authorities and governmental decision makers need to be aware of them and should develop back-up strategies to increase the resilience of critical SNs for the population – together with the relevant firms. Stress-testing methodologies in this spirit should be extended to simulate potential future crisis and how they could affect the SN and the supply of the population. If done systematically for a wide range of essential goods this should leave us better prepared for the next crisis.

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Notes

1. Time to recover measures how long it takes a supply chain node to recover after a disruption, while time to survive how long a supply chain can meet demand after a node disruption.
2. The Liquidity Coverage Ratio measures how long an *individual* bank remains liquid and solvent under specified stress scenarios (BCBS 2013).
3. Contingency plans for times of crisis are e.g. planned in the The European Food Security Crisis preparedness and response Mechanism (EFSCM) (European Commission 2021)
4. So far only parts of the US opioid distribution network (Amico, Verginer, and Schweitzer 2024), the OEMs in the global automotive supply chains network (Fessina et al. 2024), and a considerable part of the Japanse supply network (Inoue and Todo 2024) are available at the establishment-level.
5. Note, the terms supply network and supply chain network are commonly used interchangeably (e.g. Li et al. 2021).
6. Note that disruption propagation goes beyond the frequently used 'random failure targeted attack framework' (Albert, Jeong, and Barabási 2000), of removing nodes and

assess how e.g. the size of the largest connected component changes.

7. Note that further upstream in the supply chain a product, α, can also correspond to a production input, e.g. packaging material.
8. A unique aspect of this study is the explicit consideration of the population in the SN. Even in a small country the population cannot be modeled as a homogenous group when it comes to the supply of essential goods. Depending on regional differences, the level of urbanity, geographical topology and many other factors, the supply realities can be widely different and therefore disruptions in one part of the supply network can affect some parts of the population drastically, while others will not even notice the disruption. Therefore, for a reasonable granular assessment of the vulnerability of the population one should regionally differentiate the population into population nodes, based on e.g. administrative districts. This takes care of a large part of the heterogeneities. This differentiation can be extended to other socio-economic factors like access to a car, the financial situation, etc.
9. Technically a population node can be any non-overlapping representation of a country's population, e.g. households, and a geographic location.
10. In practice people living in one district can shop in other districts, and the assumption could lead to an overestimation of supply losses for localized shocks. Note this assumption can be relaxed by creating stochastic demands based on e.g. driving distance between population node and supermarket. The method of Schuster, Polleres, and Wachs (2024) for population access to medical services could be directly applied in our setting.
11. If W_{ij} correspond to the financial value of the transactions, a_i, is similar to the mark-up on the input price, and a_i would be larger than one also for supermarkets.
12. For the case where firms use multiple inputs see Diem et al. (2022).
13. Other options would be more fine-grained nutrition values. Another option is to survey the population to find what levels are tolerable for different types of essential goods.
14. See, e.g. https://www.health.harvard.edu/staying-healthy/calorie-counting-made-easy(accessed 28.11.2023)
15. For pig imports and exports into the abroad counterparts are only available as country aggregate nodes.
16. During COVID-19 the Austrian military provided logistical assistance for distribution centres of large retailers.

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Data availability statement

Data is available on reasonable request from the authors. Parts of the data are protected by non-disclosure agreements and cannot be shared.

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Appendices

Appendix A: Scopus keyword search

To highlight that systemic risk in supply networks is still rarely researched in comparison to financial systemic risk in particular in a quantitative way based on shock propagation models we conducted a systematic keyword search in Scopus. The keyword search highlights that the population is rarely considered in these models. The results are summarised in Table A1.

Appendix B: Simulation methodology for propagation of disruptions

Figure A1 illustrates one step of the recursion equation (Eq. A1) that specifies how a disrupted node propagates its disruption downstream to its buyers. The fractions next to the nodes indicate the production level at the respective iteration step relative to the undisrupted production level. The numerator indicates the current level of available output and the denominator the initial level of available output. At iteration t *node 2* is affected by a disruption (stemming from its suppliers omitted in this illustration) and the production level of *node 2* drops from 10 to 5 (i.e. the relative production level is $h_2(t) = 0.5$). At time $t + 1$ the disruption propagates to the buyers of *node 2* and their production level drops from 10 to 7 and 12 to 10 for *nodes 4* and *5*, respectively, i.e. $h_4(t + 1) = 0.7$ and $h_5(t + 1) = 0.833$. In the next iteration *nodes 4* and *5* will forward their disruption downstream to their own buyers (omitted in the illustration). These downstream shock propagation dynamics can be mathematically defined as a recursion equation that allows to estimate the supply level of each population node (district) depending on the operations of all other indirectly connected upstream nodes. The update equation is

$$h_i(t+1) = \min\left[\psi_i, \sum_{j=1}^{n} \frac{W_{ji}}{s_i^{in}} h_j(t)\right]. \tag{A1}$$

