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„Identifying Decarbonization Leverage Points in Supply Networks with Network Measures that Quantify Systemic Relevance"

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Abstract

Climate change is one of the most urgent problems of today, but the transition to a low carbon economy comes with many challenges. One of the biggest is the reorganization of economic production such that the least amount of greenhouse gases is emitted while the production of economic goods and services is kept at decent levels. In this thesis, the economy is modeled as a complex network to show how a networks perspective might inform the low carbon green transition. In order to do that the systemic relevance of each company in this economic network is quantified and compared with its greenhouse gas emissions to identify potential leverage points for decarbonization. This idea is first motivated and then demonstrated for the 30 000 companies involved in the Austrian pork supply network which is reconstructed from various data sources. The nodes in this network are individual companies such as farms, slaughterhouses, meat processors, warehouses and supermarkets. The directed weighted edges are supply and buy relations between those companies and represent the transferred number of pigs or volume of pork. Each company is dependent on its suppliers to deliver resources for its production and on its buyers to sell its products. From these interdependencies network structures arise that are vulnerable to potential cascading failures, should a node stop supplying to or buying from its neighboring nodes. The inherent systemic risk that each node poses to the whole network can be quantified by simulating its failure and observing the consequences. By summing up the losses of production a company's economic systemic risk index $ESRI$ can be calculated - a method developed by Diem et al. [1]. This measure of socio-economic relevance is compared with the CO_2 emissions of each company in the Austrian pork supply network. The CO_2 emissions associated with a particular production step are calculated using a recent life cycle assessment of Austrian pork done by Winkler et al. [2]. Companies with high emissions and low socio-economic relevance, quantified by the $ESRI$, are potential levers for decarbonization. By targeting these companies with regulatory policies or tailored carbon taxes, a maximum of saved emissions and a minimum of disruption to overall production can be expected. This finding is tested for two simple transition scenarios for the Austrian pork supply network. Thus, modeling the economy as a complex (production) network reveals greenhouse gas mitigation potentials as well as possible pitfalls of decarbonization efforts.

Zusammenfassung

Der menschengemachte Klimawandel ist eine der drängendsten Probleme unserer Zeit, aber der Übergang zu einer kohlenstoffarmen Wirtschaft ist mit vielen Herausforderungen verbunden. Eine der größten ist die Umstrukturierung der wirtschaftlichen Produktion, so dass die geringste Menge an Treibhausgasen ausgestoßen wird, während die Produktion wirtschaftlicher Güter und Dienstleistungen auf einem akzeptablen Niveau gehalten wird. In dieser Arbeit wird die Wirtschaft als komplexes Netzwerk modelliert, um zu zeigen, wie eine Netzwerkperspektive die sogenannte Green Transition hin zu einer kohlenstoffarmen Wirtschaft unterstützen kann. Zu diesem Zweck wird die systemische Relevanz jedes Unternehmens in diesem Netzwerk quantifiziert und mit seinen jährlichen Treibhausgasemissionen verglichen, um potenzielle Hebel zur Dekarbonisierung zu identifizieren. Diese Idee wird für die 30 000 Unternehmen im österreichischen Schweinefleisch-Produktionsnetzwerk demonstriert, das aus verschiedenen Datenquellen rekonstruiert wird. Die Knoten in diesem Netzwerk sind einzelne Unternehmen wie Bauernhöfe, Schlachthöfe, Fleischverarbeiter, Vertriebszentren und Supermärkte. Die gerichteten und gewichteten Kanten sind Liefer- und Kaufbeziehungen zwischen diesen Unternehmen und stellen die Anzahl der transferierten Schweine oder das Volumen des gehandelten Schweinefleisches dar. Jedes Unternehmen ist von seinen Lieferanten abhängig, die Ressourcen für dessen Produktion liefern und von seinen Käufern, um seine Produkte zu verkaufen. Aus diesen wechselseitigen Abhängigkeiten ergeben sich komplexe Netzwerkstrukturen, die anfällig für potenzielle Kaskadeneffekte sind, wenn ein Unternehmen seine Lieferungen an oder die Käufe von seinen benachbarten Unternehmen einstellt. Das systemimmanente Risiko, das jeder Knoten für das gesamte Netz darstellt, kann durch die Simulation seines Ausfalls und der Beobachtung der Folgen quantifiziert werden. Durch Aufsummieren der Produktionsverluste lässt sich der economic systemic risk index $ESRI$ eines Unternehmens berechnen - eine Methode, die von Diem et al. [1] entwickelt wurde. Dieses Maß für die sozioökonomische Relevanz wird mit den CO_2-Emissionen der einzelnen Unternehmen im österreichischen Schweinefleisch-Produktionsnetzwerk verglichen. Die CO_2-Emissionen, die mit einem bestimmten Produktionsschritt verbunden sind, werden mithilfe einer kürzlich von Winkler et al. [2] durchgeführten Lebenszyklusanalyse für österreichisches Schweinefleisch berechnet. Unternehmen mit hohen Emissionen und geringer sozioökonomischer Relevanz, die durch den $ESRI$ quantifiziert wird, sind potenzielle Hebel für die Dekarbonisierung. Wenn man diese Unternehmen mit regulatorischen Maßnahmen oder maßgeschneiderten CO_2 Steuern ins Visier nimmt, ist ein Maximum an eingesparten Emissionen und ein Minimum an Störungen der Gesamtproduktion zu erwarten. Dieses Resultat wird für zwei simple Übergangsszenarien für das österreichische Schweinefleisch-Produktionsnetzwerk getestet. Die Modellierung der Wirtschaft als komplexes (Produktions-)Netzwerk zeigt somit sowohl Potentiale zur Treibhausgasreduktion als auch mögliche Fallstricke in der Dekarbonisierung auf.

Contents

1 Introduction

The economy is the system which consists of all the processes of production and consumption of goods and services by humans for humans in order to satisfy their material and to some extent social needs and wants [3, p. 1]. From ecological economics we learn that the economy is embedded in the environment which supports it and the society it serves. Every process of production or consumption interacts with the environment via exchange of energy or material [3, p. 87]. This becomes clear when thinking of resource extraction in the form mining or waste disposal in the form of emission of greenhouse gases into Earth's atmosphere from the burning of fossil fuels. Figure 1 presents a conceptual model of the economy as a system that is embedded in its environment and its society.

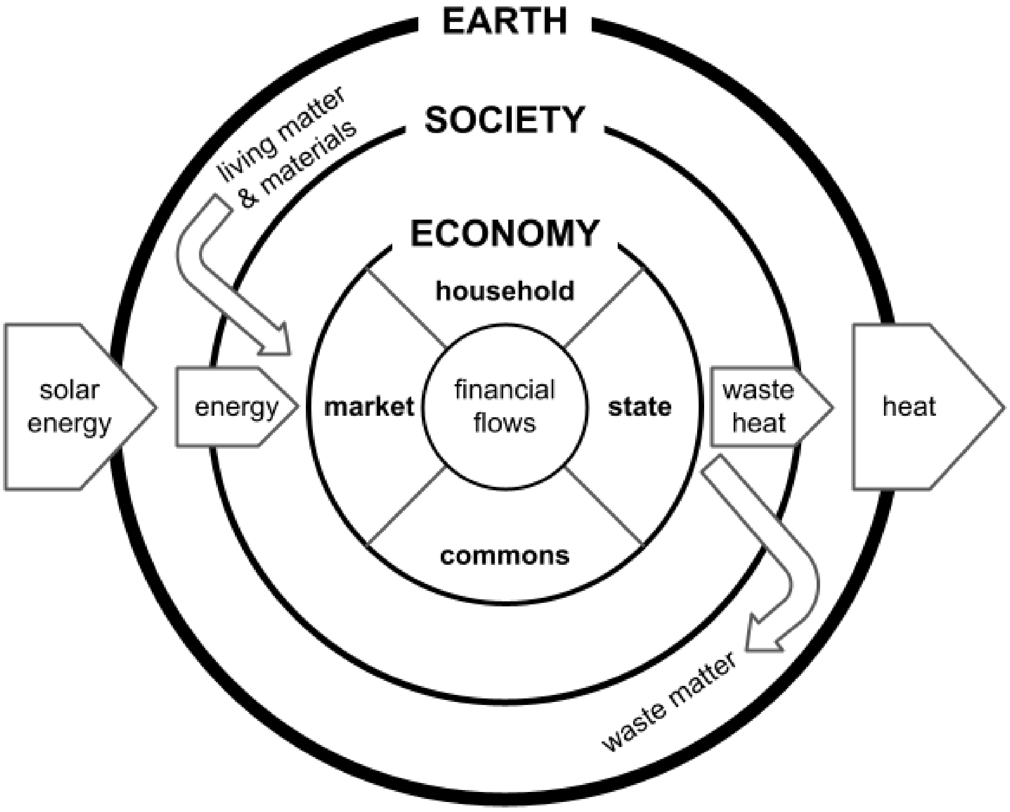


Figure 1: A conceptual model of the economy as a system driven by solar energy influx that is embedded in its environment and its society, adapted from [4, p. 71].

The current scale and style of human economic activity lead to a manifold degradation of the environment, whose consequences increasingly pose a threat to human civilization [5]. Climate change induced by the accumulation of greenhouse gases in Earth's atmosphere is among the most severe environmental problems that is directly related to the way humans currently produce and consume [6]. This is why one of the biggest and most pressing challenges of the 21st century is to manage the transition to a global economy that halts greenhouse gas production and other harmful activities. More specifically, the challenge lies in the transition from a primarily extractive to a mainly regenerative economy, while keeping production and consumption at sufficient levels to allow humans to satisfy their needs and wants [7]. In order to manage this transition it is important to examine the way the economy is currently organized.

In the 21st century it is mainly companies which produce goods and services by combining inputs to make outputs that are sold to other companies or end-consumers. If we take the perspective of a single firm, we call

the total of the buyer-supplier relations the firm is involved in the firm's supply chain. But since every company exhibits these buyer-supplier relations and many companies are specialized in just a few production steps that go into a final product or service, vast and complex networks of production arise as has been shown in the reconstruction of the total Hungarian supply network by Borsos et al. [8]. Although it has long been observed that various sectors of the economy are highly interdependent and tend to be linked in often unexpected ways, the study of these production networks is still a relatively young scientific field. Two factors are responsible. First, the rise of network science is still a fairly recent development in scientific methodology that brings about new tools and perspectives to study complex systems, such as the economy [9, p. 20]. Second, the surge in recorded and available data on an ever more granular level in all kinds of different fields allows for novel empirical and quantitative studies of (economic) systems. It is by the combination of these two developments that the literature on production networks and on complex system models in economic research has been growing in the recent years. Balint et al. identify four focal areas where complex system models have already contributed in their review paper on complex systems and climate economics [10]. The first area they identify is the analysis of climate negotiations and coalition formation. Here, complex system models have helped to understand out-of-equilibrium dynamics and opinion formation. The second area focuses more closely on the macroeconomics of climate change, where complexity has played an important role in modeling heterogeneous economic agents and the impact of climate related shocks. This line of research is on the verge of bringing about the first generation of agent-based integrated assessment models that allow to study dynamics of the green transition in much greater detail than previous models [11]. Third, they discuss how complex system models have contributed in modeling the energy market and lastly they review the growing literature on innovation dynamics and technical change which is of major importance to understand the green transition.
Another main scientific focus has been given to the study and quantification of the propagation of economic shocks through production networks and their social implications [12] [13] [1]. But not only economic questions in the narrow sense are leveraged by looking at the economy from a network point of view. By the combination of data on environmental damages like greenhouse gas emissions, caused by economic activity, and by quantifying the importance of each company of a given production network via network measures, it is possible to gain valuable insights into how to bring about a green transition. The green transition is thus understood as the reconfiguration of a production network such that the overall environmental impact is reduced while the social costs such as the loss in production are kept to a minimum. Nodes in an economic network that allow for such a reconfiguration will be considered decarbonization leverage points. As I will argue in this thesis, this approach makes the green transition, its implications, pitfalls and feasibility quantify-able, better manageable and ultimately more predictable. The thesis statement can therefore be formulated as follows:

By modeling the economy as a complex (production) network, it is possible to identify leverage points for the decarbonization of production.

I attempt to advance the research on the macroeconomics of climate change that was identified as a major research area by Balint et al. My contribution adds to the growing body of literature in which the economy is modeled as a complex network to uncover the potential pathways towards a green transition. In the following chapters I will develop the necessary theory for my methodology of comparing CO_2 emissions with a company's socio-economic relevance, present the findings for two motivating examples and test the thesis statement for a large case study of the Austrian pork production network.

2 Systemic risk in economic networks

In this section the research on systemic risk in economic networks is reviewed as this particular line of research will build the basic theoretical framework to assess the socioeconomic importance of a company in a given production network.
The potential of a system to stop functioning or to collapse from its inherent dynamics and properties is a major finding of complex systems research [9, p. 30]. These so called cascading phenomena have been observed in various theoretical models, such as the sand pile model [14], and in real world systems such as financial markets. Especially since the financial crisis of 2008 the financial system has been increasingly studied as a system susceptible to cascading failures through the default of individual banks. The study of the financial system as a complex network in which nodes represent financial institutions and links represent financial dependencies between those nodes has been pioneered by works from Allen and Gale [15], Boss et al. [16], Elsinger et. al [17]. This line of research has led to the formulation of systemic risk measures for individual financial institutions in financial networks. The DebtRank measure that was developed and popularized by Battiston et al. [18] as well as Thurner and Poledna [19] and is the most prominent financial systemic risk measure. More recently Poledna and Thurner have also formulated a systemic risk measure for individual transaction in financial networks [20] and systemic risk has been quantified in multi-layer financial networks by Poledna et al. [21].

Another body of research has in a similar manner studied the spread of shocks between economic sectors and along supply chains of individual companies. This propagation of economic shocks has been kicked off by the classical literature on input-output economics, starting with the original Leontief Input-Output analysis back in 1928 [22]. In input-output analysis the economy is modeled as an aggregation of economic sectors. Each sector takes inputs from other sectors and produces outputs that might be again inputs to one or more economic sectors or are consumed by final consumers. More recent works by Bak et al. [23], Acemoglu et al. [24], Carvalho et al. [25] and Gabaix et al. [26] have shown how demand or supply shocks to individual sectors can propagate through an input-output economy and have a detrimental effect on aggregate economic output. The propagation of shocks between economic sectors has also been used to assess the damages resulting from extreme climate events such as hurricanes by Hallegatte et al. [27]. Following the same goal, a model for damage spreading in global economic networks has been proposed by Bierkandt et al. [13] and Wenz et al. [28] in their *Acclimate* model.

A sector level representation of the economy might not always be sufficient to study the propagation of economic shocks. Economists such as Choi et al. [29] have pointed out the importance of studying supply chains on a company level. The spreading of disruptions and potential cascading failures in these company level supply networks have been studied by different researchers such as Craighead et al. [30], Świerczek [31] and Ivanov et al. [32]. But only recently have Diem et al. [1] derived a systemic risk measure for individual companies in supply networks comparable to the DebtRank measure for financial networks. This company level economic sytemic risk index $ESRI$ is the main tool to quantify sytemic relevance of companies in this thesis and is introduced in the subsequent sections. But first, the DebtRank measure for financial networks is discussed in detail as section 3 provides a motivating example of how the comparison of systemic risk measures with greenhouse gas emissions can uncover potential decarbonization leverage points in financial networks.

2.1 DebtRank

As has been foreshadowed in section 2, DebtRank has been proposed as measure of systemic risk in financial networks by Battiston et al. [18]. In essence, it is a centrality measure assigning to each node of a financial network the fraction of total economic loss that is expected as a result of the default of the node. Centrality is a measure of the importance of a node in a network for which various methods have been developed [33, p.

159].

For financial networks the adjacency matrix of the interbank liability network M_{ij} can be defined whose entries are the loans from bank j to bank i. Each bank i has capital C_i. Should i default and be no longer able to repay the loans by bank j, j looses M_{ij}. If the loss of j exceeds its capital C_j, j also defaults. The potential impact of bank i on bank j can therefore be defined as

$$W_{ij} = min\left[1, \frac{M_{ij}}{W_{ij}}\right] \quad . \tag{1}$$

By computing the sum of the outstanding exposures of bank i as $M_i = \sum_j M_j i$ the economic value v_i can be defined as as

$$v_i = \frac{M_i}{\sum_j M_j} \quad . \tag{2}$$

The sum of all economic values makes up the total economic value $V = \sum_i v_i$. In order to quantify the impacts of an initially defaulting node on nodes with network distance two or higher, the propagation of impacts has to be computed recursively. In the presence of cycles in the network W_{ij} can become greater than one. This is taken care of by introducing two state variables $h_i(t)$ and $s_i(t)$ that are assigned to each node. $h_i(t)$ represents the relative impacts on bank i at time t while $s_i(t)$ keeps track of the three potential node states: undistressed, distressed and inactive, $s_i \in \{U, D, I\}$. S_f denotes the set of nodes in distress at time $t = 1$. The algorithm is then initialized by setting $h_i(1) = \Psi$, for all $i \in S_f$; $h_i(1) = 0$, for all $i \notin S_f$, and $s_i(1) = D$, for all $i \in S_f$; $s_i(i) = U$, for all $i \notin S_f$. $\Psi \in [0, 1]$ is the parameter to set the initial level of distress, with $\Psi = 1$ meaning default. $h_i(t)$ is then recursively computed as

$$h_i(t) = min\left[1, h_i(t-1) + \sum_{j|s_j(t-1)=D} W_{ji} h_j(t-1)\right] . \tag{3}$$

Only the losses of those banks j for which $s_j(t-1) = D$ are summed up. $s_i(t)$ is updated as

$$s_i(t) = \begin{cases} D, & \text{if } h_i(t) > 0; s_i(t-1) \neq I, \\ I, & \text{if } s_i(t-1) = D, \\ s_i(t-1) & \text{otherwise} \end{cases} \quad . \tag{4}$$

The DebtRank at time $t = T$ of the nodes initially in distress is then calculated as $R_S = \sum_j h_j(T)v_j - \sum_j h_j(1)v_j$ and quantifies the resulting distress in the system minus the initial distress. If only a single bank i is contained in S_f, DebtRank measures the systemic impact of i on the network

$$R_i = \sum_j h_j(T)v_j - h_i(1)v_i \ . \tag{5}$$

2.2 Economic Systemic Risk Index ($ESRI$)

Motivated by the success of attributing financial systemic risk indices to individual actors in financial networks with the DebtRank algorithm, Diem et al. propose a measure for computing an economic systemic risks index $ESRI$ for individual companies in a given production network [1]. This section follows the derivation of the algorithm in their paper. In analogy to DebtRank the economic systemic risk index ESRI_i of a company i is defined as the fraction of production that is lost by the total production network as a consequence of the failure of i. To calculate the index one needs to know the weighted directed network of a given production system that is given by the supply and buy relations of all companies in that network. The weights of the directed network links are represented by the volumes W_{ij} that each supplier i of the network delivers to each buyer j. In-links of a node therefore represent supply transactions and out-links represent sales transactions. The unit in which the volume is measured depends on the network and the available data. In one case it might be convenient to measure volumes as prices times quantities, as it is commonly done in economics [34] [35], where in other cases one might want to measure volumes in kilograms or other physical units. What is also crucial, is to decide on an observation period for which the network is constructed, as the *ESRI* is defined as a measure on a static network. It is convenient to construct the network by incorporating all transactions within one defined year. The in-strength and the out-strength of a node i are defined as the sum of all its weighted in-links and out-links respectively

$$s_i^{in} = \sum_{j=1}^{n} W_{ji} \tag{6}$$

$$s_i^{out} = \sum_{j=1}^{n} W_{ij} \ . \tag{7}$$

2.2.1 Production functions

In economic theory production processes are often modeled with a production function f_i that defines the amount x_i of product type p_i that company i can produce with a given amount of inputs $\Pi_i = (\Pi_{i1}, \Pi_{i2}, ..., \Pi_{im})$ where Π_{ik} is the amount of input of product type k of firm i, given its available labor l_i and capital c_i [12]. These production functions allow to compute how much a given company i is still able to produce, if one of its suppliers j fails to deliver its products of product type k which reduces the availability of input Π_{ik}. The most commonly used types of production functions are the Leontief, the linear and the Cobb-Douglas production functions which are themselves special cases of the constant elasticity of substitution (CES) production function [36]. Figure 2 illustrates the characteristics of the three most commonly used production functions.

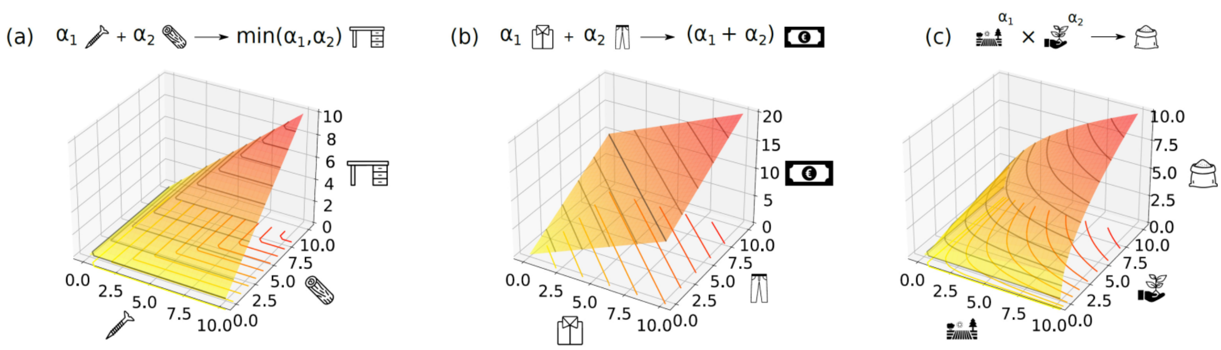


Figure 2: Toy examples of the three most commonly used production functions. Panel a) depicts a Leontief production function of a company that takes screws and wood as two essential inputs to produce tables. Panel b) depicts a linear production function of a retailer with the two non-essential inputs trousers and jackets. Panel c) depicts the Cobb-Douglas production function of a farm using the two partially substitutable inputs farm-land and fertilizer to produce crops. Taken from [1]

Figure 2a depicts the Leontief production function of the production process of company i that produces tables from wood and screws. Both inputs, screws Π_{i1} and wood Π_{i2} are essential for the production process of tables, since it follows a strict recipe of how a certain amount of wood relates to the availability of screws to manufacture a table. The amount of tables that can be produced x_i is determined by

$$x_i = \min\left(\frac{1}{\alpha_{i1}}\Pi_{i1}, \frac{1}{\alpha_{i_2}}\Pi_{i2}\right) \ , \tag{8}$$

where α_{i1} is the amount of available screws and α_{i2} is the amount of available wood.

Figure 2b depicts the linear production function of a company i that has two types of non-essential inputs:

trousers Π_{i1} and jackets Π_{i2}. The production level of the company is equivalent to the sales of these inputs and is given by

$$x_i = \frac{1}{\alpha_{i1}\Pi_{i1}} + \frac{1}{\alpha_{i2}\Pi_{i2}} \ . \tag{9}$$

In this example the availability of one product does not affect the output generated by selling the other product and therefore the overall production is just a linear combination of the available inputs where the coefficients α_{i1} and α_{i2} determine the importance of the products for the output. For this illustrative example equal importance was assumed as depicted in figure 2b .

