Simulating Supply Shocks in Global Production: a Product-Sector-Level Framework

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Abstract

This technical report presents a flexible methodology for identifying vulnerabilities in global supply chains and simulating the impact of supply disruptions. Specifically, the methodology identifies vulnerabilities at the product-level for importing sectors and simulates the effects of supply shocks on the output of importing sectors. Its granularity makes the methodology highly informative for designing targeted industrial and trade policy. The methodology proceeds in three steps. (*i*) It first constructs a global dataset of trade in intermediate products between sectors by combining trade flow data with input-output tables, (*ii*) subsequently identifies supply chain vulnerabilities at the product-level from the perspective of importing sectors or countries, and (*iii*) finally simulates the effects of supply shocks on downstream sectors' output using a readily interpretable framework.

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1 Introduction

This technical report presents a methodology for identifying vulnerabilities in global supply chains and simulating the effects of supply chain disruptions. By combining input-output data with product-level trade flows, both of these exercises can be conducted at a highly disaggregated level. The methodology proceeds in three steps: (*i*) It first constructs a global dataset of trade in intermediate products between sectors by combining trade flow data with input-output tables, (*ii*) subsequently identifies supply chain vulnerabilities at the product-level from the perspective of importing sectors or countries, and (*iii*) finally simulates the effects of supply shocks on downstream sectors' output using a readily interpretable framework.

The first step fills a data gap: Whereas data on global trade flows is readily available at the product level, input-output tables are restricted to the sector level. Combining the sector-level information embedded in input-output tables with product-level trade flows, one can create a dataset of global bilateral trade flows of intermediate goods between country-sectors. Compared with standard data sources, this approach allows for more detailed analysis of supply chain dependencies. As these dependencies may differ significantly between sectors within an importing country, this level of detail is essential for designing targeted and effective policy interventions.

The second step, identifying dependencies and vulnerabilities in global supply chains, has been at the center of policymakers' attention in the past years. Against the backdrop of the US-China trade conflict ramping up after 2016 as well as the COVID pandemic and the war on Ukraine, trade fragmentation has been on the rise. Many countries have turned their attention towards being less dependent on other countries, with the EU for instance pursuing "open strategic autonomy" (European Commission (2021), Bormans *et al.* (2025)). Achieving this goal requires identifying for which products a country or importing sector is dependent on its trading partners. This may be done either by dissecting supply chains theoretically and identifying inputs which are difficult to substitute, or by turning to the data to observe dependencies in trade flows. The former approach is widely adopted in policy applications, with countries drafting lists of strategic goods such as critical raw materials, inputs necessary for semiconductor development and production, or "dual-use" goods with both civilian and military applications. Alternatively, one can use data to identify dependencies and vulnerabilities in supply chains. For instance, an importer may be vulnerable for a given product if it either sources a given product from only a few locations or if supplies of that product are limited to a small number of producers. Following this data-driven approach, this report lays out how to identify vulnerabilities in global supply chains at the product-level. Using product-level trade flows between country-sectors, vulnerabilities may be identified from the perspective of importing countries and, more importantly, importing sectors.

In the third and final step, this report outlines a methodology for simulating the effects of a product-level supply shock on the output of downstream sectors. The framework used in this exercise is a partial equilibrium model for supply shock propagation borrowed from the production network literature. It employs a nested Constant Elasticity of Substitution (CES) structure to capture substitution between (*i*) affected and non-affected goods imports, (*ii*) affected and non-affected intermediary inputs, and (*iii*) affected intermediary inputs and non-affected value added (which includes primary factors). This setup is highly flexible in that it can capture either short- or medium-term effects of a supply shock hitting any number of exporting countries, exporting sectors, and/or products. By simulating the impact of supply shocks to vulnerable products, this model can be used to quantify how "dangerous" vulnerabilities and dependencies in supply chains may be for importers.

The subsequent section reviews related literature and details the contribution of this report. Section 3, then, outlines how to construct a dataset of global intermediate goods flows between sectors at the product-level. Building on this dataset, section 4 presents a methodology to identify dependencies in global production at the product level for importing countries and, importantly, sectors. Section 5 presents a simulation framework able to quantify the effects of supply disruptions on sectoral output, section 6 concludes.[1]

[1] This report is a first result of the ongoing development of simtool 1.0 "Globale schokken" as specified in the ECOOM year plan (Jaarplan) 2025. The second outcome in 2025 will be a practical application of the methodology presented in this report for the case of Belgium.