Note that the upstream propagation can be defined analogously. Up- and downstream propagation can also be treated differently when more data about the production process is available (Diem et al. 2022). We summarise the simulation of downstream disruption propagation in Algorithm 1.

Appendix C: Details on the network and the network construction

We briefly describe how the 23,001 nodes are distributed over the considered establishments type categories. Most nodes

Table A1. Results of the Scopus keyword search for systemic risk in different fields.

Full search string	Field limitation	Count
'systemic risk' AND ('financial' OR 'bank')	none	3, 050
'systemic risk' AND ('financial' OR 'bank') AND ('disruption' OR 'shock propagation' OR 'ripple effect' OR 'contagion' OR 'shock spreading' OR 'quantitative')	none	716
'systemic risk' AND ('supply chain' OR 'supply chains' OR 'supply network' OR 'supply networks')	none	56
'systemic risk' AND ('supply chain' OR 'supply chains' OR 'supply network' OR 'supply networks')	Business, Management and Accounting AND Decision Sciences	20
'systemic risk' AND ('supply chain' OR 'supply chains' OR 'supply network' OR 'supply networks') AND ('disruption' OR 'shock propagation' OR 'ripple effect' OR 'contagion' OR 'shock spreading' OR 'quantitative')	Business, Management and Accounting AND Decision Sciences	6
'stress testing' AND ('supply chain' OR 'supply chains' OR 'supply network' OR 'supply networks')	Business, Management and Accounting AND Decision Sciences	7
'systemic risk' AND ('supply chain' OR 'supply chains' OR 'supply network' OR 'supply networks') AND ('population' OR 'people' OR 'human' OR 'public' OR 'consumer' OR 'consumers')	none	9
'systemic risk' AND ('supply chain' OR 'supply chains' OR 'supply network' OR 'supply networks') AND ('population' OR 'people' OR 'human' OR 'public' OR 'consumer' OR 'consumers')	Business, Management and Accounting AND Decision Sciences	3

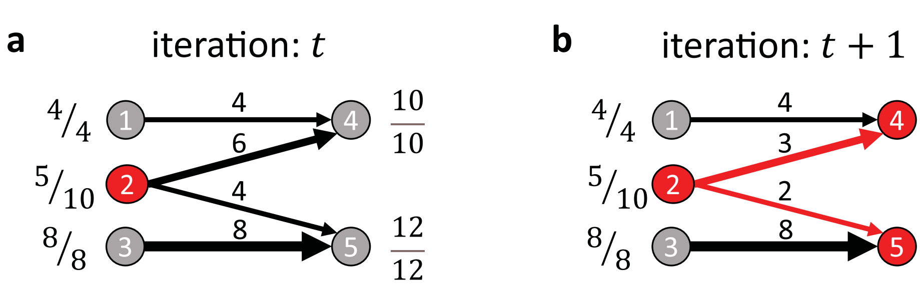

Figure A1. Example of one iteration step in the disruption propagation simulation. The fractions next to the nodes indicate the production level at the respective iteration step relative to the undisrupted production level. At iteration t node 2 is affected by a disruption (stemming from its suppliers omitted in this illustration) and the production level of node 2 drops from 10 to 5 (i.e. the relative production level is $h_2(t) = 0.5$). At time t+1 the disruption propagates to the buyers of node 2 and their production level drops from 10 to 7 and 12 to 10 for nodes 4 and 5, respectively, i.e. the relative production levels are $h_4(t + 1) = 0.7$ and $h_5(t + 1) = 0.8333$. In the next iteration nodes 4 and 5 will forward their disruption downstream to their own buyers (omitted in the illustration).

Algorithm 1. Simulation of downstream disruption propagation.