Figure 2c depicts a Cobb-Douglas production function for a company i that takes as its two inputs available farm land Π_{i1} and fertilizer Π_{i2} to produce crops x_i whose amount is determined by

$$x_i = \beta_i \Pi_{i1}^{\alpha_{i1}} \times \Pi_{i2}^{\alpha_{i2}} \ , \tag{10}$$

with $\alpha_{i1} + \alpha_{i2} = 1$. The Cobb-Douglas production function can be thought of as modeling partial substitution of inputs and as an intermediary case between the Leontief and the linear production function. As farmland becomes less available the output level could be sustained by increasing the fertilizer use and vice versa although production is impossible with a complete lack of either of the two.

2.2.2 Derivation of $ESRI$

In the spirit of the DebtRank algorithm, economic systemic risk is calculated from the effects of an initially failing company on the total production network. The failure of a company affects other companies up- and downstream of that company and the loss of supply or demand might impede their production as well, potentially leading to the failure of even more companies. How the up- and downstream effects of a failing company spread through a production network is simulated by the following recursion scheme. First, the given production network $W(0)$ and its total output, which is the sum of the out-strength of all nodes $\sum_{l=1}^{n} s_l^{out}$, is set as a baseline. Then it is recursively calculated how the production levels of other companies in the network change based on the initial failure of a company - which is equivalent of setting its production level to 0. When the production levels do not change anymore and the shock propagation stops, a new stable state is reached and the recursion stops. The economic systemic risk index $ESRI$ is then calculated as the weighted sum of the relative losses at each company, normalized by the total output of the network.
The downstream recursion is developed by relating the amount company i can produce at time $t+1$ with the inputs is has available at time t

$$x_i^d(t+1) = f_i(\Pi_{i1}(t), \Pi_{i2}(t), ..., \Pi_{im}(t)) \tag{11}$$

to the production network $W(t)$. The amount $\Pi_{ik}(t)$ company i uses from input product type k at time t is mapped to its in-links $W_{ij}(t)$ by $\Pi_{ik}(t) = \sum_{j=1}^{n} W_{ji}(t)\delta_{p_j,k}$ where p_j is the vector of all product types and $\delta_{a,b}$ is the Kronecker delta.
The upstream recursion is defined as the dependence of the output of company i on the demand for its products. Demand at time t is calculated as the sum of the out-links W_{il} of company i

$$x_i^u(t+1) = \sum_{l=1}^{n} W_{il}(t) \ . \tag{12}$$

The suppliers of company i, $W_{ji}(t)$, depend on the production x_j^d of suppliers $j \in \{1, 2, ..., n\}$ which depend on their their respective in-links and so forth. The out-links W_{il} depend on the demand generated by their buyers' $l \in \{1, 2, ..., n\}$ production x_l^u who again depend on their respective out-links and so forth. From these interrelations between companies it becomes clear that the production of each company recursively depends on the production of other companies.

In order to simulate the effects of the failure of company j an initially stable state at $t = 0$ is assumed, for which the output levels are given by $W(0)$ and $x^d(0) = x^u(0) = x(0)$ and $x_i(0) = \sum_{l=1}^{n} W_{il}(0)$. The initial shock of the failure of company j at $t = 1$ is applied by setting its upstream and downstream production to zero, $x_j^d(1) = x_j^u(1) = 0$, as well as removing all its in- and out-links, $W_{ji} = 0$ for all i and $W_{lj}(1) = 0$, for all l. This initial shock then spreads through the production network by updating the production levels of all other companies recursively until they do not change anymore. The relative production level at time t with regard to the received up- and downstream shock is determined by

$$h_i^d(t) = \frac{x_i^d(t}{x_i^d(0)} \tag{13}$$

$$h_i^u(t) = \frac{x_i^u(t)}{x_i^u(0)} \ . \tag{14}$$

The received shock is distributed among buyers and suppliers according to a proportional rationing mechanism. This means that each company propagates a shock according to the initial shares of volume of its in- and out-links. The amount of production that company i is able to realize at $t+1$, given its suppliers' production levels, $h_j^d(t)$ at time t is determined by applying the production function of company i

$$x_i^d(t+1) = f_i\left(\sum_{j=1}^{n} W_{ji} h_j^d(t)\delta_{p_j,1}, \sum_{j=1}^{n} W_{ji} h_j^d(t)\delta_{p_j,2}, ..., \sum_{j=1}^{n} W_{ji} h_j^d(t)\delta_{p_j,m}\right) \ . \tag{15}$$

The amount company i produces at $t+1$, given the production levels of its buyers, $h_l^u(t)$ at time t is determined by

$$x_i^u(t+1) = \sum_{l=1}^{n} W_{il} h_l^u(t) \ . \tag{16}$$

It is assumed that shocks are propagated immediately and no production on stock takes place. From the initial failure of company j, $h_j^u(1) = h_j^d(1) = 0$ is propagated through the network by iterating equations 15 and 16 until no further shock propagation takes place and a stable state is reached at time T, where

$$T \equiv \min_j\{t \in \mathbb{N}|\max\left(h^d(t) - h^d(t+1), h^u(t+1), h^u(t) - h^u(t+1)\right) \leq \epsilon\} \ . \tag{17}$$

$\epsilon = 10^{-2}$ is the conveniently used convergence threshold. Shock propagation stops, once the changes in production levels fall below ϵ. The final levels of production of every company i is set to $h_i(T) = min(h_i^d(T), h_i^u(T))$. Finally, the economic systemic risk index $ESRI_j$ of company i is derived by the weighting the relative losses of each company i in the production network by the out-strength s_i^{out}

$$ESRI_j = \sum_{i=1}^{n} \frac{s_i^{out}}{\sum_{l=1}^{n} s_l^{out}}(1 - h_i(T)) \ . \tag{18}$$

2.3 The $ESRI$ algorithm

To conclude the introduction of the economic systemic risk index, the algorithm will be expressed for the case of only linear production functions, as only the case of only non-essential inputs is considered for all calculations in this thesis. As a first step the downstream impact matrix Λ^d is computed from the given production network W_{ij} as

$$\Lambda_{ji}^d = \begin{cases} \frac{W_{ji}}{\sum_{l=1}^{n} W_{li}}, & \text{if } W_{ij} > 0 \\ 0, & \text{else} \end{cases} \ . \tag{19}$$

The elements of the upstream impact matrix Λ^u are defined as

$$\Lambda_{ji}^u = \begin{cases} \frac{W_{ij}}{\sum_{l=1}^{n} W_{il}}, & \text{if } W_{ij} > 0 \\ 0, & \text{else} \end{cases} \ . \tag{20}$$

To initialize the shock that propagates upstream and downstream through the production network the relative production level of the defaulting company i is set to $h_i(1) = 0$ while the relative production levels of all other companies are kept at full capacity and are therefore set to $h_j(1) = 1$. The relative production levels of all companies are stored in a vector ψ with

$$\psi_i = \begin{cases} 0, & \text{if } i \text{ is the failing company} \\ 1, & \text{else .} \end{cases} \quad . \tag{21}$$

At $t = 0$ the network operates at full capacity and therefore the relative upstream and downstream shock vectors are initialized with a vector of ones. At $t = 1$ the upstream and downstream shocks start spreading and the relative production levels are therefore set equal to ψ

$$h_i^d(0) = h_i^u(1) = 1 \tag{22}$$

$$h_i^d(1) = h_i^u(1) = \psi_i \ . \tag{23}$$

Then the update equations for the received downstream and upstream shock are iterated until convergence

$$h_i^d(t+1) = h_i^d(t) + \Lambda^d[h_i^d(t) - h_i^d(t-1)]$$
$$h_i^u(t+1) = h_i^u(t) + \Lambda^u[h_i^u(t) - h_i^u(t-1)] \ .$$

Convergence is achieved at time T when all shocks fall below the threshold $\epsilon = 10^{-2}$

$$T \equiv \min_j \{t \in \mathbb{N} | \max\left(h^d(t) - h^d(t+1), h^u(t+1), h^u(t) - h^u(t+1)\right) \leq \epsilon\} \ . \tag{24}$$

To calculate the $ESRI$ the upstream and downstream shock vectors are merged at time T by keeping the lowest level of production of each company j that is observed in either $h_j^d(T)$ or $h_j^u(T)$

$$h_j(T) = \min\{h_j^d(T), h_j^u(T)\} \ . \tag{25}$$

The $ESRI$ of company i is then calculated as the sum of lost relative production $1 - h_j(T)$ weighted by the corresponding out-strength s_j^{out}

$$ESRI_i = \sum_{j=1}^{n} \frac{s_j^{out}}{\sum_{l=1}^{n} s_l^{out}} \left(1 - h_j(T)\right) \ . \tag{26}$$

It is important to note that the $ESRI$ provides just a short-term estimation of economic systemic risk as it is assumed that neither the supply nor the demand of a shocked company are substituted by other companies. Another assumption is the separation of the the upstream and the downstream cascade. This means that a company j receiving an upstream or downstream shock from the failure of an initial company i can only forward an upstream or downstream shock respectively. This is motivated by the question of whether a company is primarily constrained by either its upstream supply or its downstream demand. A more complete picture of occurring losses based on failures of companies would need a more sophisticated mechanism for passing on shocks and distributing them among buyers and suppliers. The $ESRI$ can therefore be interpreted as an economically motivated centrality measure to compare companies with respect to their systemic relevance for a given production system rather than a precise measure for the loss of production.

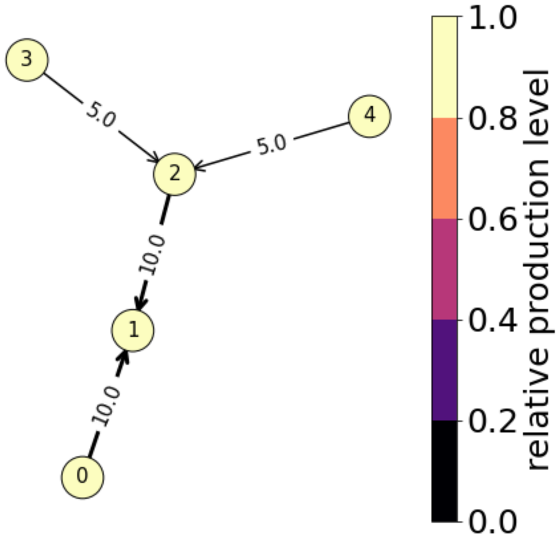
2.4 *ESRI* in a toy example

The calculation of the economic systemic risk index $ESRI$ is illustrated for a very small toy network that consists of five companies and four edges. Each edge represents the volumes - in arbitrary units - that are transacted between those companies. As the $ESRI$ is calculated from the total losses resulting from an initial failure of a company, figure 3 depicts the network M_{ij} and the relative production levels $h_j(t)$ of all nodes at each time step of the algorithm.

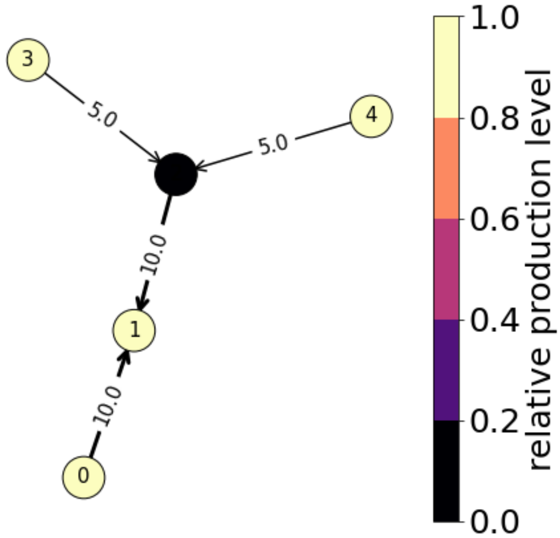
Figure 3a depicts the network at time $t = 0$ before a company fails. Figure 3b depicts the network at time $t = 1$ when company two fails and its relative production level is set to zero, $h_2(1) = 0$. Figure 3c depicts the network at time $t = 2$ when the shock spreads to adjacent upstream and downstream nodes. The relative production levels of nodes three and four drop to 0 as their demand vanishes while the relative production level of node one only drops to $h_1(2) = 0.5$ because node zero is still supplying at full capacity. The shock propagation stops after two time steps. The $ESRI$ of the initial defaulting company two is calculated according to equation 18

$$ESRI_2 = \sum_{j=1}^{n} \frac{s_j^{out}}{\sum_{l=1}^{n} s_l^{out}} \left(1 - h_j(T)\right) = \frac{10 * 1 + 5 * 1 + 5 * 1}{30} = \frac{2}{3} \,. \tag{27}$$

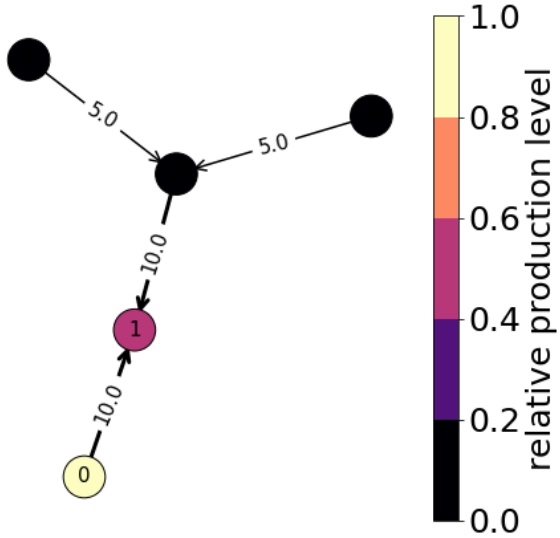
$ESRI_2 = \frac{2}{3}$ means that two thirds of total economic production would be lost, if company two would fail.



(a) Step 1 of the upstream and downstream cascade. All companies in the network operate at full capacity.



(b) Step 2 of the upstream and downstream cascade. Company two fails and the shock propagation starts.



(c) Step 3 of the upstream and downstream cascade. The initial shock spreads to neighboring companies. Nodes three and four lose all of their demand and fail as well while company one loses only half of its production as it is still supplied by company zero.

Figure 3: Economic shock propagation on a toy network consisting of five nodes and four directed weighted links. Node color indicates the relative level of production of each node after the upstream and downstream shock was received. Panel a) depicts the network before the shock propagation starts with all companies operating at full production level. Panel b) depicts the initial failure of company two and the start of the shock propagation. In Panel c) the shock spreads to the neighboring nodes and impacts their relative production level. Node three and four lose all their demand and their relative production level drop to zero while company one is still supplied by company zero and therefore loses only half of its production.

2.5 CO_2 emissions vs. *ESRI*

In this section the concept of comparing CO_2 emissions with the *ESRI* of individual companies is introduced. By identifying those nodes whose production is accompanied with high greenhouse gas emissions, but whose systemic risk is comparatively low, decarbonization leverage points in a given economic network can be detected. By targeting these companies a maximum reduction in emissions and a minimum disruption to overall production can be expected. This concept is exemplified on another toy supply network with 10 nodes and 11 directed weighted edges representing volumes of transaction in arbitrary units. Each company is assigned arbitrary CO_2 emissions. The network is depicted in figure 4.

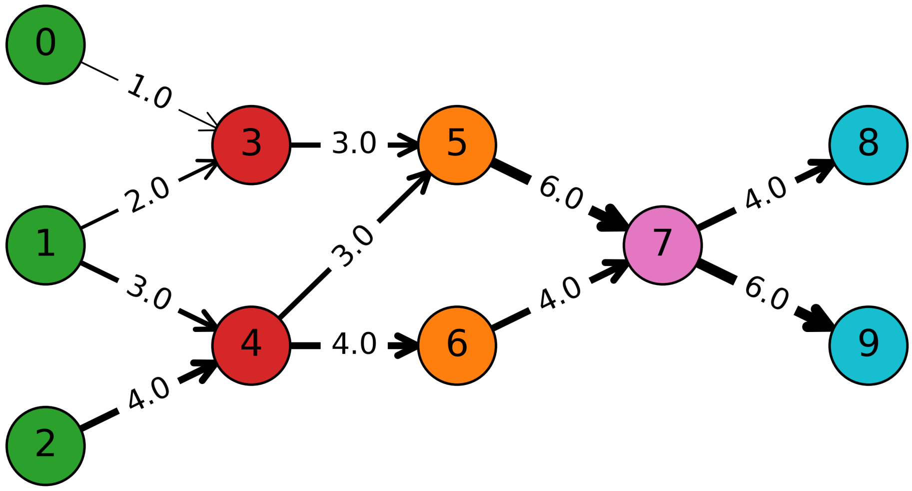


Figure 4: Toy network for the comparison of CO_2 emissions and *ESRI* of individual companies. The nodes are colored and numbered such that they can be identified in figure 5 and edge widths are scaled according to edge weights.

Table 1 lists the out-strength s_j^{out}, the CO_2 emissions and the *ESRI* of each company in the toy network. As expected, node seven has an *ESRI* of one, meaning a failure would bring the production of the whole network to a halt. Its CO_2 emissions are comparatively low. In contrast, nodes two and three have a relatively low *ESRI* but high CO_2 emissions. To study the relationship of CO_2 emissions and *ESRI* in a more systematic way they are plotted against each other in figure 5. The two-dimensional plot is divided into four sections to characterize the relationship between CO_2 emissions and the *ESRI* for nodes that fall into these sections. The red zone is associated with high emissions and a low *ESRI*. Nodes that fall into this area are considered decarbonization leverage points. The orange zone is characterized by high emissions and a high *ESRI*. Targeting companies that fall into this sector are promises high reductions in emissions but comes with a high economic systemic risk. Companies in the green zone have low emissions and are systemically not very risky. The yellow zone is associated with low emissions but a high *ESRI*. The boundaries of the zones are drawn according to the median of emissions and *ESRI* respectively. A useful drawing of the zone boundaries is dependent on the distribution of CO_2 emissions and *ESRI* respectively. This plot is called *priority plot* from here on, as it answers the question which companies in a supply network should be prioritize in decarbonization efforts.

id	out-strength s_j^{out}	CO_2 emissions	$ESRI$
0	1	4	0.1
1	5	20	0.5
2	4	16	0.4
3	3	6	0.3
4	7	14	0.7
5	6	6	0.6
6	4	4	0.4
7	10	1	1
8	0	0	0.4
9	0	0	0.6

Table 1: Out-strength s_j^{out}, CO_2 emissions and $ESRI$ for each node of the toy network depicted in figure 4.

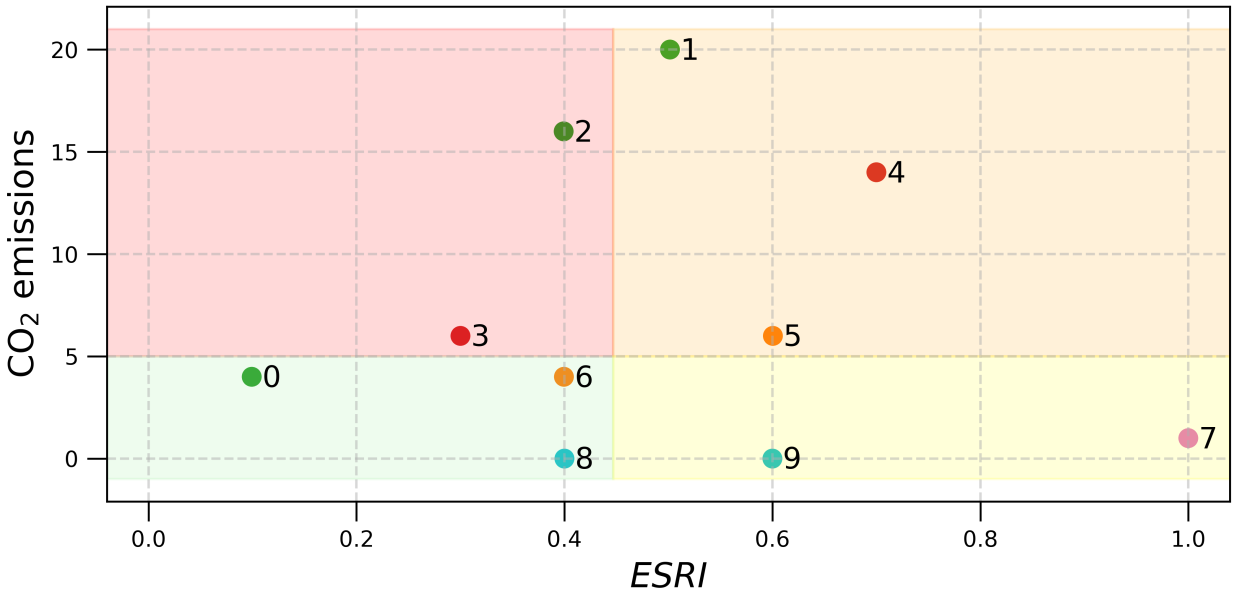


Figure 5: Priority plot for the toy network depicted in figure 4. The red zone is characterized by high emissions and a low $ESRI$ which makes companies that fall into this zone decarbonization leverage points. The orange zone is associated with high emissions and a high $ESRI$. The green zone is characterized with low emissions and a low $ESRI$ and the yellow zone delimits the zone with low emissions and a high $ESRI$.

From the priority plot in figure 5 the companies can be easily classified with respect to their decarbonization potential. Companies two and three have particularly high emissions and comparatively low economic systemic risk which makes them candidates for decarbonization leverage points in this particular production network. This is the core concept of this thesis and is further explored in applications to real economic networks in the following chapters.

3 CO_2 emissions vs. DebtRank of Austrian companies

In this section the idea of comparing systemic risk measures on economic networks with data on greenhouse gas emissions on a company level is further motivated. The CO_2 emissions of Austrian companies are compared with their DebtRank in order to identify decarbonization leverage points with respect to their financial systemic risk (FSR). In order to do that a study of financial systemic risk of Austrian companies by Poledna et al. [37], building on the master's thesis by Hinteregger [38], is extended by data on CO_2 emissions of the respective companies. The study reconstructed the liability network of 50,159 Austrian companies and 796 banks from publicly available corporate financial statements and the financial statements of banks. It covers 80.2% of total liabilities of the companies towards those banks.

3.1 Data collection and processing

To extend the financial systemic risk measure by data on greenhouse gas emissions, publicly available corporate social responsibility (CSR) reports are scanned manually. In order to yield comparable figures for emissions, only companies that report their scope 1 and scope 2 emissions in at least one of the years from 2017 to 2020 were considered. Scope 1 emissions encompass all direct emissions, e.g. from the burning of fossil fuels. Scope 2 covers all indirect emissions from the consumption of purchased electricity, heat, cooling or steam. At least one data point of annual greenhouse gas emissions could be collected for 40 of the 200 companies with the highest financial systemic risk. Figure 6 depicts the distribution of DebtRank among the 40 Austrian companies for which emissions data is available. The y-axis has been omitted, since the names of the analyzed companies cannot be made publicly available because of data protection reasons. This would be possible in combination with their CO_2 emissions. The DebtRank profile of the analyzed companies shows a few companies with comparatively high DebtRank and a long tail of companies that pose comparatively little systemic risk. Although the majority of the companies with the highest DebtRank are classified as services according to OeNACE classification [39], companies from a wide variety of industry sectors show significant financial systemic risk.