2 Related Literature and Contribution

The methodology presented here is rooted in international trade and global value chain analysis, while borrowing insights from the research on international production networks. In doing so, it largely follows the approach developed by Berthou *et al.* (2024) in their OECD working paper on granular global value chains.

Much of global value chain analysis relies on international input-output tables, for instance to produce global value chain indicators (cf. Baldwin *et al.* (2022)) or to construct counterfactuals via structural models such as Antràs and Chor (2018). The approach taken here follows a different route and uses international input-output tables as a component to create a dataset of direct trade flows at a more detailed level than traditionally available.

Identifying vulnerabilities in supply chains using trade data has become increasingly popular in policy-focused research, not least due to the increased attention to the issue by policymakers. Recent work by Dumont *et al.* (2024) for the Belgian Federal Planning Bureau or by Arjona *et al.* (2024) and Bonnet and Ciani (2023) for the European Commission illustrates this point. We contribute to this literature both by using a more granular dataset and by allowing simulation of the effects of supply disruptions.

Quantifying the potential economic losses arising from shocks to the supply of vulnerable products is rarely done in the empirical literature on global supply chains, despite being highly informative. The key reason behind this is a lack of sufficiently granular data. The contributions by Berthou *et al.* (2024) and Bachmann *et al.* (2024) stand out in this regard. The former develop a methodology largely similar to the one laid out in the previous section. Bachmann *et al.* (2024) on the other hand use a sector-level model to investigate the effects on output of a disruption to the supply of Russian gas to Germany and the EU. In doing so, they employ a state-of-the-art general equilibrium model following Baqaee and Farhi (2024). They also present a simplified, partial equilibrium model which lays the foundation for the one used by Berthou *et al.* (2024) and in this report.

Bachmann *et al.* (2024)'s research is part of a wider literature on shock propagation in production networks. The seminal work on this stems from Acemoglu *et al.* (2012), who build on a model by Long and Plosser (1983). For an overview of this literature, readers may refer to Carvalho and Tahbaz-Salehi (2019). Baqaee and Farhi (2024) bring these shock propagation models to an international trade setting. In recent years, much of the focus in empirical work on shock propagation has been focused on moving to more granular data. Oftentimes, this is done by moving to firm-level data. Relevant examples for this come from Carvalho *et al.* (2021), who study the propagation of the shock induced by the 2011 Japan earthquake across the domestic production network, and Magerman *et al.* (2017), who extend the domestic network by also accounting for firm-level import and export data. Instead of moving to the firm-level, this report details how merging input-output tables with trade flows may yield information on international trade between sectors at the product-level. The shock transmission model laid out here differs from the current literature on production networks in that it captures only direct linkages between exporters and importers.

3 Data

As detailed earlier, researchers in international economics and trade face a data gap: While trade data is available at the product-level, input-output tables are not. Typically, researchers therefore decide between using sector-level input-output data or product-level trade data. The former allows tracing value added and the propagation of shocks across the network, whereas the latter provides flows at a more detailed level yet misses the network structure. This project follows the approach posited by Berthou *et al.* (2024), combining sector-level input-output data with product-level trade flows of intermediate goods. The resulting dataset provides an exceptional degree of granularity, detailing global flows of intermediate goods between sectors at the product level.

3.1 Data Inputs: Trade Flows and Input-Output Tables

The first key ingredient to facilitate the methods presented in the following sections is data on bilateral trade flows between countries at the product-level. Such data is readily available, for instance from the United Nations, Eurostat, and research projects like BACI (cf. Gaulier and Zignago (2010)). These datasets provide statistics on trade in goods between country-pairs. An observation covers the trade flow of product p between exporting country i and importing country j, measured by value V_{ijp}. Products are typically defined by a numerical code of six to ten digits. Table 1 provides an illustration of bilateral trade flow data for two countries (Belgium and Germany) and two products (p_1 and p_2).