1. **initialise** each node with production level 100%, i.e. $h_j(0) = 1$, for all j
2. **set** the production level of the initially disrupted node i' to 0%, i.e. $h_{i'}(1) = \psi_{i'} = 0$.
3. **while** production levels of nodes are lower than in previous iteration, i.e. if $h_j(t) - h_j(t-1) < 0$ for any j **do**
   a. for each node j with lower than previous production level **do**
      i. identify all direct buyers i of the affected node
      ii. update the production level of nodes i with (Eq. 2)
      iii. update the set of nodes with lower production level than in previous iteration
   b. end for
4. **end while**
5. **return** output level of each node, $h_j(T)$, where T is the last iteration.

belong to the primary production sector (15,953) consisting of mostly different types of pig farms, but also wholesale traders and animal transporters. The category primary production is a summary term for different types of farms (e.g. breeding or fattening) and service facilities like wholesale traders, and logistic providers. We assume that the type of products delivered between node types is determined by the node types. Primary production nodes deliver living pigs to other primary production nodes and slaughterhouses. Slaughterhouses deliver pig carcasses to meat processors and cut meat parts to distribution centres directly. Meat processors deliver processed meat to distribution centres. Distribution centres deliver the received types of meat proportionally to their supermarkets and the local supermarkets within a district supply the local population of this district.

The second largest category is constituted by the different supermarket stores (3525), followed by the meat processors (2687) and slaughterhouses (749). The distribution centres of the food retailers are the smallest node group (24) illustrating their role as potential bottlenecks. We quantify the transfers between farms and to slaughterhouses in yearly numbers of pigs, whereas the other transfers are counted in kg of pork meat per year. It is considered that on average 70 kg of meat are recovered from an individual pig that is slaughtered.

For the network construction we used the following 5 data sources.

- **Animal movement data.** Records of transfers of living pigs within, out of and into Austria. The data is available daily over 2 years (2019–2020). All movements between farms and slaughterhouses are listed, as well as transfers to and from other countries. The data set is provided by the Austrian health ministry in strictly anonymised form. For the empirical analysis we use the available data from July to December 2020 representing the time span from birth to death of a pig. Note that this type of data is available for all EU countries.
- **Food retailer delivery data.** Daily incoming deliveries of pork meat products from suppliers (slaughterhouses, meat processors) to distribution centres and daily deliveries of pork meat products from distribution centres to supermarkets. The data includes the volumes (in kg) for the respective product types delivered and spans several months in 2021 for a large food retailer with a market share at the magnitude of one quarter. For other food retailers this data is imputed with publicly available data (locations of supermarket stores and distribution centres) and the imputation method described below.
- **Population census data.** Population data for each district is obtained from the Austrian statistical office.
- **List of meat processors and slaughterhouses.** All meat processors and slaughterhouses licenced in Austria and their geographical locations; obtained from the Austrian statistical office. This data is based on an EU directive and hence available for other EU member states.
- **Production volumes of slaughterhouses and meat processors.** The volumes are estimated for the largest slaughterhouses and meat processors covering around 90% of the production. The estimates were provided by the agricultural ministry for 2019.
- **Distribution centre and supermarket locations.** The geographical positions of distribution centres and supermarkets are publicly available for all major food retailers in Austria, and, hence can be web scraped.

To impute missing supply links in the network we use the following imputation rules:

- Supply relations between distribution centres and supermarkets that were not available are inferred from attributing the supermarket stores to the distribution centres of the respective food retailers according to federal state membership. The weights for the transactions are stochastically imputed by drawing link weights from the known empirical distribution of distribution centres to supermarket delivery volumes.
- The production volumes of small meat processors for which no estimates of the production volumes are available are assumed to follow an exponential distribution that is parameterised such that the remaining 10% of the production volume in Austria is attributed.
- We impute the links and the supply volumes between slaughterhouses and meat processors and from meat processors to distribution centres where not available with a geographical distance-based heuristic, i.e. meat processors buy slaughtered pigs from geographically close slaughterhouses and large slaughterhouses can supply further away meat processors. We assume the same heuristic for the links from meat processors to distribution centres where they are not known.

Identifying the data sources, obtaining access and processing the data took several months of work of one PhD student and one PostDoc researcher.