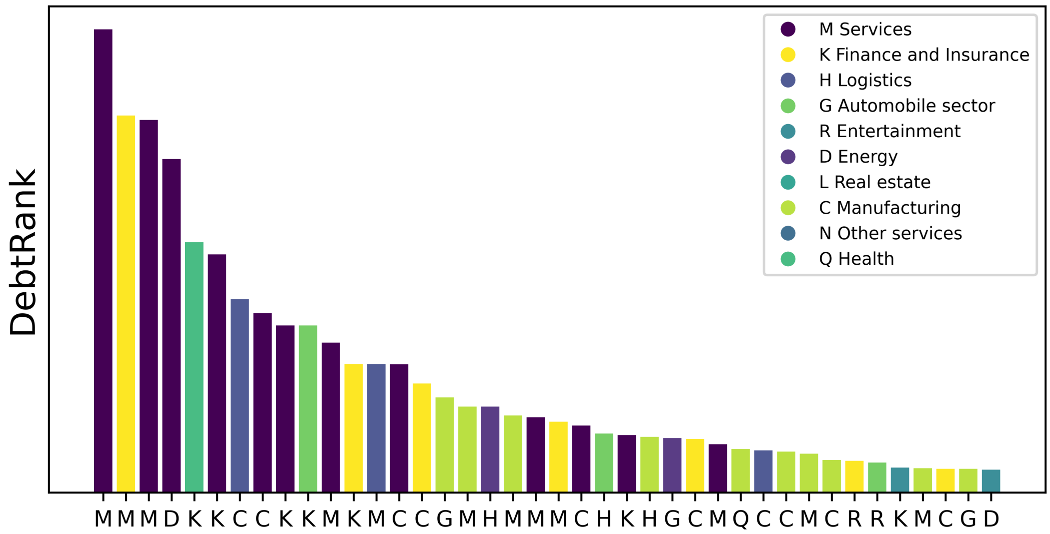


Figure 6: DebtRank of 40 Austrian companies ranked in descending order adapted from Poledna et al. [37] and Hinteregger [38]. Colors indicate the economic sector of the company according to their primary OeNACE classification.

Figure 7 depicts the distribution of CO_2 emissions among the same 40 Austrian companies. Emissions data from the earliest year between 2017 and 2020 for which reliable data is available has been used for this analysis. The annual scope 1 and scope 2 emissions vary widely and span many orders of magnitude across companies and also within the same primary OeNACE classification. Companies that are classified as finance and insurance seem to have comparatively high emissions. This is due to the fact that those are holding companies that own shares of producing companies.

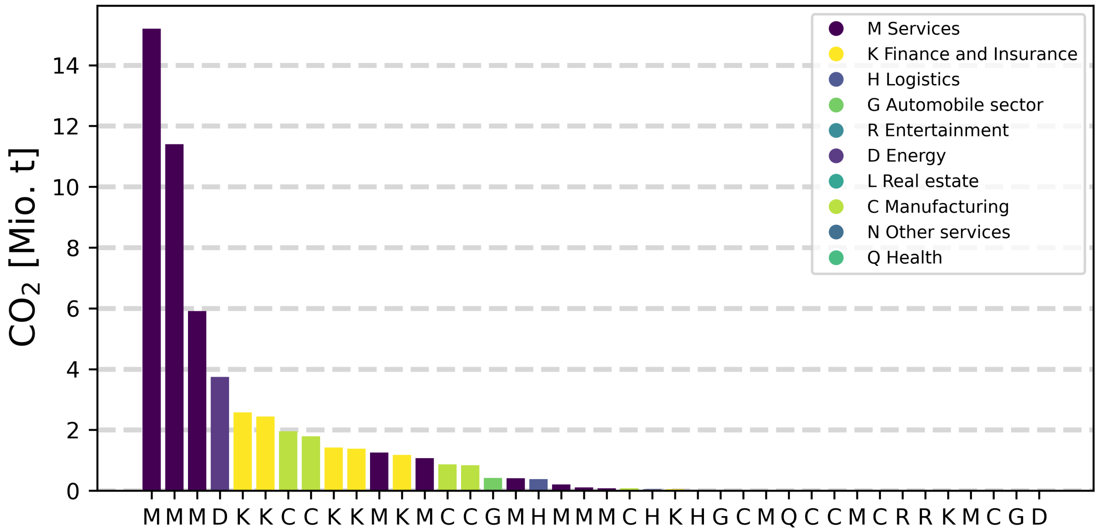


Figure 7: Distribution of annual CO_2 equivalent emissions of 40 Austrian companies ranked in descending order. Colors indicate the economic sector of the company according to their primary OeNACE classification.

3.2 Results and discussion

Figure 8 depicts the priority plot that combines data on CO_2 emissions and Debtrank of 40 Austrian companies. The background is divided into 4 zones that are bounded by the mean DebtRank and the 90.0 percentile respectively. The red zone indicates high emissions and low financial systemic risk. The orange zone indicates high emissions and high FSR. The green zone indicates low emissions and low FSR and the yellow zone indicates low emissions and high FSR.

Companies that reside in the red zone can be considered decarbonization leverage points in the observed financial system since these companies produce comparatively high annual greenhouse gas emissions and low systemic relevance. The two companies in the red zone make up 9,652,289 t or 17.5 % of the total CO_2 emissions of all 40 companies while their combined DebtRank sums to 0.14 which means 14 % of the total financial volume of the network would be affected by the default of these companies. Therefore, policymakers might target these companies first in their decarbonization efforts since a disruption to their business causes comparatively little financial distress for the overall financial network. To measure the systemic relevance of a company solely by its financial systemic risk, i.e. its DebtRank, yields of course only limited insight into their overall economic systemic relevance. However it motivates the approach of identifying companies with significant emissions and low systemic risk as potential decarbonization leverage points. In the following chapter the assessment of a companies' financial systemic risk with the DebtRank measure will be extended by calculating its economic systemic risk with the $ESRI$ for one illustrative example.

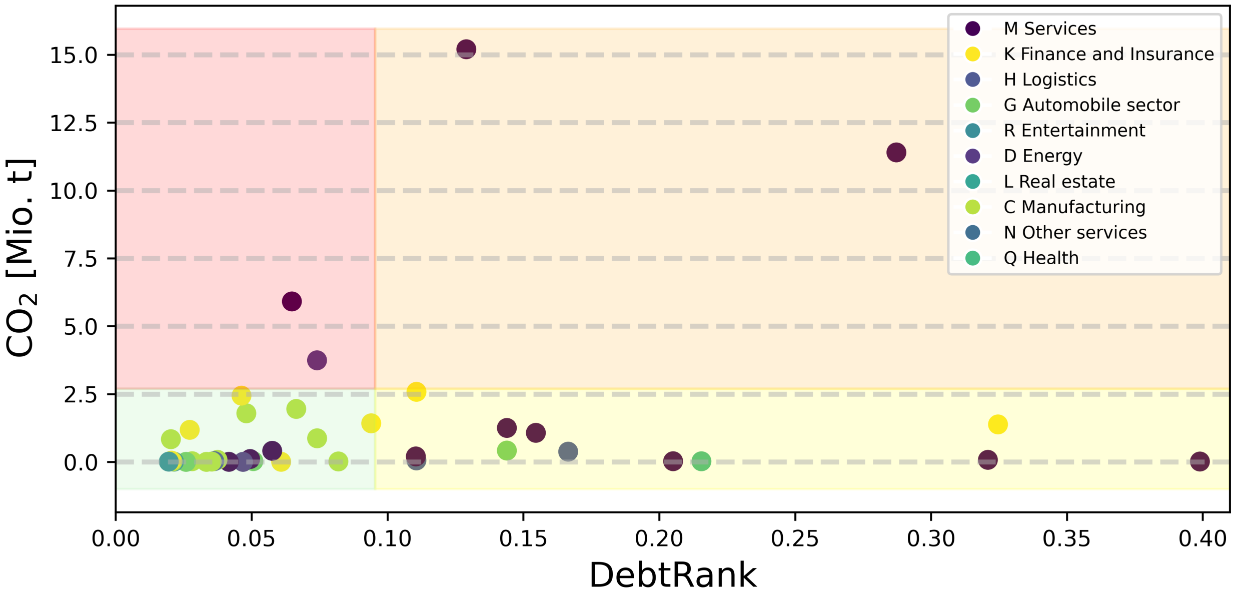


Figure 8: Annual CO_2 emissions vs. DebtRank of selected Austrian companies. Colors of points indicate the economic sector of the company according to their primary OeNACE classification.

4 The bigger picture: CO_2 emissions vs. DebtRank vs. $ESRI$

From the previous chapters we have learned how comparing financial or economic systemic risk with the CO_2 emissions of companies can help in identifying decarbonization leverage points in a given financial or production network. In this chapter the greater vision of combining the three measures $ESRI$, DebtRank and CO_2 emissions is laid out and discussed for a large Austrian steel producer.
All the three measures $ESRI$, DebtRank and CO_2 emissions tell us something about the risk a company is posing to its economic, financial and natural environment. If one agrees that the decarbonization of our economy is urgently needed and the transition towards a low carbon economy should be as smooth as possible in terms of societal stress in terms of job and production loss, management and therefore knowledge of the risk each company is posing to the financial, economic and natural system is needed. Ideally, a localization of each company in the three-dimensional space of DebtRank, $ESRI$ and CO_2 emissions would be possible to identify those companies that pose the least financial and economic risk to an economy and produce the most greenhouse gas emissions. These companies can then be targeted explicitly by policies that aim at reducing greenhouse gas emissions.

4.1 Data collection and processing

In general we do not know or are not able to compute either of the risk indicators for a given company, because of a lack of data on supplier-buyer relations, financial liabilities and greenhouse gas output. What is presented here is an attempt at approximating those indicators for the Austrian steel producer voestalpine AG for which approximate data could be compiled.

4.1.1 $ESRI$ of voestalpine AG

Supply chain data for voestaline AG is compiled by querying the Bloomberg terminal [40] with the help of the projcet JRC LIVE that is listed in the acknowledgment section. Two kinds of production networks are obtained by querying the Bloomberg database for supplier and buyer information of voestalpine AG. The first is called the ego-network of voestalpine AG which includes every company in the Bloomberg database that is listed as direct supplier or buyer of voestalpine AG or is a supplier/buyer of a supplier/buyer of voestalpine AG and so forth. Only links to companies are kept that are connected to voestalpine AG via a path. The resulting network consisting of 1058 companies and 2035 links is depicted in figure 9.
The second network is called the total-network and contains the same nodes and links as the ego-network but additionally consists of other companies that suppliers or buyers of voestalpine AG share a supply or or buy relation with. If, for example, a supplier of voestalpine AG also supplies another company, this link and the other company is included in the total-network. The resulting network consisting of 7993 nodes and 19301 links is depicted in figure 10.

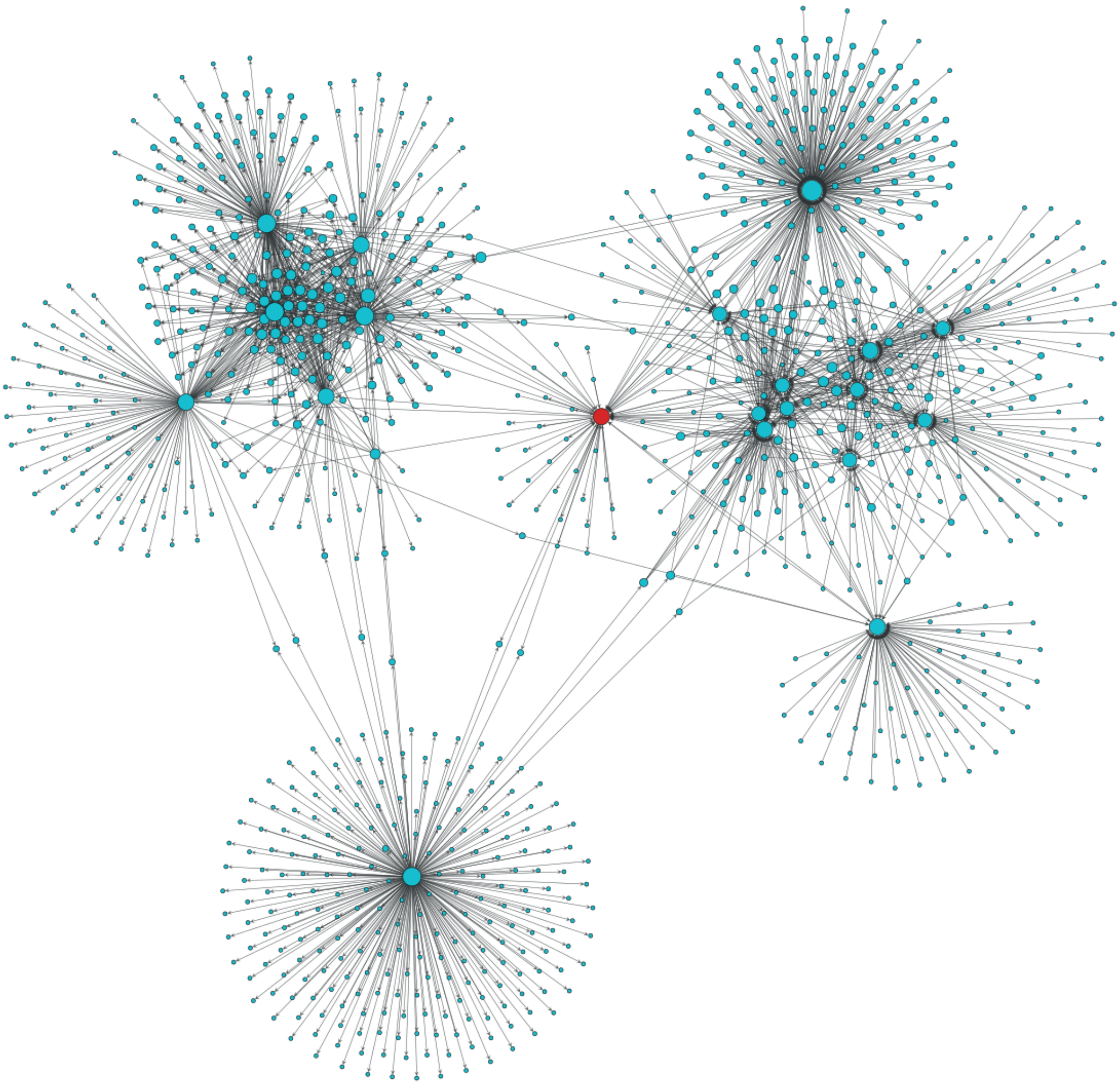


Figure 9: The ego-network of voestalpine AG as it is reconstructed by querying the Bloomberg database. The node representing voestalpine AG is colored in red and all other companies are colored in light-blue. The node size is scaled according to the node degree. The graph is drawn using the force-directed graph drawing algorithm by Hu [41].

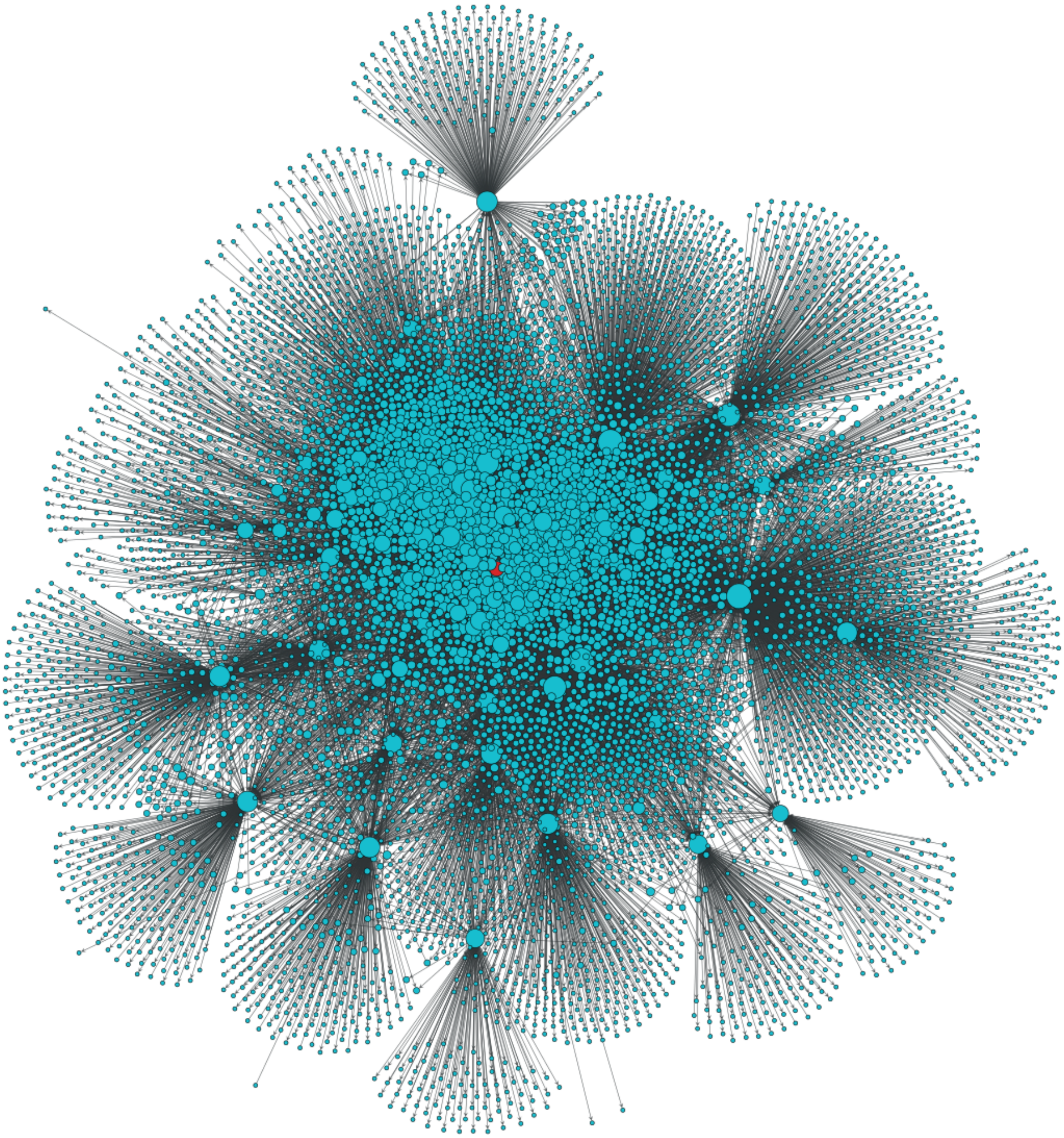


Figure 10: The total-network of voestalpine AG as it is reconstructed from querying the Bloomberg database. The node representing voestalpine AG is colored in red and all other companies are colored in light-blue. The node size is scaled according to the node degree. The graph is drawn using the force-directed graph drawing algorithm by Hu [41].

As the Bloomberg database does not contain information on the volume that is transacted in a supply or buy relation the calculation of the $ESRI$ has to be adjusted. For an approximate calculation of the $ESRI$ of each company in the two networks, the out-strength of each company is set to $s_i^{out} = 1$. Therefore every company contributes the same output to the total production of the network and its $ESRI$ is only dependent on its position in the network. Figure 11 depicts the $ESRI$ profile for the ego-network of voestalpine AG. It is not surprising that voestalpine AG carries the most economic systemic risk with $ESRI_{\text{voest-ego}} = 0.63$ in the ego-network, as it is the focal company of the network that is connected via a path with each other node.

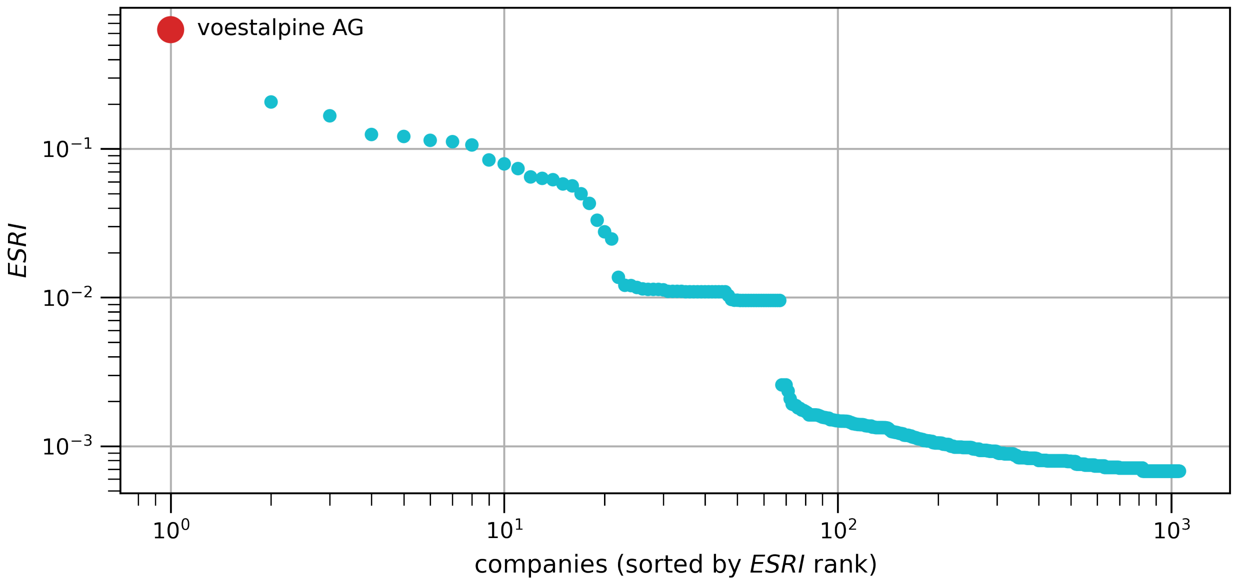


Figure 11: The $ESRI$ profile of the ego-network of voestalpine AG. The dot representing voestalpine AG is colored in red and all other companies are colored in light-blue.

Figure 12 depicts the $ESRI$ profile for the total-network of voestalpine AG. In this network voestalpine AG has an $ESRI$ of $ESRI_{\text{voest-total}} = 0.003$ and is only the 49th riskiest company. This makes sense, since there are many more companies included in the network which makes it more likely that companies are included that supply or buy from a lot more companies than voestalpine AG does. This gives these companies a higher $ESRI$ in this simple setting of equal out-strength.

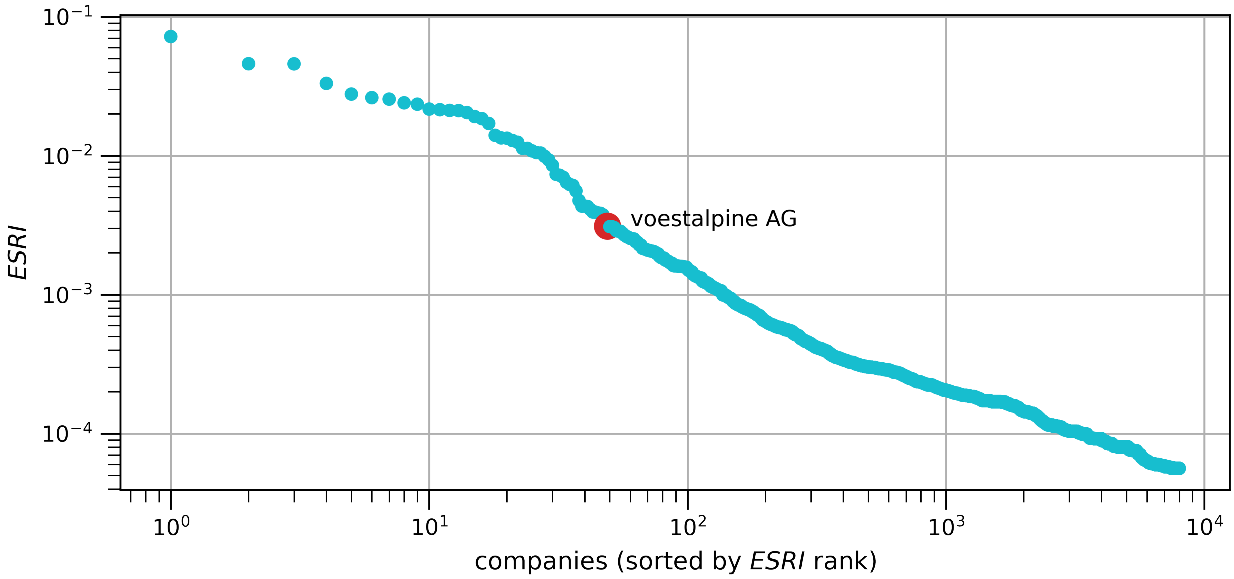


Figure 12: The ESRI profile of the total-network of voestalpine AG. The dot representing voestalpine AG is colored in red and all other companies are colored in light-blue.