Table 1: Example - Product-Level Trade Data

Exporting Country	Importing Country	Product	Trade Value V_{ijp}
BE	DE	p_1	500
BE	DE	p_2	900
DE	BE	p_1	700
DE	BE	p_2	400
⋮	⋮	⋮	⋮

The second key ingredient are international input-output tables. For a given country-sector, these tables show in the corresponding row its sales to all purchasing country-sectors and in the corresponding column where it sources its inputs. The resulting matrix of "intermediate" flows Z between country-sectors forms the heart of any input-output table. These intermediate flows are complemented by information on how much of a sector's output goes to a country's final demand F. Reading across a row, then, gives the output of a given sector used as intermediate input and for final consumption. Summing these components provides total output as revenue of that sector (last column). In contrast, each column lists intermediate input purchases of a sector along with information on the sector's value added VA. Summing these components provides total output as cost of production of that sector (last row). This also reveals the underlying interpretation of value added: it is primarily a composite of primary factors, such as labor and capital, that sectors require alongside intermediate inputs in the production process. In input-output tables, value added generally also covers taxes less subsidies on production.

Due to their steep data requirements, international input-output tables are a relatively new phenomenon. Even today, global input-output tables typically work with a rest-of-world (ROW) aggregate that groups all countries for which detailed data is not (yet) available. This ROW aggregate is treated as if it was one large country, with inputs and outputs disaggregated between sectors. Table 2 provides an example of an international input-output table for Belgium (BE), Germany (DE), and a ROW aggregate for two sectors (Manufacturing and Other).

Table 2: Example - International Input-Output Table

		Intermediate Demand (Z)						Final Demand (F)			Tot. Rev.
Country	Industry	BE		DE		ROW		BE	DE	ROW	
		Man.	Other	Man.	Other	Man.	Other				
BE	Man.	100	500	50	150	100	400	300	50	200	1850
	Other	200	900	150	400	200	950	750	250	500	4300
DE	Man.	350	150	400	300	100	50	100	200	50	1700
	Other	550	400	800	900	50	150	200	500	100	3650
ROW	Man.	50	400	50	100	500	750	300	50	500	2700
	Other	150	750	150	300	900	1500	700	150	900	5500
Value Added (VA)		450	1200	100	1500	850	1700				
Tot. expend.		1850	4300	1700	3650	2700	5500				

3.2 Combining Datasets

This section details how the two data formats detailed in the previous section may be combined to obtain trade flows of intermediate goods at the product-level between country-sectors. Consider first the dimensions of product-level bilateral trade data and international input-output tables. The former provide flows of product p between exporting country i and importing country j, which we denote V_{ijp}. For the latter, a cell in the Z matrix of intermediate input flows provides the value of goods and services provided by one country-sector ir to another country-sector js, denoted Z_{ijrs}. As evident from the subscripts of Z and V, both data sources contain information on exporting and importing countries. The goal of merging is to combine the additional information contained in each of the two datasets, i.e., on sectors and products, to obtain intermediate flows Z_{ijprs}.

A preliminary, practical step is to restrict trade flows to intermediate goods, as this project is concerned with import dependencies and vulnerabilities in production, which by definition depends only on intermediate goods. Restricting product-level trade flows to intermediate goods can be done via correspondence tables matching all products to an end-use category (one of which is intermediate use).

The first challenge to combining trade data and input-output data, then, is to match intermediate goods p uniquely to a producing sector r. Similar to the end-use categories, correspondence tables exist which assign to each product (at least) one producing sector. Uniquely assigning each intermediate trade flow a producing industry r allows us to rewrite flows V_{ijp} as V_{ijpr}.

The second, crucial step required to build the sector-product-level dataset is a so-called "proportionality assumption". It defines how flows V_{ijpr} are distributed over importing sectors s. Specifically, the proportionality assumption states that product-level flows between exporting sector ir and importing sector js mimic flows at the sector-level: If 5% of ir's production exported to country j go to sector s, it is also true for each intermediate good produced by ir that 5% of exports to country j go to sector s. Applying this assumption requires both the augmented trade flows V_{ijpr} and information from international input-output tables. Put simply, this is where the two main data sources are merged.