Appendix D: Economic relevance of the Austrian pork supply network

For several reasons the pork SN is an interesting network to apply our methodology. The supply chain management literature focused on meat SNs already in earlier studies investigating, for example, the lean supply chain concept (Taylor 2006; Perez et al. 2010), outsourcing of processing steps (Hsiao et al. 2010) or supply chain robustness (Vlajic, Van der Vorst, and Haijema 2012). From an economic perspective the sector is of considerable size even for a small country. The gross value of primary production of pig farming amounts to 831 million Euros in Austria, whereas the revenues of the slaughterhouses and meat processors in Austria amounts to 4.7 billion Euros (Austrian Ministry of Agriculture 2021). From a population perspective the pork SN is a prime example of an essential food SN. It is the most important type of meat and thus contributes to a large part of people's nutrition in the country of consideration. In general pork meat is in many countries a key source of protein and thus a key component for basic food supply and consequently relevant for the population´s long term well-being.

Appendix E: Sensitivity analysis for the critical supply threshold, λ

In Section 3.2, we set the critical supply threshold to 66% of supply remaining ($\lambda = 0.66$) based on a weight loss guide suggesting a save reduction of calories is between 57% and 78%, i.e. $\lambda \in [0.57, 78]$. Here we provide a detailed sensitive analysis of $ESRI_i^{crit}$ wrt. to λ.

Figure E1 shows the results of Figure 4 for the lowest and highest value of the critical supply threshold. Note that $\lambda = 0.78$, is the most conservative threshold where a supply loss of 22% is deemed already critical for the supply of the population (see Figure E1(a)), while $\lambda = 0.57$ is the least conservative threshold where the population can lose up to 43% of supply before it is deemed critically affected (see Figure E1(b)). The results in Figure 2 show that our findings are robust wrt. to the critical supply threshold, i.e. the same types of establishments are identified as risky – distribution centres, followed by slaughterhouses and meat processors. For $\lambda = 0.78$ the individual $ESRI_i^{crit}$-values are by design higher than in Figure 4 for, while the opposite is true of for $\lambda = 0.57$.

Figure E2 shows the systemic risk rankings across all 23,001 nodes for all values $\lambda \in [0.57, 78]$. Panel a shows the systemic risk ranking of the 100 most risky nodes for each threshold value. It is clearly visible that $ESRI_i^{crit}$ drops with the threshold becoming lower and fewer nodes display $ESRI_i^{crit}$-value larger than zero, while the overall shape of the distribution stays similar. Figure E2(b) shows again the $ESRI_i^{crit}$-distribution for each threshold $\in [0.57, 78]$, but this time every distribution is sorted according to the distribution of $\lambda = 0.78$. It becomes noticeable that the systemic risk values for some individual establishments can vary strongly with the threshold, e.g. for the node ranked most risky wrt. $\lambda = 0.78$ (very left), while for nodes the values remain comparable, e.g. the second most risky node (second from the left). This shows that the systemic risk ranking of establishments can change when changing the critical supply threshold, λ.