4.1.2 DebtRank of voestalpine AG

The financial systemic risk of voestalpine AG is obtained from the DebtRank value computed in the study on financial systemic risk of Austrian companies by Poledna et al. [37]. The data used in this study has to be treated confidentially due to the usage of data on financial liabilities owned by the central bank of Austria. Therefore, the computed value for the DebtRank of voestalpine AG cannot be disclosed.

4.1.3 CO_2 emissions of voestalpine AG

Data on CO_2 emissions of voestalpine AG is collected from their publicly available corporate social responsibility report 2020 [42]. In this report, voestalpine AG states that it has produced 13.61 Mt of CO_2-equivalent scope 1 emissions, 0.94 Mt of CO_2-equivalent scope 2 emissions and 9.34 Mt of CO_2-equivalent scope 3 emissions in the year 2019. This amounts to 23.89 Mt of CO_2-equivalent emissions in all scopes.

4.2 Result

By compiling these measures it is possible to locate the company in the three-dimensional space of DebtRank, $ESRI$ and CO_2 emissions. Figure 13 depicts voestalpine AG in this space. $ESRI_{voest-ego}$ is used for measuring economic systemic risk and the tick labels of the DebtRank axis are omitted in order to keep the real value confidential.

To locate only one point in this DebtRank-$ESRI$-CO_2 space is of course of limited use, since this space needs to be populated with many different companies in a given economy in order to identify potential decarbonization leverage points. Nevertheless, figure 13 shows how, in the future, it might be possible to better manage the green transition by locating more and more companies in this newly defined Debtrank-$ESRI$-CO_2 space.

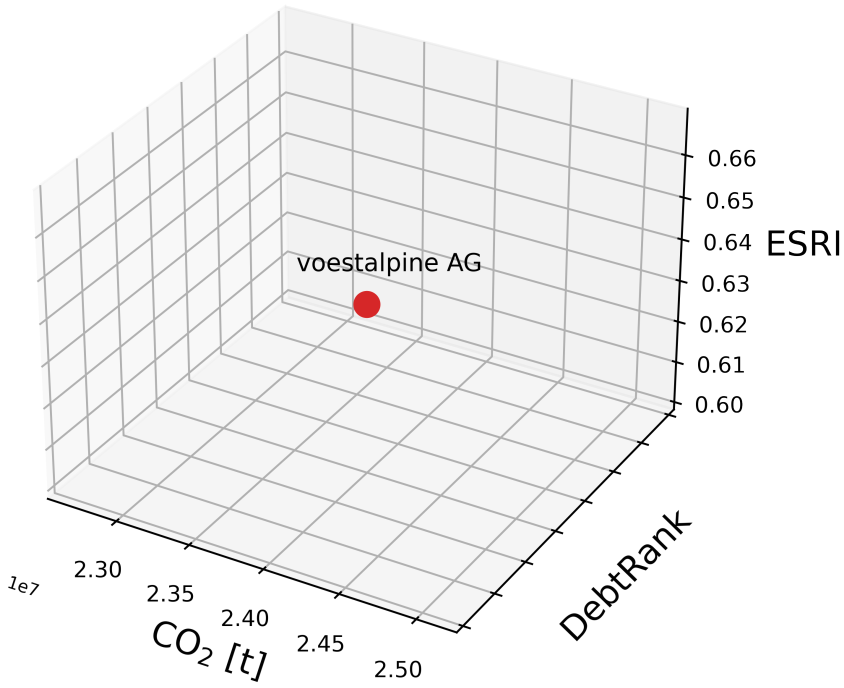


Figure 13: voestalpine AG in the three-dimensional DebtRank-$ESRI$-CO2 space. The tick-labels of the DebtRank axis are omitted in order to keep the real value confidential. In order to compare companies with regards to their financial, economic and environmental relevance to identify decarbonization leverage points more data is needed in each dimension.

5 Case Study: The Austrian pork supply network

In this chapter the developed methodology of comparing CO_2 emissions of individual companies with their Economic Systemic Risk Index $ESRI$ in a production network is applied to the Austrian pork supply network. The Austrian pork supply network is chosen as a case study, as the complete network was compiled for a related project on economic systemic risk done at the Complexity Science Hub Vienna. The next sections on the reconstruction of the network follow the respective description in the final report of this project [43]. First, the data and the modeling assumptions that go into the reconstruction of the network as well as the underlying database infrastructure are discussed. Second, the network is characterized with some standard network measures. Finally, the results from comparing CO_2 emissions and the $ESRI$ in the priority plot introduced in section 2.5 for this particular network are presented for the total network and each facility class.

5.1 Data, modeling and assumptions

The goal of the data collection and modeling effort is to obtain a weighted directed network that represents the annual flows of pigs and pork among the facilities involved in the Austrian pork supply network, which are represented by nodes. A link from node i to node j represents the amount of pigs or pork that is shipped from node i to node j within one year. Crucial to the reconstruction of a production network from data is the development of a conceptual model that guides the data collection and linking as well as the drawing of system boundaries. The conceptual model that is used for the reconstruction of the Austrian pork supply network is depicted in figure 14. Considered classes of facilities are farms, slaughterhouses, meat processors, warehouses and supermarkets. The flows between facilities are either measured in numbers of pigs in the case of farm-farm and farm-slaughterhouse links or tonnes of pork for every other type of link. The availability of data for each class of facilities and the flows between them are indicated by a color scheme. For green facility classes and flows the reconstructed network consists of purely empirical data and complete coverage is granted. The flows from meat processors to warehouses and from warehouses to supermarkets are colored in orange, as the data is only partially available and has to be extrapolated and sampled from an empirical distribution. The flows from slaughterhouses to meat processors are depicted in red as no empirical data could was available and the links have to be modeled from assumptions about their distribution. The conceptual model of the Austrian pork supply network depicts three classes of nodes in red. These are the classes of facilities and types of products that were conceptually excluded from the network. Among these are all auxiliary products a farm needs in order to grow pigs such as fodder, as well as all auxiliary products that are needed at the stages of slaughtering the pigs and processing their meat such as packaging material. At the stage of final consumption of pork only supermarkets and their warehouses are considered, excluding any type of gastronomy.

5.1.1 Facilities

The reconstruction of the Austrian pork supply network involves the collection and integration of various datasets from several data sources. This work is done in collaboration with William Schueller whose paper on the food supply risk of Austrian pork is in preparation [44]. Data on Austrian farms and slaughterhouses is collected from the Verbrauchergesundheitsinformationssystem (VIS) [45] which is run by Statistics Austria and contains the veterinary information system (VIS). The provided data covers the district affiliation of each anonymized Austrian slaughterhouse and pig farmer as well as the animal population of the latter for the years 2019 and 2020. As the data on farmers is not publicly available, a request had to be made by the Federal Ministry of Agriculture, Regions and Tourism. This data can only be processed on a secure dedicated server.
In principle, a list of approved slaughterhouses and meat processors is publicly available through Statistics Austria as well [46] and can be combined with the data from the veterinary information system to identify overlapping facilities. But since the data from the veterinary information system had been anonymized, it is

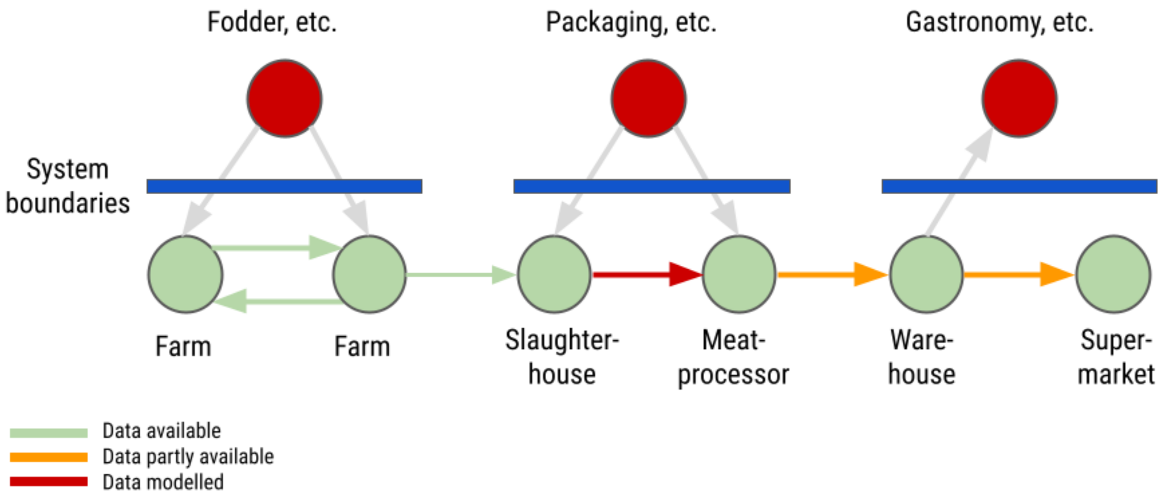


Figure 14: Conceptual model of the Austrian pork supply network. Nodes depict classes of facilities, arrows depict flows between those facilities. Successfully collected data for a class of facilities or flows is depicted in green, partially collected and partially modeled data is depicted in orange and data that had to be modeled completely from assumptions is depicted in red. Adapted from Diem et al. [43].

not entirely possible to align the slaughterhouses found in both databases. Therefore it is assumed that meat processors found in the Statistics Austria database that also slaughter themselves are already covered in the veterinary information system and are hence removed from the data to avoid double coverage of facilities.
Data on the geolocations and capacities of warehouses and supermarkets from the four biggest food retailers in Austria - Hofer, Lidl, Rewe and Spar - is collected from publicly available sources. Table 2 summarizes the collected data on the facilities involved in the Austrian pork supply network. The final network contains 33 117 nodes in total.

facility type	count	localized	capacity/volume	data source	time horizon
farm	26 008	yes	yes	VIS	2019, 2020
slaughterhouse	880	yes	yes	VIS	2019, 2020
meat processor	2 680	yes	no	Statistics Austria	2021
warehouse	24	yes	partially	supermarkets	2021
supermarket	3 525	yes	partially	supermarkets	2021
total	33 117				

Table 2: Summary of the data collection on facilities involved in the Austrian pork supply network.

5.1.2 Flows between facilities

Data on the flows of pigs and pork between the facilities listed in table 2 is collected from different data sources. The movements of pigs between farms and other farms and farms and slaughterhouses are obtained through the veterinary information system (VIS) for the years 2019 and 2020. Any movement of pigs between any facilities has to be recorded by this system by Austrian law. Pigs are also traded between farms as some farms specialize in raising piglets while other farms specialize in fattening pigs.
Flows of pork from slaughterhouses to meat processors are not available and have to be estimated by linking slaughterhouses and meat processors stochastically based on the consumption levels of meat processors and the proximity of slaughterhouses and meat processors.
In cooperation with one of the large retailers in Austria the flows of pork from meat processors to warehouses and warehouses to supermarkets can quantified and extrapolated to the three remaining food retailers. Data on

these flows are collected for June and July 2021. From this two months period the flows are extrapolated to the whole year and from there to the other food retailers. Table 3 summarizes the collected and partially modeled data on the flows between facilities involved in the Austrian pork supply network. The network contains 80881 links in total.

link type	count	volume	data source	time horizon
farm - farm	40 089	yes	VIS	2019, 2020
farm - slaughterhouse	27 370	yes	VIS	2019, 2020
slaughterhouse - meat processor	2 992	no	estimation	2019, 2020
meat processor - warehouse	2 746	partially	supermarkets	June/July 2021
warehouse - supermarket	3 525	partially	supermarkets	June/July 2021
total	80 881			

Table 3: Summary of the data collection on flows between facilities involved in the Austrian pork supply network.

5.1.3 Database and server

As the data is collected from various data owners in various data formats and additional data modeling is needed a database architecture is set up in collaboration with William Schueller to integrate the data into the final network model. Raw data gets transferred on the secure dedicated server where it is extracted and loaded into a specified database. These databases are then integrated into the final database on which the Austrian pork supply network is assembled and the data analysis takes place. Figure 15 illustrates the data transfer and the integration process.

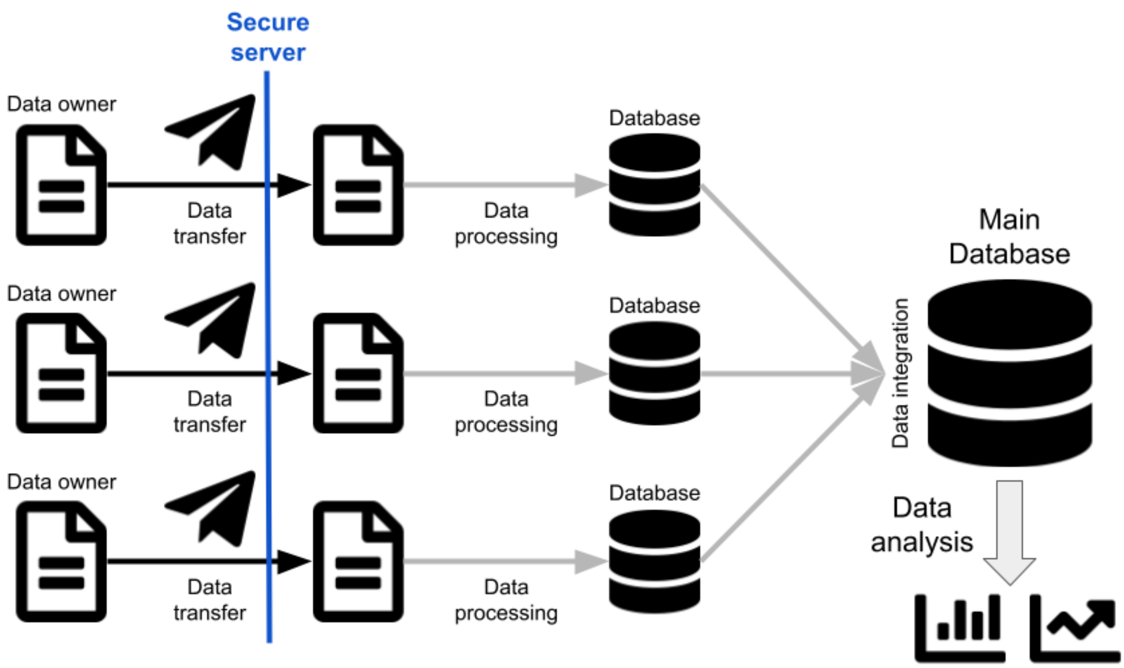


Figure 15: Schematic depiction of the database infrastructure set up in collaboration with William Schueller. Data gets transferred from data owners to a secure dedicated server in various raw formats. The data is then extracted and loaded into a specified database. Data from different databases is then integrated into a main database on which the data analysis is performed. Adapted from Diem et al. [43].

The conceptual database model is realized with the open source PostgreSQL [47] relational database. An entity-relationship diagram of the various tables and keys that make up the database is depicted in the appendix in figure 35 and 36. The dedicated server on which the data integration and processing takes place is secured by two-factor authentication and is only accessible to pre-registered devices.

5.1.4 Network model of Austrian pork supply

After the completion of the various data processing steps and the integration into the described database a network model is constructed. In this network model, individual facilities are represented by nodes and flows or trade relations between facilities within the year of observation 2020 are represented by directed weighted edges. To align the empirical and modeled data with the conceptual model of the Austrian pork supply network described in section 5.1 every facility is given a specified facility type, being either *farm*, *slaughterhouse*, *meat processor*, *warehouse* or *supermarket*. The facilities are then linked via routes that specify the volume of pigs or pork that is shipped from facility i to facility j within one year. An adjacency matrix W is constructed with its elements W_{ij} representing the amount of pigs or pork that is shipped from facility i to facility j. Figure 16 depicts how a coherent network is constructed from the relations between facilities in the database.

Since the veterinary information system data is anonymized, as described in 5.1.1, the meat processors known to supply the cooperating food retailer cannot be matched with the facilities from the VIS data set. Thus, they have to be imputed by computer simulations. For this purpose, the suppliers named by the food retailers are matched with the meat processors from the Statistics Austria data set on meat processors [46] and receive an estimated processing volume. The remaining processing volume is then distributed over all other known meat processors by fitting an exponential function to the known data points and drawing estimates for the volume of processed meat from this empirical distribution. The meat processing plants are connected to the slaughterhouses from the VIS data using an iterative allocation procedure such that the geographically closest nodes are connected with a higher probability.

A second stochastic estimation is necessary, because only the supply relationships of one single food retailer could be collected. Since the distribution structures from a retailers warehouse to the respective supermarkets can be approximated by the federal state affiliation of the supermarkets and warehouses, only the delivery volumes are missing. For this purpose, it is assumed that the distribution of delivery volumes from warehouses to supermarkets is comparable between the different food retailers. This is not necessarily an accurate representation of reality, but is the best possible approximation, given the available data. This resulted in an estimation of the output volumes of warehouses, which must be covered by supply relationships from meat processors. Since these are also unknown, these supply relationships are estimated by an iterative volume distribution procedure. For each warehouse, the algorithm searches for the nearest meat processor that still has available supply volume and creates a supply relationship between the two facilities. This scheme is repeated for all warehouses until the required volumes are covered by supply relationships. These modeling steps are necessary to obtain a coherent network that forms the basis for further analysis.

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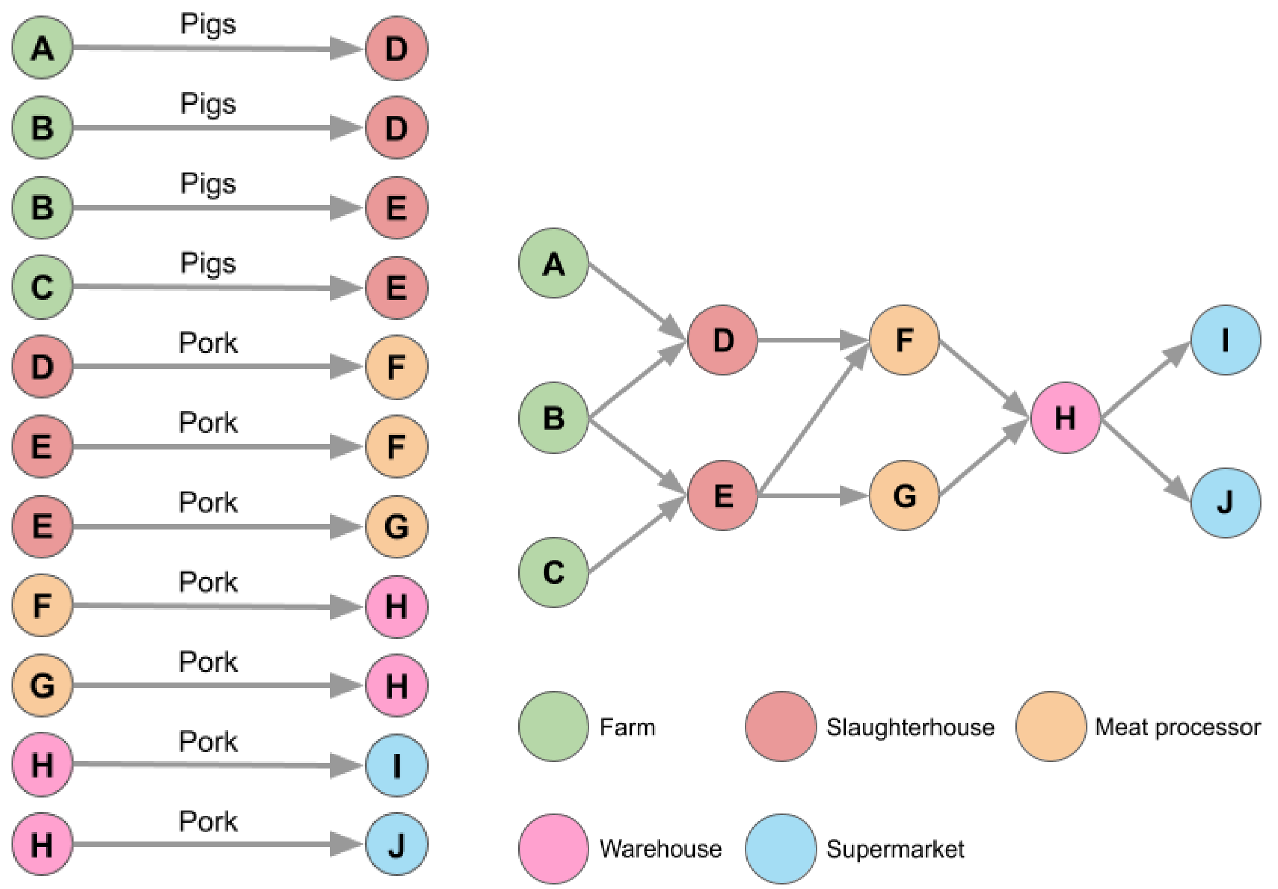


(a) Dummy links in the database between suppliers (left) and buyers (right).

(b) A dummy supply network constructed from links between facilities in the database.

Figure 16: Illustration of the process of translating relations between facilities in the database depicted in figure 16a into a network model of Austrian pork depicted in figure 16b. Node colors indicate the facility classes. Adapted from Diem et al. [43].

In order to compare the volumes of inputs and outputs of different facility classes and to compare the economic systemic risk index $ESRI$ it is necessary to transform the weighted directed links between nodes to the same unit. The edge weights of the network are therefore converted to the common unit tonnes of pork. For links between slaughterhouses and meat processors, meat processors and warehouses and warehouses and supermarkets the edge weights had to be divided by 1 000 as the flows are given in kilograms. For links between farms and farms and farms and slaughterhouses a conversion from pigs to pork had to be done. According to data from Statistics Austria [48] an average pig weighs 123.6 kg at the time of slaughtering and yields 99.5 kg of pork. Therefore each link between facilities representing a number of pigs that are transferred is multiplied by the factor of 99.5 and divided by 1 000 to arrive at the common unit for edge weights tonnes of pork.

Figure 17 depicts a network plot of the final network model of Austrian pork for the year 2020 with all 33 117 nodes and 80 881 links. It can be observed that there are some chains of farms trading pigs among each other at the outskirts of the network plot. This is a behavior that occurs due to specialization of farms in certain processing steps, such as breeding piglets and fattening pigs. Supermarkets appear in clusters around warehouses. Warehouses, meat processors and slaughterhouses are pushed to the center of the network plot as these are the nodes with high in- and out-degree.