Sector-level shares can be readily computed from input-output tables by dividing a given intermediate flow between two sectors, denoted Z_{ijrs}, by the total intermediate input purchases of the importing country j from country-sector ir, denoted Z_{ijr}. This provides the share c_{ijrs} of intermediate input flows from ir to country j that go as an input to sector s.

$$c_{ijrs} = \frac{Z_{ijrs}}{Z_{ijr}}$$

The resulting shares c_{ijrs} can be matched with the augmented trade flows V_{ijpr} for each combination of exporting country-sector and importing country (i.e., via a many-to-many merge along dimensions i, j, r in technical terms). Trade flows V_{ijpr} to country j are then distributed across purchasing sectors s according to the shares. As products are uniquely matched to producing sectors, and using Z and V interchangeably to denote flows between sectors, we can write the following.

$$Z_{ijps} = Z_{ijprs} = V_{ijprs} = c_{ijrs} * V_{ijpr}$$

The resulting bilateral product-sector-level international trade flows provide an exceptional degree of granularity. The data are structured as bilateral, product-level trade flow data (similar to Table 1) where importer and exporter are defined as a country-sector combination. Two notes are in order. First, the data do not serve as input-output tables at the product-level. For this, one would require information on which products are used in the production of other products (cf. Fetzer *et al.* (2024)) along with the respective input shares. Second, while they are not directly observed, product-sector-level trade flows calculated via the method shown here represent a data-based approximation of real trade flows. The following sections show how this highly granular information can be used for the analysis of global supply chains.

4 Identifying Granular Dependencies and Vulnerabilities

One important research exercise profiting from information on global, product-sector-level trade flows is the identification of supply chain dependencies and vulnerabilities. Specifically, compared with similar analysis using traditional product-level trade flows, the dataset detailed in the previous section allows identifying vulnerabilities at the sector-level. This naturally requires a definition of what constitutes a supply chain vulnerability. This section lays out three widely used metrics employed in a similar fashion also by Berthou *et al.* (2024) and the European Commission (2021). These metrics together serve to gauge the extent of a vulnerability. In conjunction with threshold values, they can be used to categorize a product as a vulnerability for an importing country or sector.

All three metrics are calculated per product. The first metric captures how geographically concentrated the imports of a sector or country are. A higher value indicates that, for the product in question, the majority of imports come from only one or very few locations. Consider as an example a scenario where the Belgian pharmaceutical sector imports certain products almost exclusively from Germany and the Netherlands. A supply shock to one of these main sources could then have severe consequences for the importing sector. This is particularly true in the short run, where the importer might not be able to source from an alternative supplier in time or switching suppliers may be costly due to searching or transport costs. The metric is calculated as a Herfindahl-Hirschman index (HHI), denoted HHI^M. Like all HHIs, it is bounded between 0 and 1. HHI^M is calculated by squaring the share of each origin in the imports of a given product and then summing across origins:

$$HHI^M_{jp} = \sum_{i=1} \left(\frac{V_{ijp}}{V_{jp}} \right)^2 \text{ for countries, and}$$

$$HHI^M_{jps} = \sum_{i=1} \left(\frac{V_{ijprs}}{V_{jps}} \right)^2 \text{ for sectors.}$$

In the calculation for sectors, we exploit the fact that any product matches uniquely to a producing sector. As a result, we can simply sum over origin countries i. By looking at these equations, it is also clear that the metric reaches its upper limit of 1 when all imports come from a single origin (i.e., that origin's share in imports is 100%).

The second metric is again an HHI, denoted HHI^X_p. It measures the concentration of global exports for a given product. Again, a value closer to 1 indicates that a larger share of global exports comes from fewer suppliers. Note that HHI^X_p is independent of whether we take the perspective of an importing country or sector, as the calculation only hinges on country-level exports and global exports of a product.

$$HHI_p^X = \sum_{i=1} \left(\frac{V_{ip}}{V_p} \right)^2$$

An example for a product with a high HHI_p^X are rare earth elements, where China provides the vast majority of global exports. In case of a disruption to Chinese supply, importers of rare earth elements might not be able to substitute by shifting imports to alternative sources due to a lack of options. This particular example has received significant attention from policymakers, for instance in the form of the U.S. Department of Defense (2025)'s recent efforts to establish domestic 'Mine-to-Magnet' supply chains.