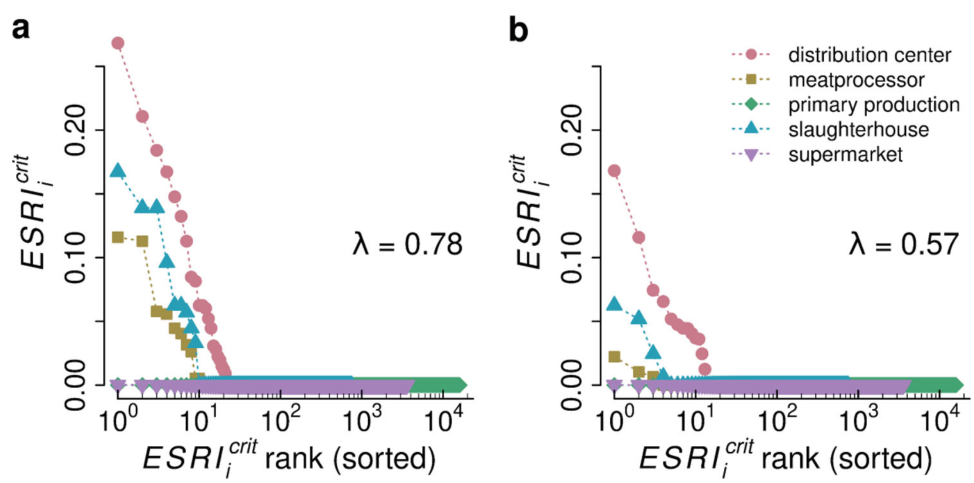

Figure E1. Systemic risk ranking for 23,001 nodes in the Austrian pork supply network wrt., $ESRI_i^{crit}$ for two different critical supply thresholds, λ. The x-axis (log-scale) shows the nodes ranked with respect to $ESRI_i^{crit}$ for each node type separately; most risky nodes are to the very left. The y-axis shows the nodes' respective systemic risk index. (a) Critical-supply-loss-threshold of $\lambda = 0.78$, most conservative threshold given by weight loss guides. We see the same pattern as in Figure 4(a), distribution centres are the riskiest node types followed by slaughterhouses and meat processors. Note that the levels $ESRI_i^{crit}$ are higher than in Figure 3, as here already a supply loss of 22% leads to a district being critically affected. Hence, more nodes are deemed critical. (b) Critical-supply-loss-threshold of $\lambda = 0.57$, least conservative threshold given by weight loss guides. We see the same pattern as in Figure 4(a), distribution centres are the riskiest node types followed by slaughterhouses and meat processors. Note that the levels $ESRI_i^{crit}$ are substantially lower than in Figure 4(a), as here only supply losses of above 43% lead to a district being critically affected. Hence, fewer nodes are deemed critical.

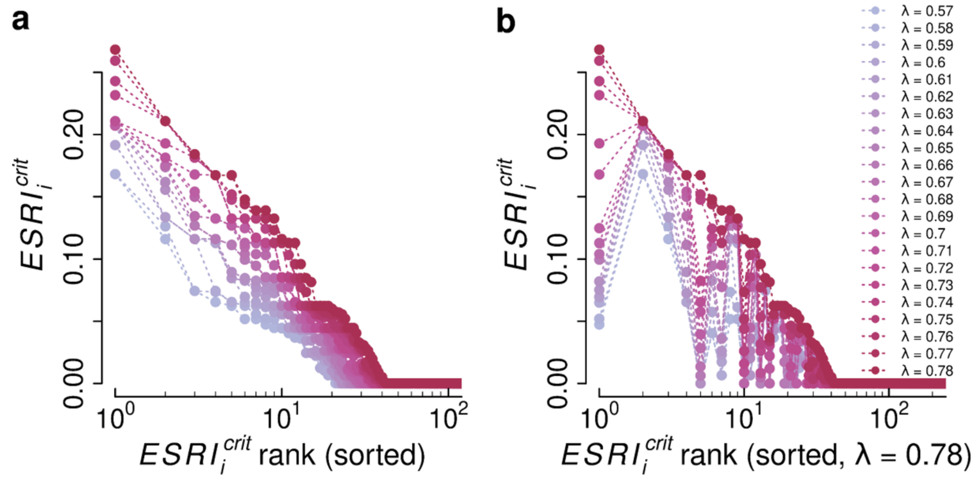

Figure E2. Systemic risk ranking for 23,001 nodes in the Austrian pork supply network wrt., $ESRI_i^{crit}$ for the hundred most critical nodes, for all critical supply thresholds, $0.57 \leq \lambda \leq 0.78$. Darker red colours correspond to high λ-values, fading colours to lower λ-values. (a) $ESRI_i^{crit}$ distributions sorted individually for each λ-value. The x-axis (log-scale) shows the nodes ranked with respect to $ESRI_i^{crit}$ for each λ-value separately; most risky nodes are to the very left. The y-axis shows the nodes' respective systemic risk index for the given λ-value. The figure shows how $ESRI_i^{crit}$ drops when the critical supply threshold λ increases. (b) All $ESRI_i^{crit}$ distributions sorted according to $\lambda = 0.78$. The x-axis (log-scale) shows the nodes ranked with respect to their $ESRI_i^{crit}$ for $\lambda = 0.78$, i.e. circles in the same vertical line correspond always to same node. The y-axis shows the nodes' respective systemic risk index for the respective λ-value. Note that the top curve in panel a and b are the same. We clearly see that for the node with the highest $ESRI_i^{crit}$ for $\lambda = 0.78$ (very left) its systemic risk drops while the threshold becomes lower, while for node ranked second the $ESRI_i^{crit}$ value remains relatively stable for different thresholds. Overall, we see that the changing the threshold can change the ranking of nodes wrt. $ESRI_i^{crit}$.