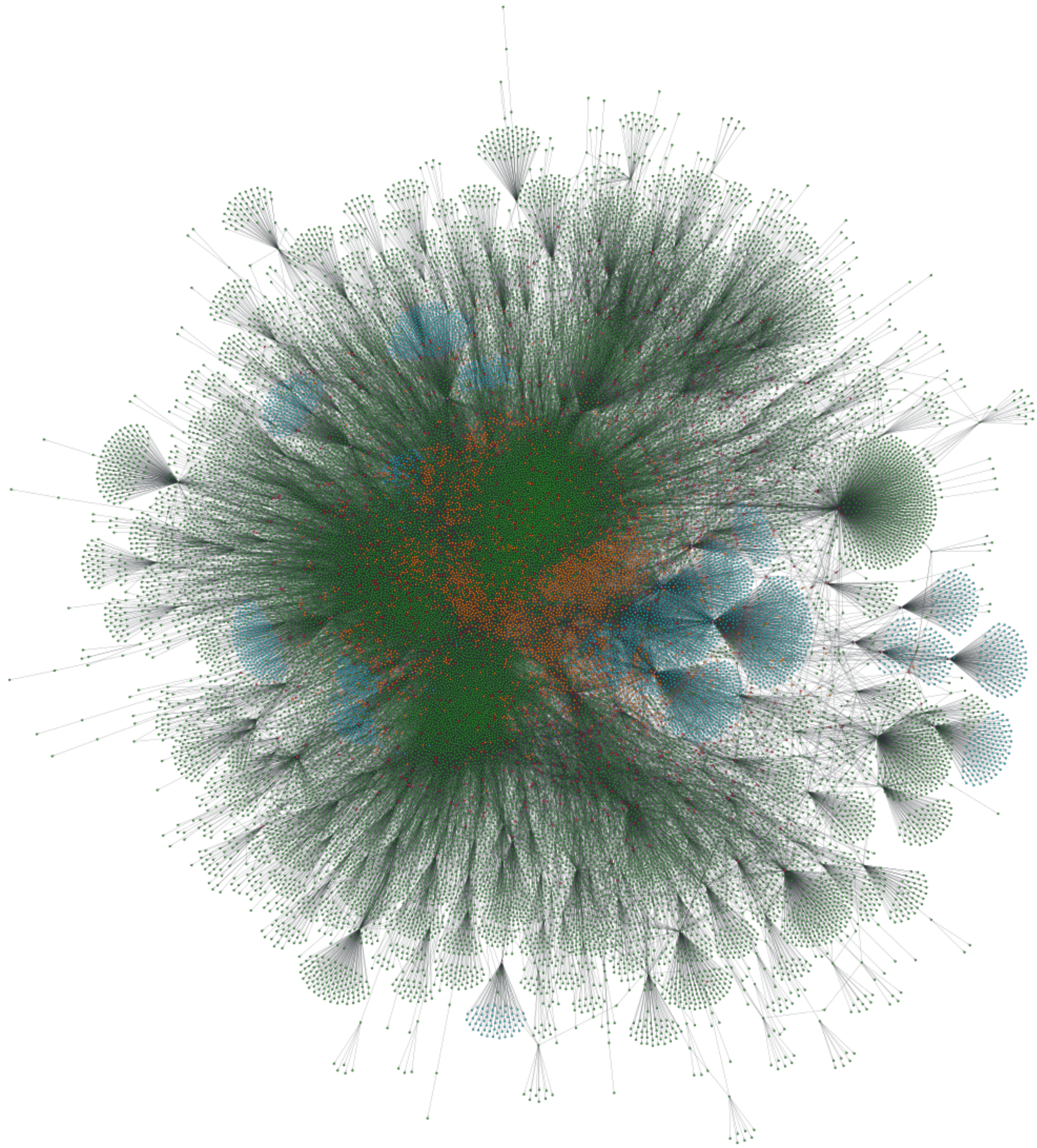


Figure 17: Network plot of the 33 117 companies in the Austrian pork supply network as it is reconstructed for the year 2020. Node size is equal for all nodes and nodes are colored according to their respective facility type: green - farms; red - slaughterhouses; orange - meat processors; pink - warehouses; blue - supermarkets. The graph is drawn using the force-directed graph drawing algorithm by Hu [41].

Figure 18 depicts a layered network plot of the Austrian pork supply network. Nodes are forced into a tree like structure. Thus, the general flow of pigs and pork from farms via slaughterhouses, meat processors and warehouses to supermarkets becomes apparent.

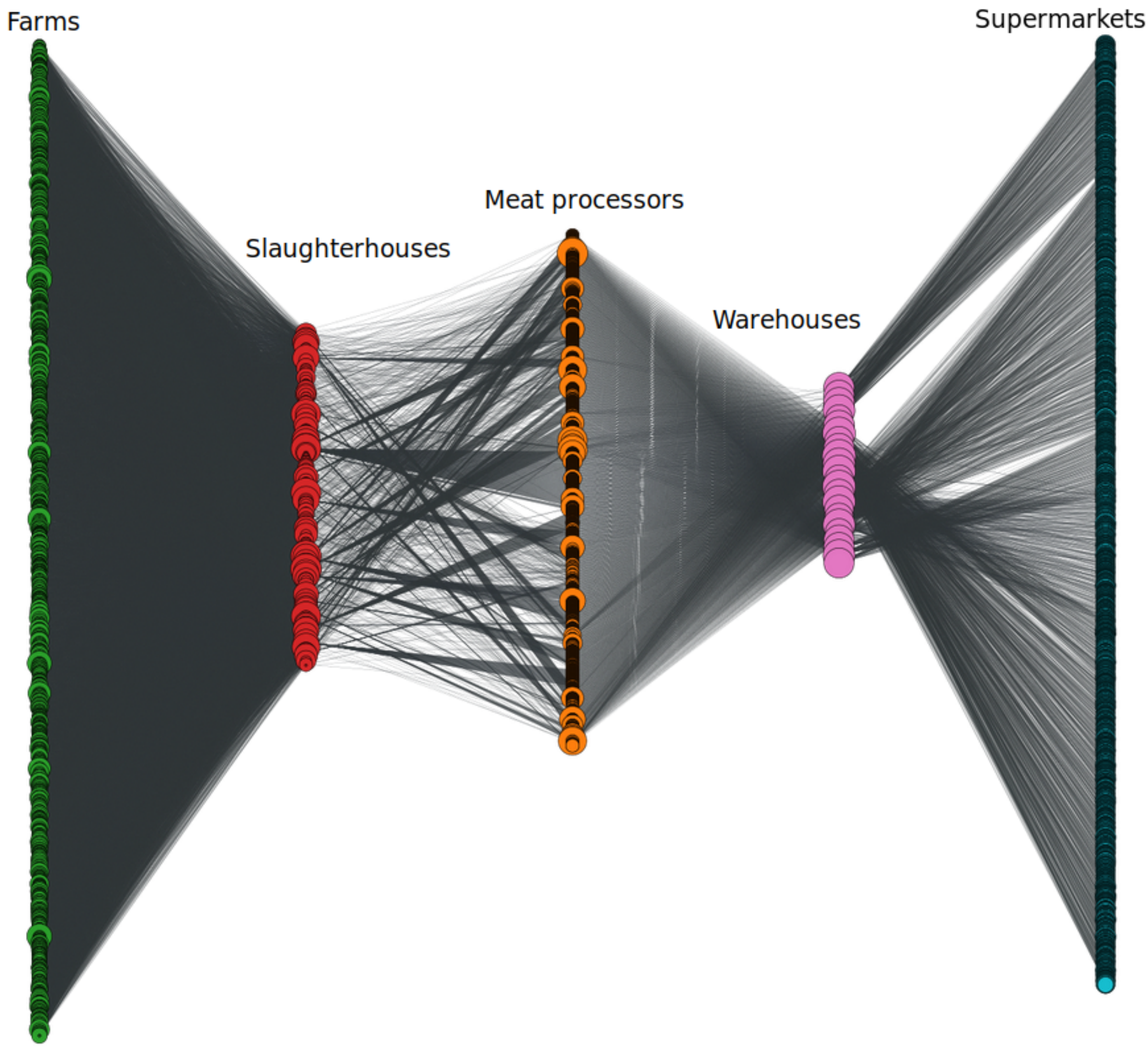


Figure 18: Layered network plot of the Austrian pork supply network as it is reconstructed for the year 2020. Nodes are scaled according to out-strength and colored according to facility type: green - farms; red - slaughterhouses; orange - meat processors; pink - warehouses; blue - supermarkets. The graph is drawn by forcing facility classes to a fixed horizontal coordinate in order to produce a layered layout.

5.2 Characterization of the Austrian pork supply network

In this subsection the Austrian pork supply network, as it was reconstructed according to the processing steps described in 5.1, is characterized with standard network measures such as the degree and strength distributions, the distributions of betweenness and the local clustering coefficient and an analysis of the average nearest neighbor degree distribution. The peculiarities of individual facility classes is discussed and how these relate to the underlying data and modeling assumptions. Finally, the distribution of the economic systemic risk index $ESRI$ for the companies in the Austrian pork supply network is discussed.

Figure 19 depicts the complementary cumulative distribution functions (ccdf) of in-degree k^{in}, out-degree k^{out} and total degree k for all nodes together and dis-aggregated by facility class, respectively. The complementary cumulative distribution function is calculated by sorting the degrees of nodes of a network in descending order, assigning their rank r_i from 1 to n and plotting r_i/n as a function of degree k [33, p. 323]. The complementary cumulative distribution function, plotted in a double-logarithmic plot, is useful for examining heavy tailed (degree) distributions as it answers the question, what fraction of instances of a quantity of interest, such as the degree, lies above a certain level.

The ccdfs of in-degree k^{in} depicted in figures 19a and 19b show that roughly 20 % of all nodes have an in-degree of $k^{in} = 2$ or higher. A majority of nodes has a an in-degree of $k^{in} = 1$, most of them being supermarkets and farms. In the case of supermarkets this is true by construction, as every supermarket is supplied by only one warehouse. The ccdfs also reveal that the slaughterhouses exhibit the most extreme values of in-degree, ranging from a couple of hundreds to over 1 000 in-links. Meat processors have an in-degree of $k^{in} = 1$ or $k^{in} = 2$ which is an artifact from the stochastic matching between slaughterhouses and meat processors as described in section 5.1.4. The fact that for some facility classes in figure 19b the ccdf(k^{in}) does not start at 1 indicates that there are instances of that class in the network that have an in-degree of $k^{in} = 0$.

The ccdfs of out-degree k^{out} depicted in figures 19c and 19d show a similar behavior as the ccdfs of in-degree k^{in}. An outstanding feature is the fact that supermarkets disappear from figure 19d, as they are considered to be sinks of the network and do not have any out-links. Meat processors display a variety of out-degrees, with the majority still concentrated at $k^{out} = 1$. This is an artifact from the stochastic matching between meat processors and warehouses as described in section 5.1.4.

The ccdfs of the total degree k depicted in figures 19e and 19f combine many of the already described features for k^{in} and k^{out}. The node classes spanning the most orders of magnitude and showing the most extreme heavy tailed distributions are farms and slaughterhouses, while warehouses show consistently high degrees, as one might suspect.

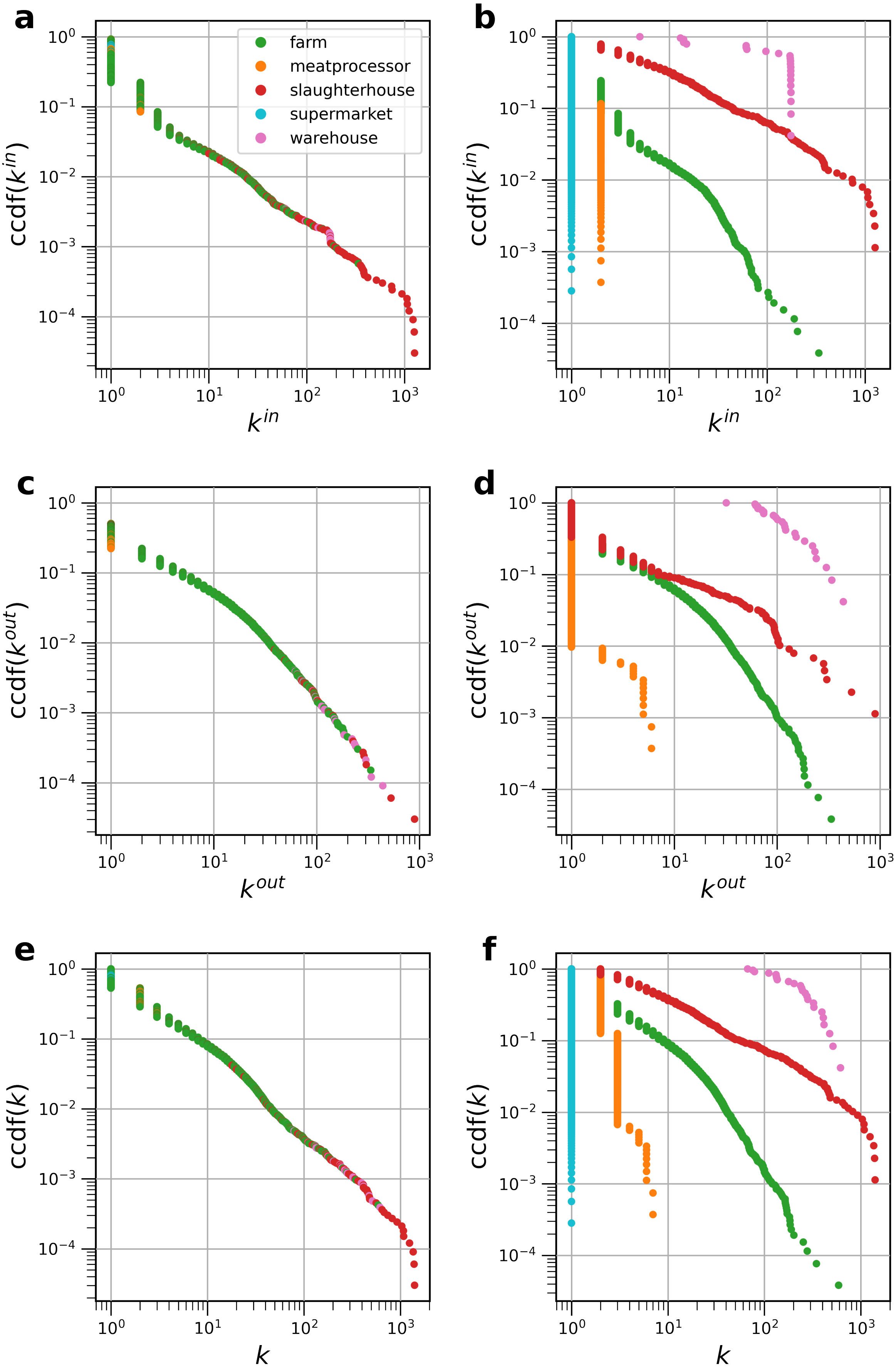


Figure 19: Complementary cumulative distribution functions (ccdf) for a) in-degree k^{in}, b) in-degree k^{in} disaggregated by facility class, c) out-degree k^{out}, d) out-degree k^{out} disaggregated by facility class and d) total-degree k, e) total-degree k disaggregated by facility class of the Austrian pork supply network.

Figure 20 depicts the complementary cumulative distribution functions of in-strength s^{in}, out-strength s^{out} and total strength s for all nodes together and dis-aggregated by facility class, respectively. The ccdfs of in-strength s^{in} depicted in figure 20a and 20b show that about 30 % of nodes have an in-strength of $s^{in} = 1$ or greater. As all the volumes transacted in the network have been converted to tonnes of pork, the strengths are not as low as one might suspect on first sight. The in-strengths are highest for warehouses as these are the bottlenecks of the network through which all of the pork has to pass. A large fraction of meat processors display an in-strength of 100. This is an artifact from the exponential fit that was applied to estimate the processed volume of meat processors from empirical data as described in section 5.1. 100 tonnes of processed pork is set as a lower bound for this exponential fit. The fact that around 10 % of meat processors have lower in-strengths is due to the stochastic matching between slaughterhouses and meat processors. Supermarkets show a very narrow range on in-strengths.

The ccdfs of out-strength s^{out} depicted in figure 20c and 20d show a very similar behavior as the distributions for the in-strengths s^{in}. Again, the 1 tonne lower boundary for the meat processors shows up. The supermarkets are missing from the dis-aggregated plot in figure 20d as they do not have any out-links.

The ccdfs of total strength s depicted in figure 20e and 20f combine many of the features already described above and show similar behavior to the distributions for total degree k. Farms seem to have two regimes with most farms having very little strength and some displaying very high values. Warehouses are strongly separated from the other facility classes by their high strengths.

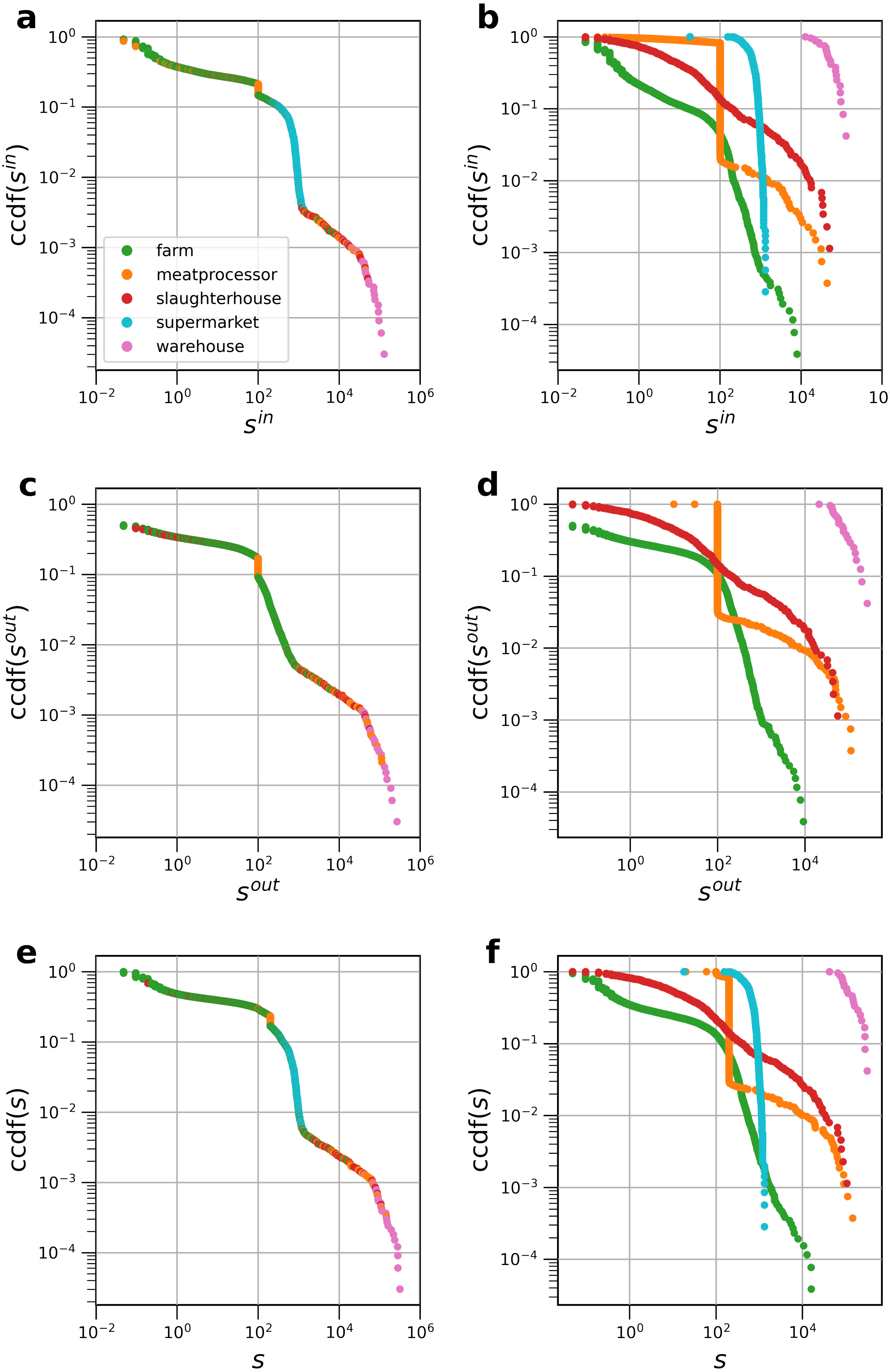


Figure 20: Complementary cumulative distribution functions (ccdf) for a) in-strength s^{in}, b) in-strength s^{in} disaggregated by facility class, c) out-strength s^{out}, d) out-strength s^{out} disaggregated by facility class and d) total-strength s, e) total-strength s disaggregated by facility class of the Austrian pork supply network.

Figure 21 depicts the complementary cumulative distribution functions for the betweenness centrality b for all nodes together and dis-aggregated by facility class, respectively. Betweenness centrality is a network measure that quantifies how important a node is with respect to its role of connecting to other nodes. The betweenness centrality b_i of node i is defined as

$$b_i = \binom{N-1}{2}^{-1} \sum_{k \neq i} \sum_{j \neq i} \frac{n_i(k,j)}{n(k,j)} \tag{28}$$

with $n_i(j,k)$ being the number of geodesic paths between node j and k that contain node i. A geodesic path is the shortest path in a network connecting two nodes i and j. Betweenness centrality quantifies for how many pairs of nodes their respective dstance would increase due to a removal of node i. It is particularly useful for detecting bottlenecks in a network [9, p. 155,156]. In figure 21b the warehouses show a consistently high betweenness centrality b, therefore being the most important facility class with respect to connecting different regions of the network. Some farms and slaughterhouses also display high relatively high betweenness centralities b, underlining their importance as connectors and potential bottlenecks of the network.

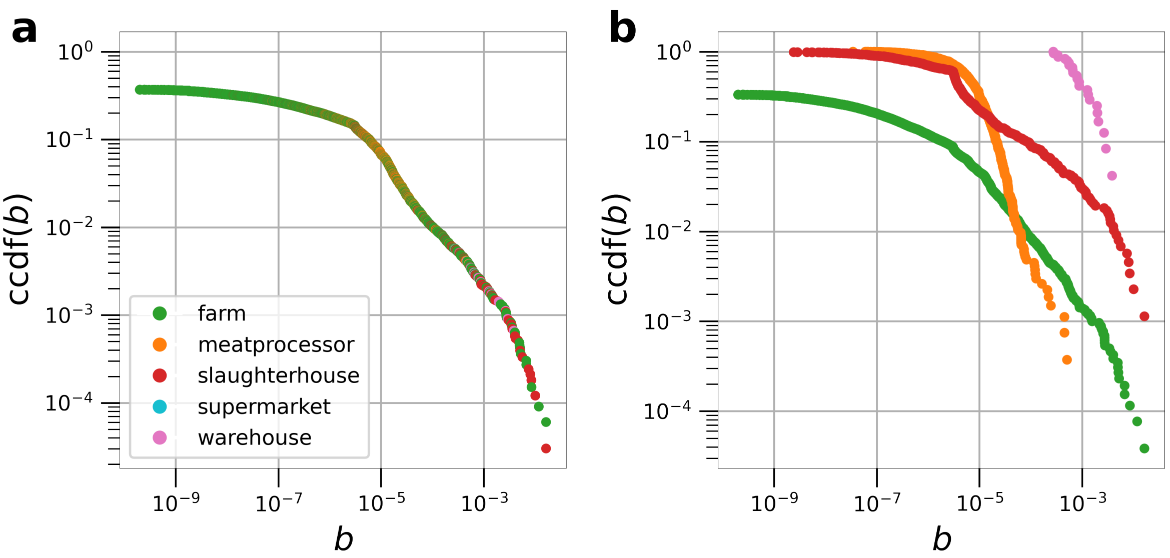


Figure 21: Complementary cumulative distribution functions (ccdf) for a) betweenness centrality b and b) betweenness centrality b disaggregated by facility class of the Austrian pork supply network.