The final criterion captures whether a country is a net importer or net exporter of a given product. The underlying idea is that a net exporter of a good has sufficient domestic production to cover demand in case of a supply disruption abroad. The criterion is defined as a binary variable at the level of the importing country:

$$net\_M_{ip} = \begin{cases} 1 & \text{if } imp_{ip} > exp_{ip} \\ 0 & \text{otherwise.} \end{cases}$$

In conjunction, the three metrics provide a comprehensive indication of whether an importing country or sector is vulnerable to supply disruptions for a given product. For empirical applications, setting defined thresholds allows us to categorize products as "vulnerabilities". From the perspective of an importing sector r located in i, consider the three metrics in reverse order. Starting with the binary variable, i must be a net importer of p, meaning net_M_{ip} must be equal to 1. In addition, both HHIs must exceed their respective thresholds. The literature typically uses thresholds between 0.25 and 0.5 (Dumont *et al.* (2024), Bonnet and Ciani (2023), European Commission (2021)), with a higher threshold indicating a stricter definition of what qualifies as a vulnerability. If all three criteria are met, an intermediate product is considered a vulnerability for the importing sector in question. Compared to similar approaches at the country-level, this definition of vulnerabilities at the sector-level allows for more targeted research and policy efforts.

5 Simulation Framework

We now turn to presenting a simulation framework capturing the effects of supply disruptions on the output of importing sectors. Importantly, it can simulate disruptions to the supply of intermediate goods identified as vulnerabilities, allowing us to quantify the risk associated with these vulnerabilities. More generally, the framework can simulate an arbitrarily large supply shock to any number of intermediate goods, producing sectors, or exporting countries. The simulation then yields the changes in output of all sectors abroad resulting from a supply disruption. This combination of global coverage and high granularity is facilitated by datasets of the type detailed in section 3. Note that the structure of these datasets prevents analysis of how shocks propagate through the network via indirect linkages. The model presented here is borrowed from Berthou *et al.* (2024), who build on the "simplified model" presented in Bachmann *et al.* (2024), who use it as an approximation of the state-of-the-art quantitative general equilibrium approach by Baqaee and Farhi (2024). As such, it is firmly rooted in the literature on production networks in international trade.

As there are many types of possible supply disruptions, let us first define the type of shocks considered here. Shocks are taken to exogenously affect producers, meaning they are unexpected and outside of the control of the affected producers. In the baseline specification, the resulting decrease in production translates into a uniform reduction of exports to all purchasing sectors (in relative terms). If we speak of a 20% shock to the production of rare earth elements in China, for instance, this is represented in the framework as a 20% reduction in Chinese exports to all purchasing sector abroad. This format of shocks plausibly covers natural disasters as well as negative technology shocks. Examples of the latter include IT systems crashes, hacking attacks, machine failure, and energy price shocks. Technically, the framework also allows simulation of shocks affecting only a subset of importers or affecting importers to different extents. Supply shocks of this kind include transport disruptions (e.g., the 2021 Suez canal blockade caused by the container ship *Ever Given*) and geopolitical shocks like sanctions or export quotas.[2] Note, however, that these shocks rarely are exogenous and there often are underlying dynamics which the framework presented here cannot fully capture.

The simulated effects on output obtained via the framework shown here are relevant for the analysis of short- to medium-term scenarios, defined as up to one year after the shock. The frictionless, partial equilibrium nature of the model renders it unsuit-

[2]Tariff shocks cannot be captured by this framework without additional information. Tariffs are typically modeled as price wedges, whereas the framework shown here works with shocks to quantities.

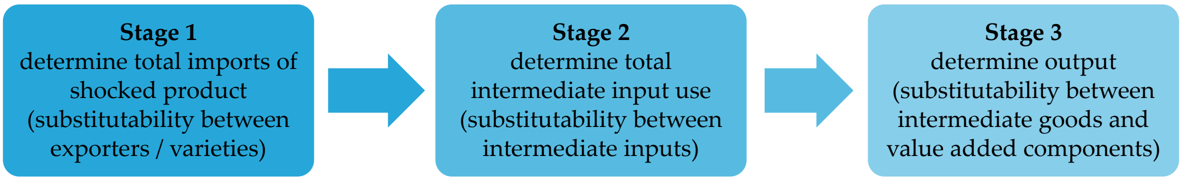

Figure 1: Each step of the CES simulation framework captures one form of subsitutability. This allows producers to attenuate the effects on output of a supply disruption.

able to the analysis of long-term effects. Factor prices, policy decisions, and financial frictions all play an increasingly important role as time passes. Beyond the horizon of one year, simulation results may therefore diverge significantly from what can be considered realistic.