Figure 22 depicts the complementary cumulative distribution functions for the local clustering coefficients cc for all nodes together and dis-aggregated by facility class, respectively. The local clustering coefficient cc measures the fraction of actual versus possible numbers of closed triads, which are cycles of length three, in the immediate neighborhood of node i. The local clustering coefficient cc_i of node i is defined as

$$cc_i = \frac{W_{ii}^3}{k_i(k_i - 1)} \tag{29}$$

with k_i being the neighbors of node i and W_{ii}^3 being the number of cycles of length three [9, p. 157]. The fact that 50 % of slaughterhouses and 20 % of farms display a local clustering coefficient that is greater than zero implies that there are indeed many cycles among these node classes. On the one hand, this is due to the fact that many farms send and receive pigs to and from other farms and some of those relations form triads. On the other hand, some nodes that are labeled as slaughterhouses are also farms and are therefore also part of these triad-forming processes. This ambiguity in labels stems from the integration procedure of the pig movement data from the VIS into the database. Every facility that slaughtered at least one pig in the year 2020 was given the facility label *slaughterhouse*, regardless of its potential additional function as a farm. This is a potential problem with respect to calculating the economic systemic risk index $ESRI$, as the importance of those facilities could be overestimated. But since their transacted volumes are very small in comparison to other facilities of interest, this did not pose a problem for the task at hand, as is shown in section 5.4. Other node classes are completely missing in the local clustering coefficient distribution, indicating the absence of cycles of length 3.

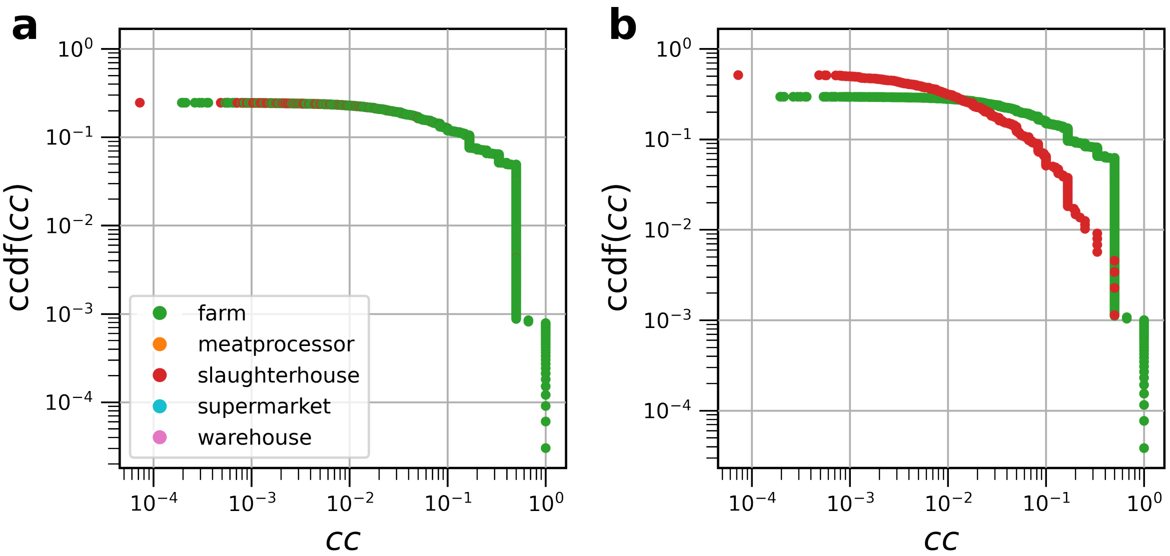


Figure 22: Complementary cumulative distribution functions (ccdf) for a) the local clustering coefficient cc and b) the local clustering coefficient cc disaggregated by facility type of the Austrian pork supply network. Only farms and slaughterhouses are displaying a non-zero local clustering coefficient.

As the network has many cycles, the existence of a strongly connected component can be suspected. A strongly connected component of a directed network is the maximal induced subnetwork for which there exists a path in each direction between each pair of nodes. The strongly connected component of the Austrian pork supply network is depicted in figure 23 and exists of an impressive 1 425 nodes and 4 135 edges, solely containing slaughterhouses and meat processors.

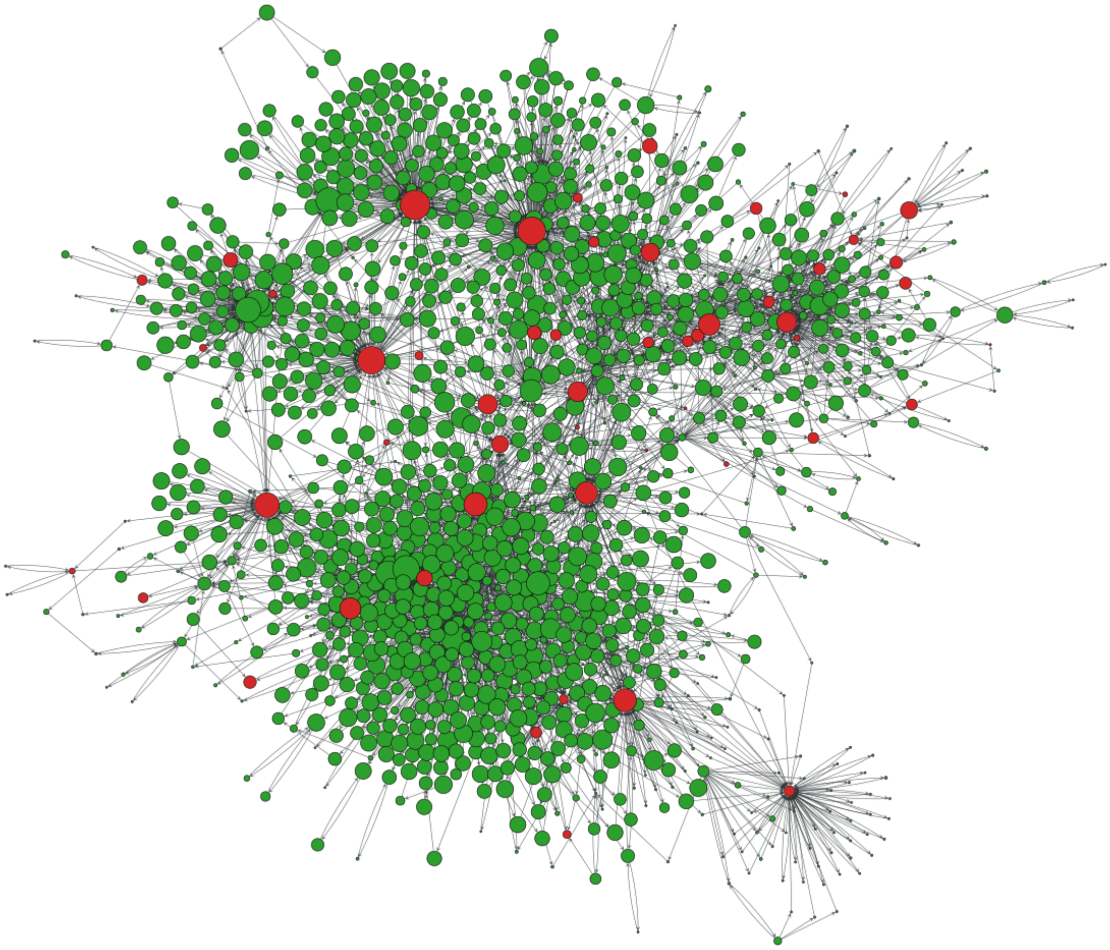


Figure 23: Strongly connected component of the Austrian pork supply network encompassing 1 425 nodes and 4 135 edges. Only farms (green) and slaughterhouses (red) are part of the strongly connected component. Nodes are scaled according to degree and the graph is drawn using the force-directed graph drawing algorithm by Hu [41].

Another important network characteristic is the average nearest-neighbor degree distribution knn(k). The average nearest-neighbor degree measures how likely it is that a randomly selected node is a neighbor of a node i with degree k_i. The average nearest-neighbor is important in answering the question whether nodes with low/high degree preferably connect to nodes with low/high degree respectively. The assortativity r of a network quantifies this concept by measuring the Pearson correlation coefficient between the degree distribution and the average nearest neighbor distribution [9, p. 152]. An assortativity of $r > 0$ means that nodes of low/high degree tend to connect also to nodes of low/high degree. In contrast, a network is called disassortative if $r < 0$, meaning that nodes of low/high degree tend to connect to nodes of high/low degree.

Figure 24a shows the average nearest-neighbor degree distribution for the Austrian pork supply network with error bars depicting the variance within each degree k. The distribution reveals two regimes of the average nearest-neighbor degree. Nodes with low degree tend to be linked to nodes with low degree while nodes with high degree tend to be linked to nodes with low degree as well. This trend becomes even clearer in the log-binned version of the average nearest neighbor distribution in figure 24b. Log-binning of a distribution means computing a histogram of the distribution with bins that are equidistant on a logarithmic scale. This type of binning is especially helpful to investigate the overarching trends in fat-tailed distributions [33, p. 319].

The assortativity of the Austrian pork supply network amounts to $r = -0.01127 \pm 0.0004$. This means that the network is slightly disassortative, but there is almost no correlation between the degree distribution and the average nearest-neighbor distribution. This corresponds to the two regimes that are observed in the nearest-neighbor distribution.

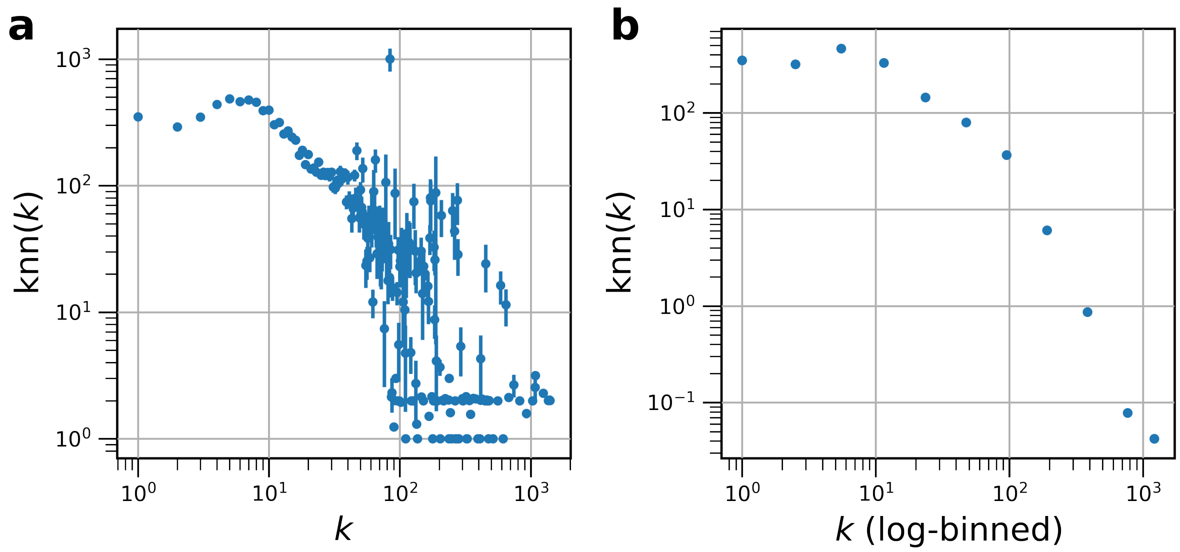


Figure 24: a) Average nearest neighbor degree distribution knn(k) for the Austrian pork supply network with error bars displaying the variance nearest neighbor degree within each node degree. b) Log-binned average nearest neighbor degree distribution knn(k) for the Austrian pork supply network without error bars.

Figure 25 depicts the distribution of the economic systemic risk index $ESRI$ among companies in the Austrian pork supply network. As expected, the warehouses display the highest systemic relevance as they form bottlenecks for the network through which all of the pork has to pass in order to arrive at the supermarkets. Meat processors also display a high systemic relevance as they directly supply the systemically relevant warehouses and have a high out-strength s^{out}. Interestingly also two farms display a disproportionally high systemic relevance. By further inspection it turnes out that one of these farms has a high out-strength, but almost no in-strength and is also classified as a breeding facility many other farms depend on. In general, slaughterhouses have a higher $ESRI$ than farms. Supermarkets are the least systemically risky nodes in the network as their individual failure affects only a small portion of the total out-strength of warehouses.

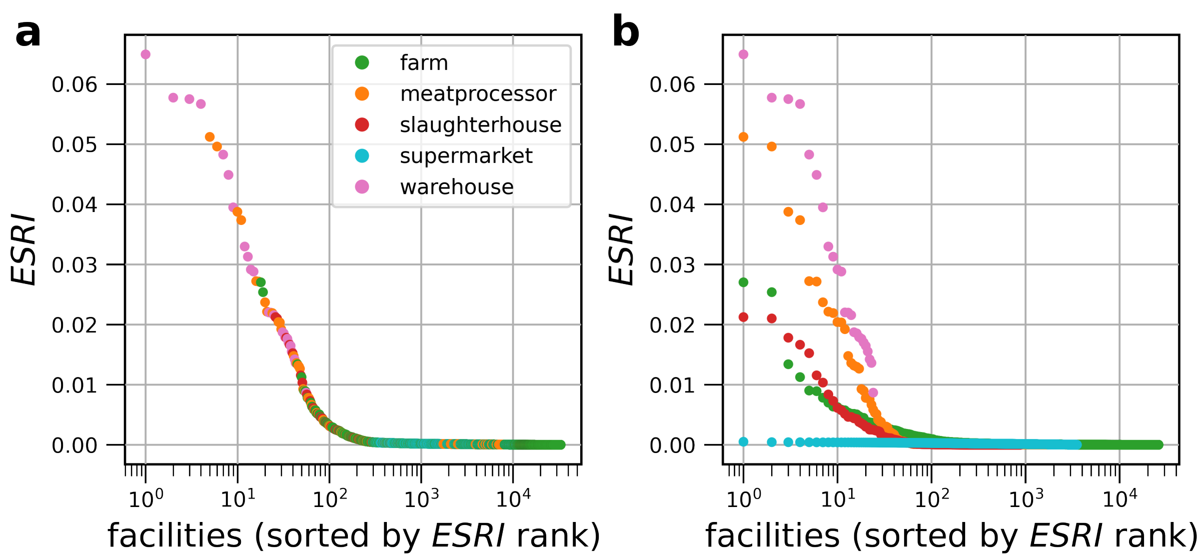


Figure 25: Economic systemic risk index $ESRI$ distribution for a) all companies and b) all companies disaggregated by facility class in the Austrian pork supply network versus their respective $ESRI$ rank.

5.3 Attribution of CO_2 emissions to companies in the Austrian pork supply network

In order to get an estimate of annual CO_2 emissions for each facility in the Austrian pork supply network, a recent life cycle assessment of fresh Austrian pork is consulted. In their paper [2] Winkler et al. compute the global warming potential of a kilogram of fresh Austrian pork for each step of production. They identify five steps of production that each factor into the total environmental impact. They discriminate between the life cycle modules *agriculture*, *slaughterhouse*, *trade*, *consumption* and *transport*. They find that the largest environmental impact is generated at the agricultural stage and each subsequent production step increases the environmental footprint of fresh Austrian pork only marginally. Table 4 shows the identified global warming potential of a kilogram of fresh Austrian pork for the different steps of production calculated as CO_2 equivalent emissions.

life cycle module	**global warming potential [kg CO_2-eq]**
agriculture	4.383
slaughterhouse	0.142
trade	0.008
consumption	0.050
transport	0.168

Table 4: Emission factors for a kilogram of fresh Austrian pork at each production step- Adapted from [2].

In order to attribute annual CO_2 emission to each facility in the Austrian pork supply network these categories are mapped to the identified facility types and multiplied by the total kilograms of pork that is originating at each facility in the network. The emission factor for the *agricultural* stage is used to calculate the emissions of *farms* and the one identified for *slaughterhouses* is used for *slaughterhouses*. Since there is no explicit module for meat processors it is assumed that *meat processors* have the same emission factor per kilogram of pork. The emission factor calculated for the *trade* module is used both for the *warehouses* and the *supermarkets*. The consumption and the transport module are omitted, because neither final stage consumption nor the physical transports of pigs or pork between the facilities are considered in the network. Table 5 give an overview of the mapping between life cycle modules in [2] and the facility types in the reconstructed network.

facility type	**life cycle module**	**global warming potential [kg CO_2-eq]**
farm	agriculture	4.383
slaughterhouse	slaughterhouse	0.142
meat processor	slaughterhouse	0.142
warehouse	trade	0.008
supermarket	trade	0.008

Table 5: Mapping of life cycle modules and facility types in the Austrian pork supply network with their respective emission factors taken from [2].

By aggregating the pork that is originating at each facility in the Austrian pork supply network and multiplying by its respective emission factor it is possible to estimate its annual CO_2 emissions. Figure 26a and figure 26b depict the distribution of annual CO_2 emissions for all facilities and for each facility type. As can be already expected from their high emission factor, farms are the highest emitting facilities in the Austrian pork supply network, followed by meat processors that have high out-strengths s^{out}. Slaughterhouses range among the third highest emitting facilities, followed by warehouses and supermarkets.

The total CO_2 emissions of the Austrian pork supply network amount to 3,909,715 tonnes of CO_2. In 2019, Austria's total CO_2 equivalent emissions were 79,800,000 tonnes and Austria's total agricultural emissions were

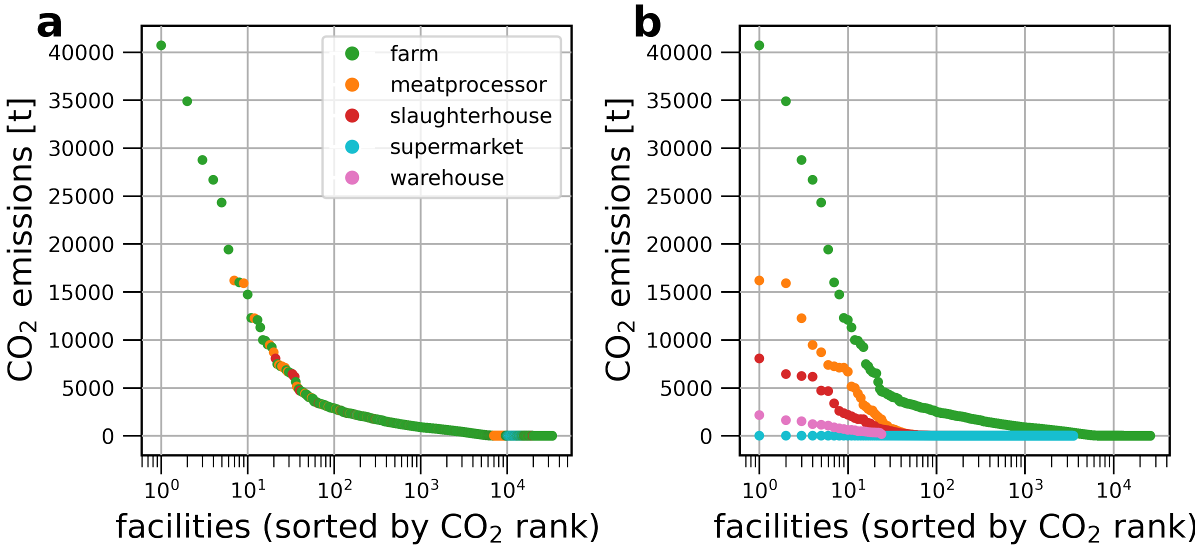


Figure 26: Annual tonnes of CO_2 emissions for a) all companies and b) all companies disaggregated by facility class in the Austrian pork supply network versus their respective CO_2 rank.

8 100 000 tonnes in 2019 [49]. The emissions calculated from the Austrian pork supply network amount to 4.9 % of Austria's total emissions and 48.3 % of Austria's agricultural emissions. This is likely to be an overestimation that stems from the fact that in this reconstructed network there is no discrimination of farms with respect to their function. As has been discussed in section 5.1 some farms specialize in raising piglets and others in fattening pigs. But there is only one emission factor for the agricultural module in the life cycle assessment by Winkler et al. [2] that takes the whole farming process into account. This emission factor is applied to all farms not considering there specific contribution to the production process which is the reason for the overestimation of agricultural emissions. As stated by Statistik Austria [48] a total of 5 068 000 pigs were slaughtered in Austria in 2020. If this figure is multiplied with the average amount of pork that is yielded by a single pig [48] and the total emission factor of Austrian pork as calculated by Winkler et al. total emissions of Austrian pork production amount to $5\,068\,000 * 99.5\ \text{kg} * 4.751 \frac{CO_2}{kg} = 2\,395\,767$ Mt CO_2. This is roughly two thirds of the emissions that are calculated from the Austrian pork supply network which makes it still a useful estimation.

5.4 Decarbonization importance vs. socio-economic importance: CO_2 emissions vs. $ESRI$

The attributed annual CO_2 emissions for each facility in the Austrian pork supply network can now be compared with their respective economic systemic risk index $ESRI$. This allows to identify those companies that pose the least economic risk to the overall production of the network while emitting the most CO_2. In order to single out those companies, the thresholds $\tau_{\mathrm{CO_2}}$ and τ_{ESRI} have to be set for both CO_2 emissions and $ESRI$ to draw the boundaries of the four sections of the priority plot introduced in section 2.5. For all plots and further analyses the threshold τ is chosen according to the 99.9 percentile of both CO_2 emissions and $ESRI$ such that only the most polluting and economically riskiest companies lie above the threshold. This is of course arbitrary, but by experimenting with the threshold it was found that by choosing the values as such it it possible to identify the outliers among the companies. The threshold for emissions is $\tau_{\mathrm{CO_2}} = 6\,221$ t CO_2 and the threshold for the $ESRI$ is $\tau_{\mathrm{ESRI}} = 0.018$.

Figure 27 depicts the annual CO_2 emissions of all companies versus their respective $ESRI$. Almost exclusively farms fall into the red zone of the priority plot, which makes sense since they also stand out in the distribution of CO_2 in figure 26 and range among the least risky nodes in figure 25. Only two slaughterhouses right on the edge between the red and the green zone in figure 27 are still included in the red zone. Other slaughterhouses and meat processors lie around an imaginary line that stretches from the green to the orange zone. Warehouses are the most economically risky and among the least pollutant companies and lie on an imaginary line that stretches from the green zone to the yellow zone. These lines are due to the fact that the $ESRI$ scales linearly with the out-strength of a node, if only linear production functions are considered and the network operates in a tree-like structure. Two farms display disproportionally high systemic risk and fall into the yellow zone. This phenomenon is explained in the discussion of the distribution of $ESRI$ in figure 25. Supermarkets neither have a high $ESRI$ nor high CO_2 emissions and fall exclusively in the green zone near the origin of the priority plot. The vast majority of nodes lies close to the origin and therefore in the green zone, which further motivates the setting of the thresholds such that the outliers can be identified.

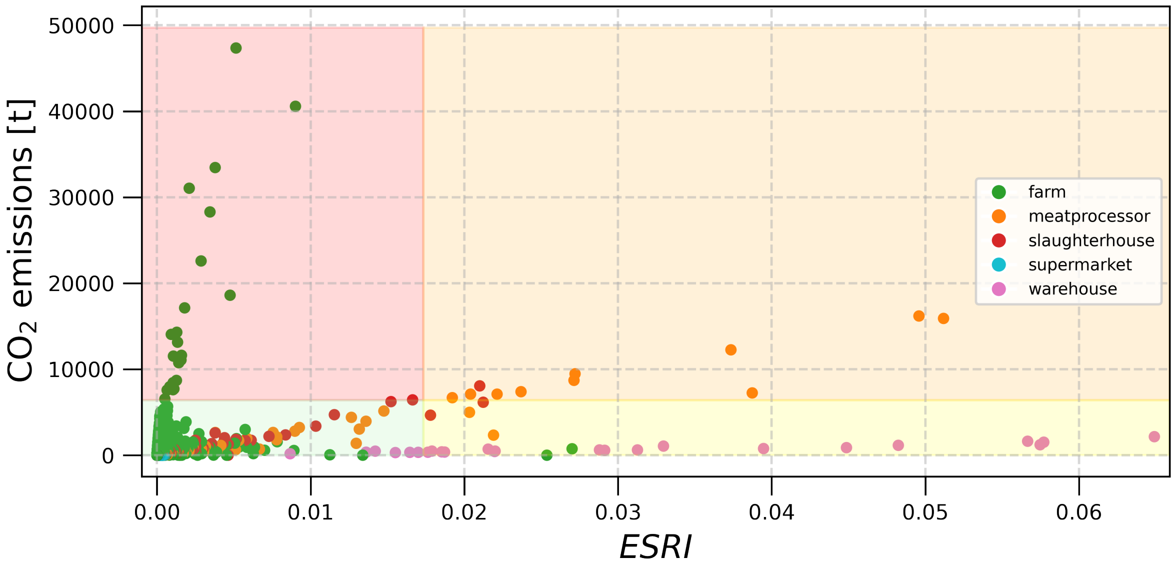


Figure 27: Priority plot for the Austrian pork supply network displaying annual CO_2 emissions versus economic systemic risk index $ESRI$ for all companies. The red zone indicates high emissions and low economic systemic risk which makes companies falling into this zone potential decarbonization leverage points.

By considering companies of all facility types in the priority plot in figure 27, it is possible to identify the most polluting and least risky companies of the total network. But this comes with a bias towards facility types that have inherently high emissions such as farms and an inherently low $ESRI$ such as warehouses. In order to complete the picture it is important to also look at individual facility classes to identify the nodes within each category which are particularly pollutant and pose the least economic risk. Figure 28 depicts the priority plots for farms, slaughterhouses and meat processors. In figure 28a it becomes apparent that farms operate in roughly two regimes. There are farms that produce a lot of pigs and therefore CO_2 emissions, but have a relatively low $ESRI$ and there are farms that do not produce many pigs, but have a relatively high $ESRI$. This can be explained by the fact that a lot of farms are actually supplying other farms with piglets or small pigs which makes them become very important for the network to produce its output. On the other hand there are farms that are just very large, but do not form bottlenecks for the network and which are therefore good candidates for decarbonization leverage points.

From the priority plot for slaughterhouses in figure 28b it becomes even more apparent that for this facility type CO_2 scales almost linearly with $ESRI$. Almost all slaughterhouses fall into the green zone and only one shows up in the red zone. This is interesting as some slaughterhouses are part of the strongly connected component of the network depicted in figure 23 and one could have expected that a high interdependence with other nodes would increase the $ESRI$ even more for some slaughterhouses.

The priority plot for the meat processors in figure 28c shows a similar picture as for the slaughterhouses. CO_2 emissions scale almost linearly with $ESRI$. In both cases this could be due to the stochastic matching between slaughterhouses, meat processors and warehouses as explained in section 5.1. Again almost all meat processors fall into the green zone while only one meat processor shows up in the red zone and two in the orange zone.

Figure 29a shows the distribution of warehouses in the priority plot. All warehouses fall into the green zone and follow a similar straight line as the slaughterhouses and the meat processors.

In figure 29b the priority plot for supermarkets is depicted. The CO_2 emissions of supermarkets scale perfectly linearly with their $ESRI$ because each supermarket has only one in-link representing the fraction of pork that is originating at its respective supplying warehouse. This a consequence of the construction of the network as discussed in section 5.1.2.

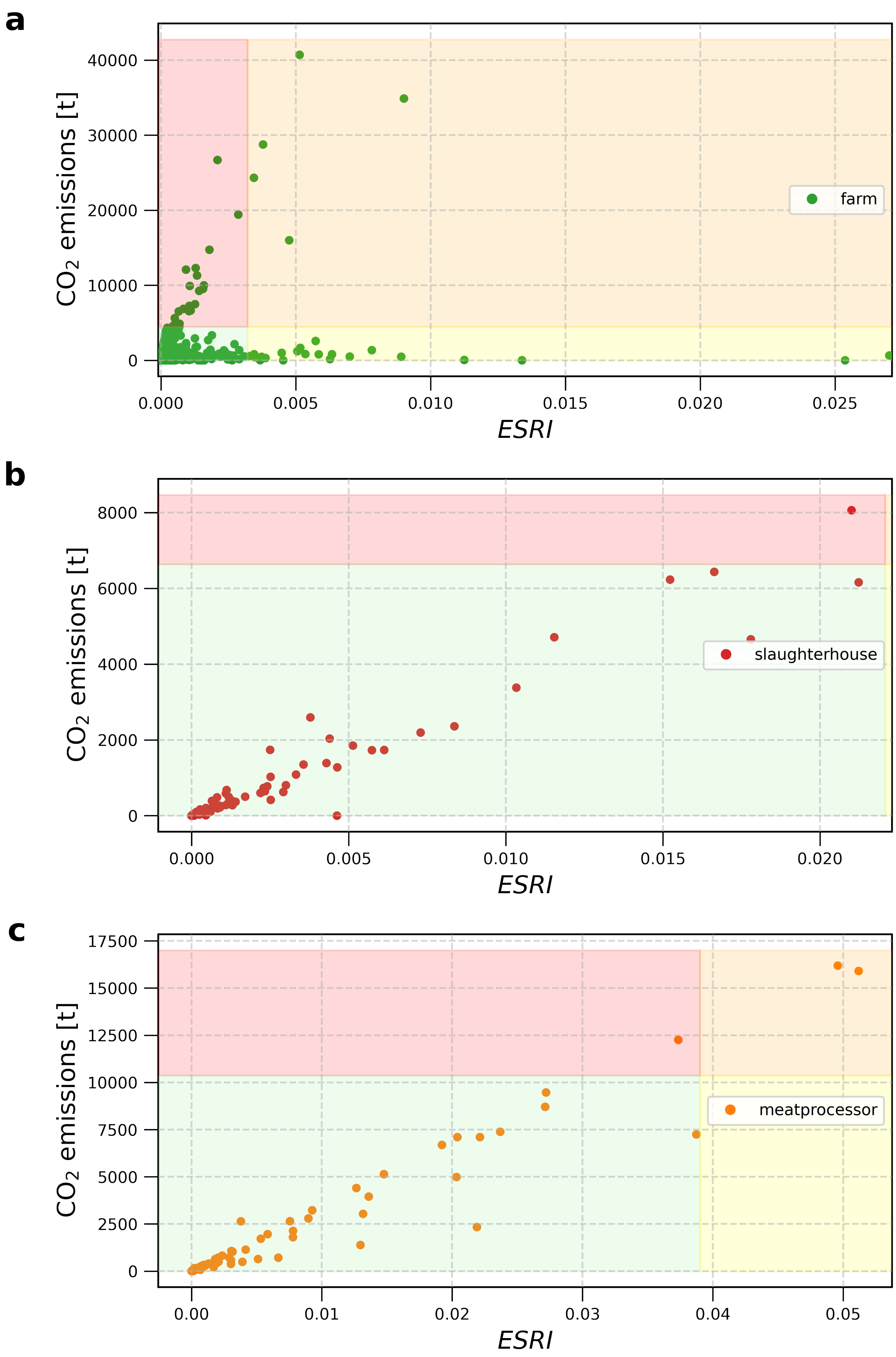
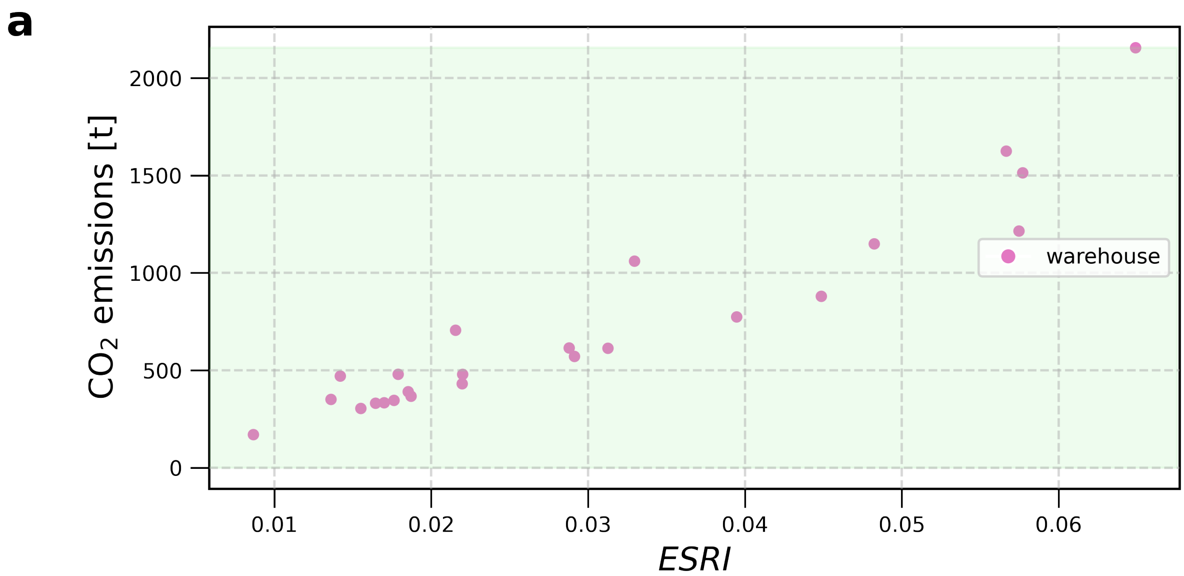


Figure 28: Priority plot for the Austrian pork supply network displaying annual CO_2 emissions versus economic systemic risk index *ESRI* for a) farms, b) slaughterhouses and c) meat processors. Many farms fall into the red zone of the priority plot, but only one slaughterhouse and one meat processor respectively which makes them potential decarbonization leverage points.



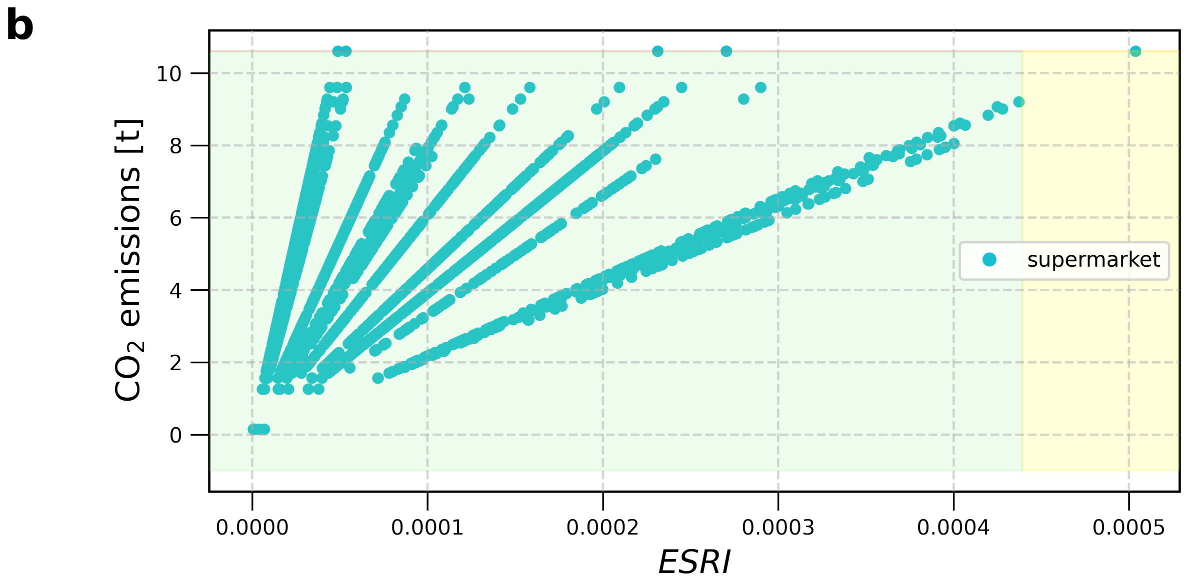


Figure 29: Priority plot for the Austrian pork supply network displaying annual CO_2 emissions versus economic systemic risk index $ESRI$ for a) warehouses and b) supermarkets. Neither warehouses nor supermarkets fall into the red zone of the priority plot.

6 Green transition scenarios for the Austrian pork supply network

To answer the research question, how the modeling of the economy as a production network might inform the green transition, it is time to look at potential transition scenarios for the Austrian pork supply network. Now that the relationship between CO_2 emissions and $ESRI$ is established for all companies in the pork supply network, the question arises how much the overall CO_2 emissions could be reduced by removing these companies from the network and how the overall production would suffer from such a removal. The first transition scenario is therefore called "remove dirtiest companies".

6.1 "Remove dirtiest companies" transition

The failure of a company in a supply network has implications for companies that are either dependent on its supply as inputs for their production or on its demand to sell their products. In the "remove dirtiest companies" scenario the companies of the Austrian pork supply network which have been identified as decarbonization leverage points are removed from the network. This scenario also serves as a proof of concept of the applied methodology of comparing CO_2 emissions with the economic systemic risk index $ESRI$ for each company as a higher drop in CO_2 emissions than in total production is expected by removing these companies. The production levels of the identified decarbonization levers - the companies that fall into the red zone in figure 27 - are set to $h = 0$ and the effects in the network are observed. The losses of all companies are summed up and compared with the initial overall production of the network to evaluate, if the removal of the identified companies actually reduces emissions in a way that causes the least disruption to the economic system. Figure 30 depicts the priority plot for all companies in the Austrian pork supply network with all nodes in the red zone being removed. The removed nodes are listed in table 6 along with their out-strength s_j^{out}, their $ESRI$ and their CO_2 emissions. Except for two slaughterhouses only farms are removed in this scenario. This makes sense since farms are by the largest contributes of CO_2 emissions in the network while having a low $ESRI$ in general.

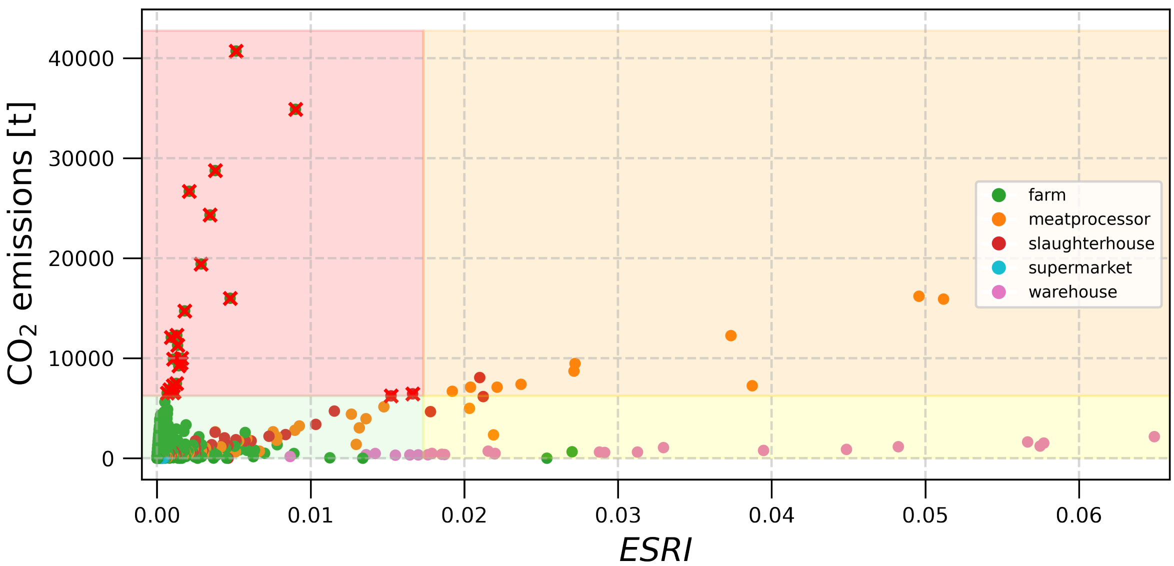


Figure 30: "Remove dirtiest companies" scenario for all nodes of the Austrian pork supply network. All companies in the red zone of the priority plot of figure 27 are removed from the network and marked with a red x.

The removal of the companies listed in table 6 reduces the total output of the network by 1 402 461 tonnes which amounts to 28.6 %. At 1 423 773 tonnes of CO_2 emissions are eliminated which makes up 36.4 % of total emissions. This result shows that by eliminating only the decarbonization leverage points of the network a larger relative share of emissions is reduced than total production lost.

id	facility type	out-strength s_j^{out} [t pork]	$ESRI$	emissions [t]
37431	farm	1484.77	0.0007	6507.73
9401	farm	1562.32	0.0008	6847.67
37107	farm	2755.41	0.0009	12076.96
22011	farm	1493.20	0.0010	6544.71
18477	farm	1653.83	0.0011	7248.74
23722	farm	2259.82	0.0011	9904.78
18184	farm	1513.38	0.0011	6633.16
18055	farm	1705.46	0.0013	7475.01
33244	farm	2803.49	0.0013	12287.69
32728	farm	2577.05	0.0013	11295.19
30524	farm	2108.73	0.0014	9242.55
8995	farm	2171.52	0.0016	9517.78
16049	farm	2278.18	0.0016	9985.24
21819	farm	3359.81	0.0018	14726.06
32545	farm	6088.33	0.0021	26685.16
24268	farm	4429.61	0.0029	19414.99
29446	farm	5547.68	0.0034	24315.48
15563	farm	6559.72	0.0038	28751.24
24183	farm	3648.28	0.0048	15990.42
39308	farm	9285.98	0.0051	40700.47
15457	farm	7956.91	0.0090	34875.13
21643	slaughterhouse	43870.72	0.0152	6229.64
25039	slaughterhouse	45313.76	0.0166	6434.55

Table 6: List of companies that are removed from the Austrian pork supply network in the "remove dirtiest companies" scenario. Columns indicate their respective out-strength s_j^{out}, their $ESRI$ and their annual CO_2 emissions.

6.1.1 "Remove dirtiest farms" transition

Since in figure 30 all nodes are considered together, the question arises how much would be gained from the elimination of the dirtiest companies within each facility class. Figure 31 depicts the elimination of the most polluting and least systemically relevant farms and table 7 lists them together with their node properties.

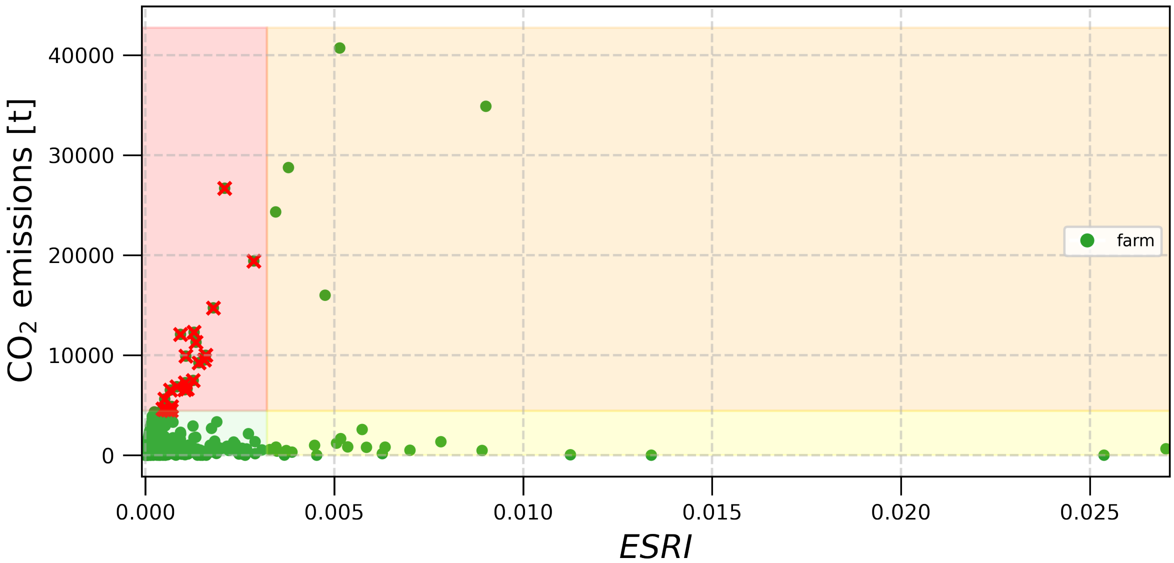


Figure 31: "Remove dirtiest companies" scenario for farms of the Austrian pork supply network. All farms in the red zone of the priority plot of figure 28a are removed from the network and marked with a red x.

id	facility type	out-strength s_j^{out} [t pork]	$ESRI$	emissions [t]
33731	farm	1054.46	0.0005	4621.70
28212	farm	1040.03	0.0005	4558.46
42695	farm	1281.28	0.0005	5615.87
18467	farm	1034.33	0.0006	4533.46
37431	farm	1484.77	0.0007	6507.73
8424	farm	1015.68	0.0007	4451.73
27799	farm	1111.65	0.0007	4872.34
9401	farm	1562.32	0.0008	6847.67
37107	farm	2755.41	0.0009	12076.96
22011	farm	1493.20	0.0010	6544.71
18477	farm	1653.83	0.0011	7248.74
23722	farm	2259.82	0.0011	9904.78
18184	farm	1513.38	0.0011	6633.16
18055	farm	1705.46	0.0013	7475.01
33244	farm	2803.49	0.0013	12287.69
32728	farm	2577.05	0.0013	11295.19
30524	farm	2108.73	0.0014	9242.55
8995	farm	2171.52	0.0016	9517.78
16049	farm	2278.18	0.0016	9985.24
21819	farm	3359.81	0.0018	14726.06
32545	farm	6088.33	0.0021	26685.16
24268	farm	4429.61	0.0029	19414.99

Table 7: List of farms that are removed from the Austrian pork supply network in the "remove dirtiest companies" scenario. Columns indicate their respective out-strength s_j^{out}, their $ESRI$ and their annual CO_2 emissions.

The removal of the farms listed in table 7 reduces the total output of the network by 487 208 tonnes which amounts to 9.9 %. At the same time the removal of those farms eliminates 545,808 tonnes of CO_2 emissions which makes up 13.9 % of total emissions. Thus the network loses less relative output than relative emissions by the removal of these farms.

6.1.2 "Remove dirtiest slaughterhouses" transition

Figure 32 depicts the elimination of the most polluting and least systemically relevant slaughterhouse and table 8 lists it together with its node properties.