5.1 CES Model

The model works via three nested equations assuming constant elasticity of substitution (CES) with constant returns to scale.[3] Each equation captures one form of input substitution in production, progressively zooming out from the product-level to the sector's output. The first choice is between suppliers of a product, then between intermediate inputs, and finally between intermediate inputs and value added in the production process. Figure 1 outlines the model's three stages.

Upon introducing a supply disruption to the system, the first CES equation determines the importing country-sector js's total import demand for products p across all shocked and non-shocked exporters i, denoted X'_{jps}.

$$X'_{jps} = \sum_i \left(\omega_{ijps}^{\frac{1}{\varepsilon}} Z'^{\frac{\varepsilon-1}{\varepsilon}}_{ijps} \right)^{\frac{\varepsilon}{\varepsilon-1}} \tag{1}$$

In this expression, Z'_{ijps} are exports of product p from i to js after introducing a shock to the system. The ω_{ijps} are the shares of exporters i in the importing country-sector js's import demand for p. These shares sum to one and can be calculated directly from the data. Lastly, the parameter ε represents the elasticity of substitution between suppliers of a product. Intuitively, the equation captures how country-sectors may shift their import demand for a product across exporters of similar products in response to a shock. Again using the example of rare earth elements, a disruption to

[3]Constant elasticity of substitution in production means that the ease with which one input can be replaced with another input is independent of how much output is produced. Constant returns to scale entails that if inputs increase by some proportion, output increases with the same proportion regardless of the level of output.

Chinese exports of rare earth elements will lead importing sectors to search for alternative sources and suppliers. This may be difficult for various reasons, for instance a lack of non-Chinese export supply (high HHI_p^X) or high switching costs. Unless we assume products from different producers are perfectly substitutable, equation (1) also implements a type of Armington (1969) assumption: For a product p, each exporting country that an importer sources from produces a variety of p offering distinct value in the importing sector's production process.

Subsequently, equation (2) follows the same structure as equation (1) and determines country-sectors' total intermediate input use M'_{js} following a shock, taking into account the import demand X'_{jps} computed in equation (1).

$$M'_{js} = \sum_{p} \left(\alpha_{jps}^{\frac{1}{\sigma}} X'^{\frac{\sigma-1}{\sigma}}_{jps} \right)^{\frac{\sigma}{\sigma-1}} \tag{2}$$

The parameter σ captures the elasticity of substitution between intermediate inputs. A higher σ indicates that imports of the shocked product (e.g., rare earth elements) can more easily be replaced by other intermediate inputs in the production process. α_{jps} is observed in the data as the pre-shock share of product p imports in js's total intermediate input use.[4]

In the third and final step of the nested CES structure, country-sectors combine intermediate inputs and the primary factors bundled in value added VA_{js} to produce output $\hat{Y}_{js}$.

$$Y'_{js} = \left(\rho_{js}^{\frac{1}{\mu}} M'^{\frac{\mu-1}{\mu}}_{js} + (1-\rho_{js})^{\frac{1}{\mu}} VA_{js}^{\frac{\mu-1}{\mu}} \right)^{\frac{\mu}{\mu-1}} \tag{3}$$

Again, the result of equation (2), intermediate input use $\hat{M}_{js}$, is used in the calculation. μ is the elasticity of substitution between intermediate inputs and value added, capturing how easily intermediate inputs may be replaced by factors such as capital and labor in the production process. The observed shares of value added and intermediate inputs, which can be calculated from the input-output tables, correspond to ρ_{js} and $(1-\rho_{js})$, respectively. Altogether, equation (3) determines sectoral output Y'_{js} following a supply disruption. The model thereby quantifies the risk that supply chain vulnerabilities pose to importing sectors.