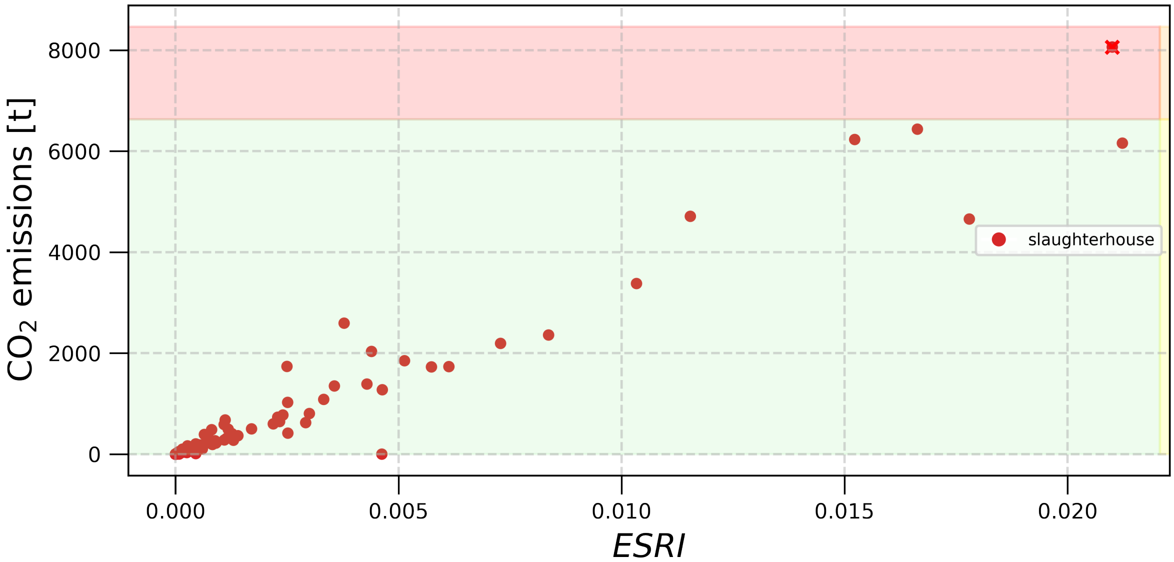


Figure 32: "Remove dirtiest companies" scenario for slaughterhouses of the Austrian pork supply network. The slaughterhouse in the red zone of the priority plot of figure 28b is removed from the network and marked with a red x.

id	**facility type**	**out-strength s_j^{out} [t pork]**	*ESRI*	**emissions [t]**
24132	slaughterhouse	56769.55	0.0210	8061.28

Table 8: List of slaughterhouses that are removed from the Austrian pork supply network in the "remove dirtiest companies" scenario. Columns indicate their respective out-strength s_j^{out}, their *ESRI* and their annual CO_2 emissions.

The removal of the slaughterhouse listed in table 8 reduces the total output of the network by 660,518 tonnes which amounts to 13.4 %. At the same time the removal of this slaughterhouse eliminates 477 525 tonnes of CO_2 emissions which makes up 12.2 % of total emissions. Therefore the network loses almost the same percentage of output and emissions from the removal of this slaughterhouse. This is reasonable since CO_2 emissions scale almost linearly with *ESRI* for slaughterhouses, so there is not much to be gained by the removal of slaughterhouses.

6.1.3 "Remove dirtiest meat processors" transition

Figure 33 depicts the elimination of the most polluting and least systemically relevant meat processor and table 9 lists it together with its node properties.

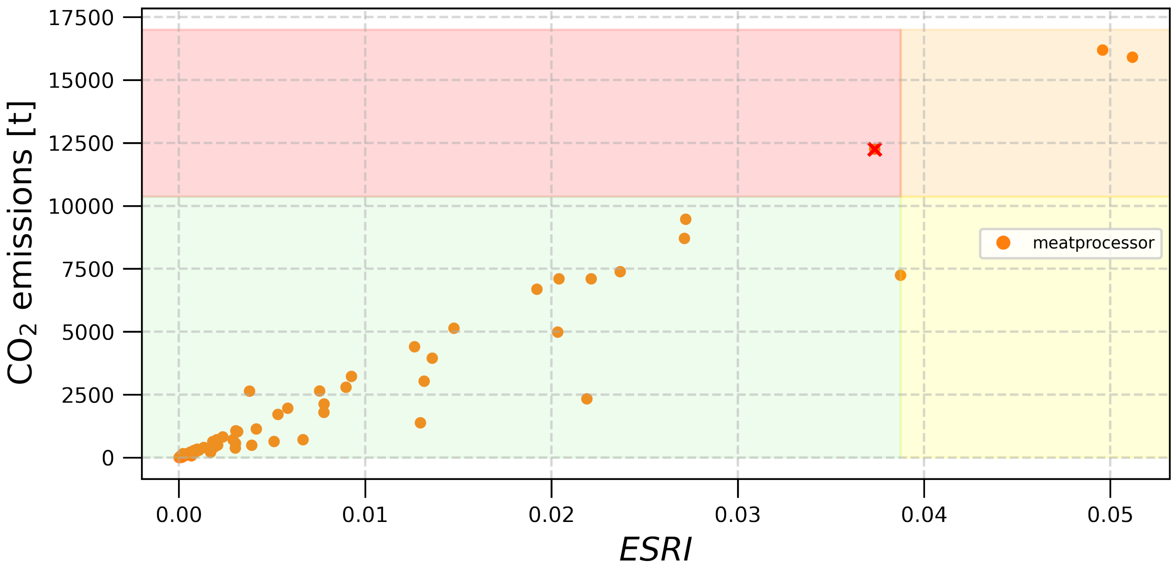


Figure 33: "Remove dirtiest companies" scenario for meat processors of the Austrian pork supply network. The meat processor in the red zone of the priority plot of figure 28c is removed from the network and marked with a red x.

id	facility type	out-strength s_j^{out} [t pork]	*ESRI*	emissions [t]
1085	meatprocessor	86288.03	0.0374	12252.90

Table 9: List of meat processors that are removed from the Austrian pork supply network in the "remove dirtiest companies" scenario. Columns indicate their respective out-strength s_j^{out}, their *ESRI* and their annual CO_2 emissions.

The removal of the meat processor listed in table 9 reduces the total output of the network by 195 148 tonnes which amounts to 3.9 %. At the same time the removal of this slaughterhouse eliminates 45 568 tonnes of CO_2 emissions which makes up 1.2 % of total emissions. Therefore the network loses more relative output than emissions from the removal of this meat processor. This is also reasonable since CO_2 emissions again scale almost linearly with *ESRI* for meat processors, but indicates that not much is to be gained from the removal of meat processors.

As can be seen in figure 29 no decarbonization leverage points can be identified for the warehouses and the supermarkets. This makes sense since warehouses are too systemically important and hardly contribute to overall CO_2 emissions while supermarkets are both not systemically risky nor polluting.

The "remove dirtiest companies" transition scenario evaluates the methodology of comparing systemic risk measures with greenhouse gas emissions in the priority plot in order to identify decarbonization leverage points in economic networks. The setting of the thresholds τ_{CO2} and τ_{ESRI} in the priority plot proved to be crucial and dependent on the particular network properties. Thus the drawing of the priority plot should be primarily regarded as a tool for exploration of potential decarbonization leverage points. What is considered to be a true decarbonization lever in a given economic network still depends on the particularities of that network and has to be considered from different perspectives as well.

6.2 "Vegetarian" transition

In this section a second potential transition scenario for the Austrian pork supply network, named the "vegetarian" transition, is explored. What would happen to Austrian pork production, if the Austrian population would halve its consumption of pork over night. Would production fall accordingly? And how much CO_2 emissions would be saved? The second transition scenario explores a demand sided shock at the supermarkets in which the demand for pork is reduced by 50 %.

The relative production levels h_j of every supermarket are set to 0.5 and the resulting losses of the network observed. It turns out that halving the demand at the supermarket level essentially also reduces the total output and total emissions by half. Lost production amounts to 2 445 180 tonnes which is 49.9 % of initial production. Emissions are reduced by 1 936 638 tonnes of CO_2 which amounts to a drop of 49.5 % of initial emissions. The effect on each individual company is also shown in figure 34 in which emissions after the shock are plotted against emissions before the shock.

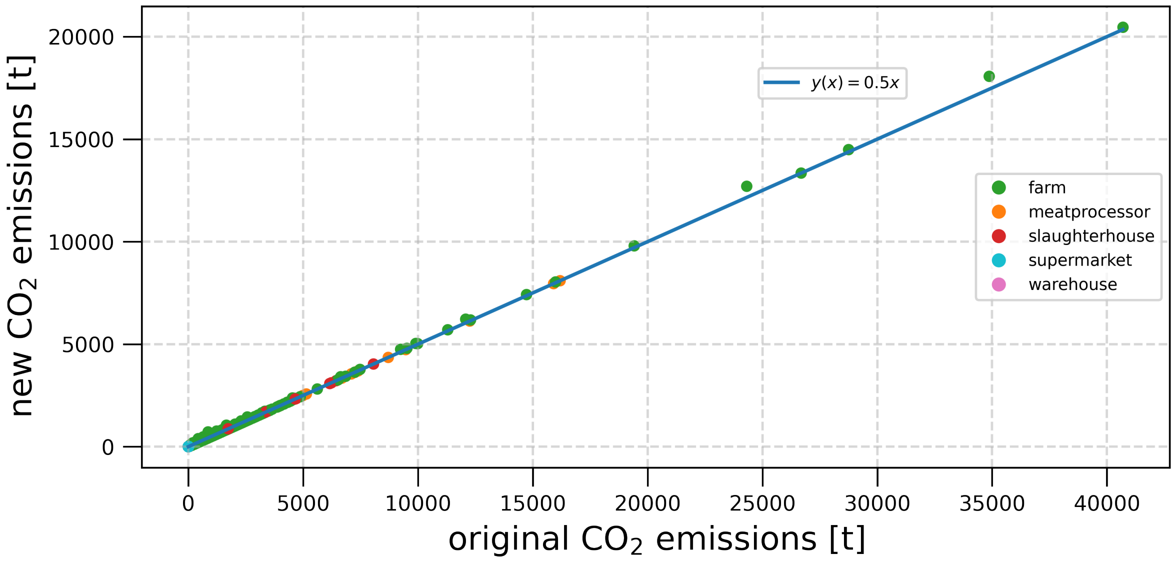


Figure 34: Resulting CO_2 emissions versus original CO_2 emissions of every company in the Austrian pork supply network for a demand sided shock at the supermarkets in which consumption of pork is reduced by 50 %.

It is not surprising that the drop in demand at supermarkets translates perfectly to the production levels of almost every single node of the network. There is a path to each node of the network to all supermarkets and since only linear production functions are considered, each node passes on their received shock accordingly. There are a few nodes whose emissions stay above the reference line that is drawn by the function $y(x) = 0.5x$. This can be explained by the fact that these nodes are part of the strongly connected component which allows for a non-linear propagation of shocks. It is important to note that the *ESRI* can only assess short-term economic systemic risk as the network is assumed to be static and no restructuring takes place. If the demand of pork meat would be to drop substantially, it will most likely happen over a longer time period in which adjustments in the network will take place gradually. The proposed "vegetarian" transition scenario only provides a worst case estimation for a drop in demand in the short-term, but still serves as a useful first approximation of how the production network might respond.

7 Conclusion and future research

In this thesis I explore the question of how the modeling of the economy as a (production) network might inform the green transition with a special focus on the reduction of greenhouse gas emissions. I argued that by quantifying the socio-economic relevance of individual companies via systemic risk measures and comparing these measures with the greenhouse gas emissions of those companies, leverage points for the decarbonization of the economy can be identified.
In section 2 of this thesis, the efforts of quantifying systemic risk in economic networks in order to estimate the socio-economic relevance of economic sectors and individual companies are reviewed. DebtRank is introduced as a measure to quantify systemic risk in financial networks by assigning an index to each node that estimates the fraction of total financial volume that is affected by the default of single financial institutions. Motivated by this line of research, Diem et al. introduced the economic systemic risk index $ESRI$ in order to quantify systemic risk of individual companies in production networks [1]. Taking this as a proxy for the socio-economic relevance of companies, the idea of comparing the $ESRI$ with CO_2 emissions is introduced. A toy example in section 2.5 motivates the so called priority plot in which CO_2 emissions are plotted against the $ESRI$. The two-dimensional plane of CO_2 emissions versus $ESRI$ is divided into four areas that correspond to high emissions - low economic systemic risk (red); high emissions - high economic systemic risk (orange); low emissions - low economic systemic risk (green) and low emissions - high economic systemic risk (yellow). Companies that fall into the zone of high emissions and low economic systemic risk are considered to be decarbonization leverage points as a potential disruption to their business is of minimal impact to the overall economy while a reduction of their emissions is maximal.

In section 3, the idea of comparing systemic risk measures with CO_2 emissions is tested for Austrian companies, whose DebtRanks are known from previous studies by Hinteregger [38] and Poledna et al. [37]. Two companies are identified as decarbonization levers, whose combined CO_2 emissions make up 40 % of the total emissions while their combined DebtRank only sums to 14 %. This indicates that the priority plot is actually a useful concept to identify companies that minimize socio-economic loss and maximize emission reduction.

Since only considering either financial systemic risk or economic systemic risk gives only partial insight into the overall socio-economic relevance of a company, the idea of combining DebtRank, $ESRI$ and CO_2 emissions in a three dimensional plot is presented in section 4. Approximate numbers for all measures are obtained for the large Austrian steel producer voestalpine AG.

In section 5, which is the main part of this thesis, a case study of identifying decarbonization leverage points in the complete Austrian pork supply network is presented. The data collection and processing is discussed in detail, as well as the assumptions that go into the modeling of partially missing data. The resulting complex network is characterized by standard network measures and the attribution of CO_2 emissions to every company with the help of a recent life cycle analysis of Austrian pork [2] is discussed. The priority plot is constructed for all companies and each facility class in order to identify potential decarbonization leverage points in the network.

The thesis closes with an exploration of two simple transition scenarios for the Austrian pork supply network that are motivated by the economic systemic risk index $ESRI$. In the first transition scenario that is called "remove dirtiest companies", the identified decarbonization levers are simply eliminated from the network. The resulting losses in output and CO_2 emissions of every company are summed up and compared with their initial values. By removing all 23 companies that fall into the red zone of the priority plot in figure 27 the network looses 28.6 % of overall production, but 36.4 % of CO_2 emissions. This serves also as a proof of concept that the proposed methodology successfully identifies those companies that minimize the loss in production and

maximize the reduction in CO_2 emissions. Similar results are observed for the removal of the most polluting companies within each facility class.
The second transition scenario is called "vegetarian" transition and answers the question how total production would change, if demand for pork would drop by 50 % at the supermarket level. It turns out that overall production of pork as well as emissions are essentially halved as well. This makes sense, since only linear production functions are considered for the calculation of $ESRI$ which implies that each company is only constrained by the total amount of pork it is able to receive from and sell to other companies. More interesting results are to be expected, if more products and therefore heterogeneous production functions are considered.

By referring to the discussed results, I am confident to answer the thesis statement positively. Modeling the economy as a complex (production) network of individual companies allows for the identification of decarbonization leverage points. These are considered to be companies that are high contributors to overall CO_2 emissions, but display a relatively low socio-economic relevance - quantified either as financial systemic risk or economic systemic risk. By targeting these companies with regulatory policies or tailored carbon taxation schemes, a maximum in reduced CO_2 emissions can be expected while socio-economic loss is minimized. With this approach, the green transition, its implications, pitfalls, and feasibility become quantify-able, better manageable and ultimately more predictable. Of course this work comes with several limitations, one of the most important being a lack of high quality granular data on both the explored supply networks as well as CO_2 emissions of individual companies. Even though the complete Austrian pork supply network is reconstructed in unprecedented detail, some data modeling is still necessary to close data gaps. The second limitation is the construction of the systemic risk measures that can only serve as a useful proxy for the true social relevance of individual companies. The economic systemic risk index $ESRI$ is constructed for a static network and does not consider potential substitution of either loss of demand or production which is not quite resembling the real world. But since the study of economic systemic risk of individual companies is still a very recent development, it is a very useful first approximation to rank companies with respect to their socio-economic relevance.

Potential future research includes the extension of the proposed framework by building an agent-based model that allows for the reconfiguration of the production network in the presence of economic shocks. This would allow to study the effects of policy interventions on the development of the economy in unprecedented detail. As has become very clear during the ongoing COVID-19 pandemic, evidence-based policy is urgently needed in order to tackle the great challenges that we face today. The same is true for the necessary green transition and I hope that I could convince the reader that complex systems science will play an important role in building the tools that allow us to make the right decisions at the right time.

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Appendix

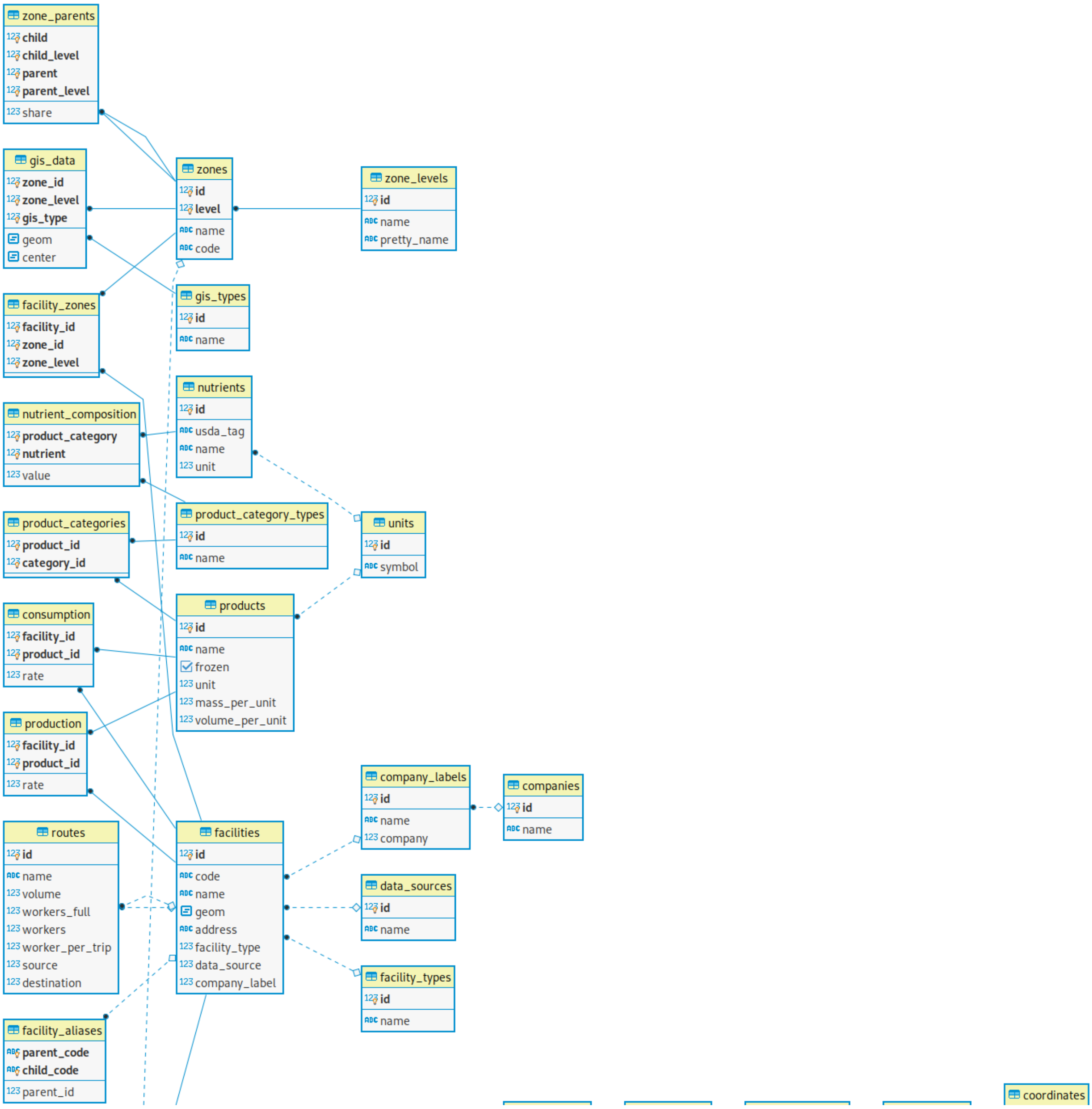

Figure 35: Entity-relationship diagram of the relational database in which the nodes and edges of the Austrian pork supply network are stored [1/2]. Created in collaboration with William Schueller.

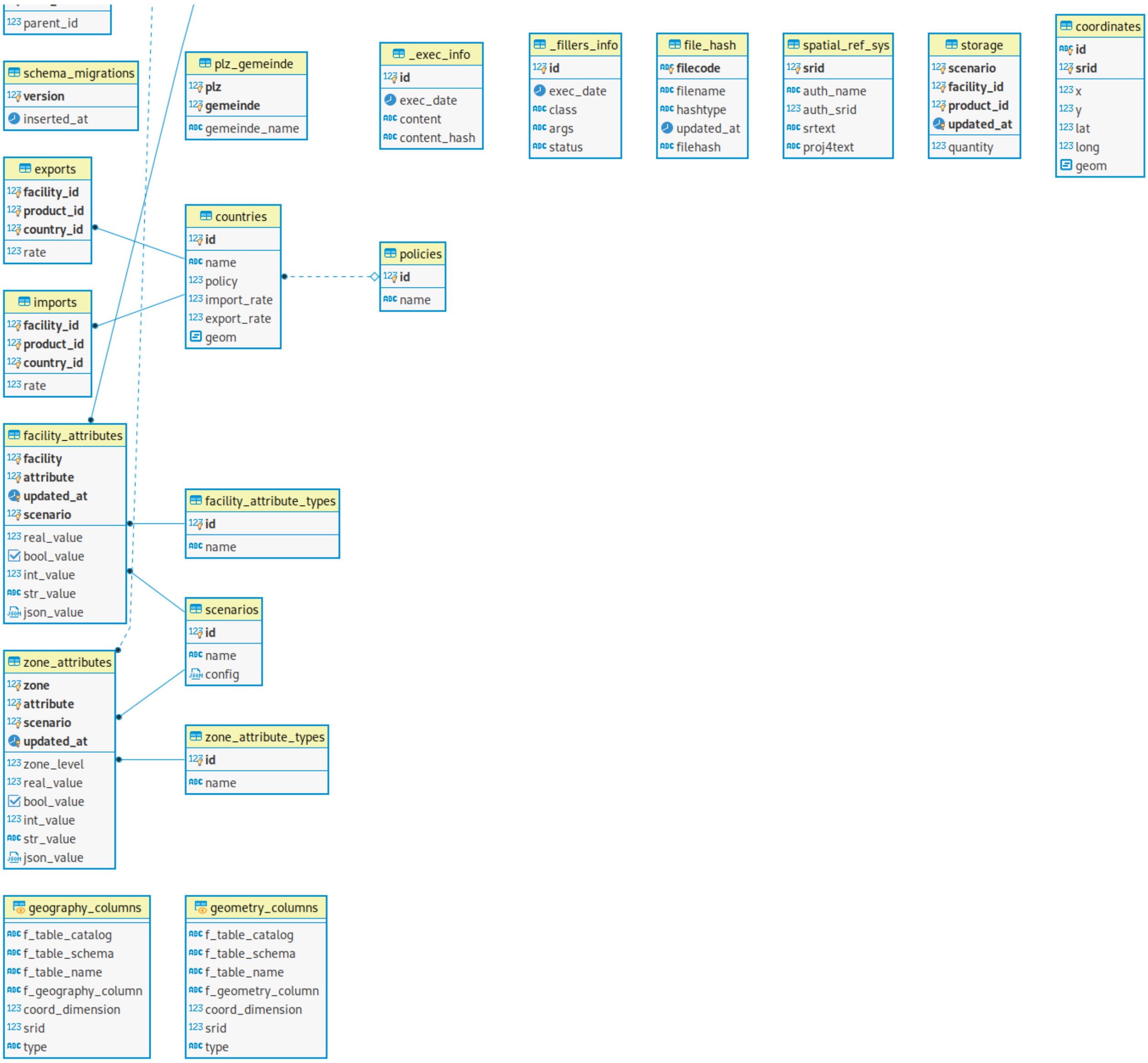

Figure 36: Entity-relationship diagram of the relational database in which the nodes and edges of the Austrian pork supply network are stored [2/2]. Created in collaboration with William Schueller.