[4]With some abuse of notation, we impose $\sum_p \alpha_{jps} = 1$. Computing α_{jps} as $\frac{X_{jps}}{M_{js}}$ leads to $\sum_p \alpha_{jps} < 1$ because domestic flows at the product level as well as services trade are unobserved in the combined dataset, but included in M_{js}. We solve this by adding a composite input which makes up for the difference between X_{jps} and M_{js}.

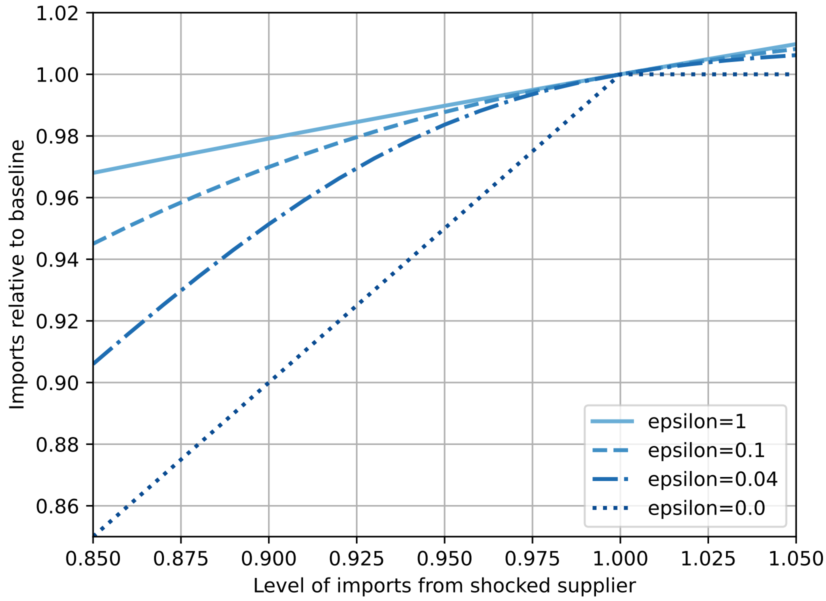

Figure 2: Imports $\hat{X}_{jps}$ depending on shock size for varying levels of ε. Calculated via equation (1). Shocked supplier's share in imports of p by importer js set at 20% (ω_{ijps} of 0.2).
Source: own calculations.

5.2 Simulation, Elasticities, and Input Shares

We now turn to building intuition for the model outlined in the previous subsection by discussing how the model may be applied and interpreted. In doing so, we first explain our simulation approach before examining in turn the crucial roles played by the elasticity parameters and input shares.

To make both the shocks and the results intuitively interpretable, we express all variables as relative deviations from baseline when simulating the model. This allows us to directly compare the impact of a shock on importing sectors of different sizes. We express deviations from baseline using hat algebra (Dekle *et al.* (2007)), meaning that for some variable with baseline level X and value after the shock X', we calculate $\hat{X} = \frac{X'}{X}$. By normalizing all inputs to one and holding all input shares constant, we can easily introduce shocks to the system. For a disruption reducing exports by 20% (i.e., $Z'_{ijps} = 0.8$), we set $\hat{Z}_{ijps} = \frac{0.8}{1} = Z'_{ijps}$. The simulated effects on output are similarly easy to interpret, with $\hat{Y}_{js} = 0.95$, for instance, indicating a 5% drop in output.

When simulating effects of a given supply shock, the only components affecting results are the three elasticity parameters and the input shares. All other variables are defined by the supply shock or normalized to one. While input shares are calculated directly from the data, elasticity parameters may either be estimated or taken from the literature.

As stated earlier, the simulation framework is designed to simulate the short- to medium-term effects of supply disruptions on the output of importing sectors. The key to modeling the effects at different horizons in this model lies in the elasticity parameters, which may be very different depending on the time frame. Consider as an example the elasticity of substitution in equation (1) between varieties of a product p from different suppliers, some of which are affected by a shock: Within the first weeks or months, producers may not be able to compensate the drop in imports of an intermediate good by shifting to other suppliers. Possible reasons include that the varieties are not immediately substitutable in the production process, high costs of searching for a new supplier, or time required for transport. Over the course of a year, however, producers may well be able to substitute away from the shocked suppliers and thereby stabilize their output by setting up relations with new suppliers or adjusting their production process to accommodate different varieties of a product. This is reflected in a higher elasticity of substitution in the medium term compared to the short-term.

Figure 2 shows how this concept can be implemented in the model. It graphs how shocks to one supplier (x-axis) map into changes in the total imports of product p by the importing sector (y-axis). Keeping all else constant, the shapes of the curves depend only on the elasticity of substitution ε. Note that, as the three equations are structurally identical, the graph also translates to equations (2) and (3). Generally speaking, it maps the link between changes in an input and the resulting change in output in CES functions of the kind used here. The two special cases shown here are Cobb-Douglas ($\varepsilon = 1$) and Leontief ($\varepsilon = 0$) production. For the former, the impact of shocks is roughly proportional to the shocked supplier's share in imports of p by producer js, which is here set at 20%. For a drop of supplies from i of 10%, output hence drops by slightly by more than 2%. For the Leontief case, output drops one-to-one with input, regardless of the supplier's share in imports. The reason is that inputs are treated as perfect complements in this scenario, meaning a drop in one input cannot be compensated via other inputs. Interestingly, elasticities even slightly larger larger than zero are far closer to the Cobb-Douglas case than the Leontief case, particularly for small changes in the input (cf. Bachmann *et al.* (2024)). This highlights how small changes to the elasticity of substitution between inputs can greatly attenuate the consequences of supply disruptions. When trying to improve the resilience of domestic production, focusing on substitutability (for instance by standardizing products or processes) may therefore be a worthwhile alternative to decreasing import concentration.

Figure 3, then, shows results using equation (1) for different input shares. Specifically, it shows for a shock resulting in a 50% drop in supplies of product p from country i, how country-sector js's total imports of p change (y-axis) depending on i's share in

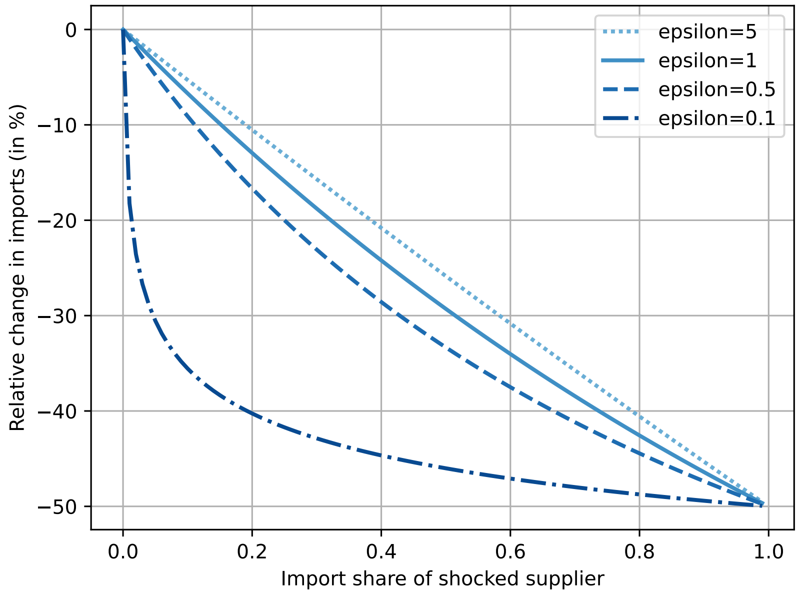

Figure 3: Relative change in imports in percent (i.e., $(\hat{X}_{jps} - 1) * 100$), depending on shocked supplier's share in imports of p by importer js, denoted ω_{ijps}.
Source: own calculations.

js's imports of p (x-axis). As in figure 2, the shapes of the curves depend only on the elasticity of substitution ε. Again, results for equations (2) and (3) would look identical when plugging in identical values. First considering the two extreme values on the x-axis, we can see that if js sources no imports of p from i ($\omega_{ijps} = 0$), it remains unaffected by the shock. In contrast, in models accounting for indirect linkages, these linkages could result in a non-zero effect on js even if it does not directly import p from the shocked exporter i. At the other extreme, for an input share of 1 (i.e., 100%), the 50% drop in supplies of p from i transmits one-to-one into a 50% drop in imports of product p by js. These results are independent of the chosen elasticity of substitution.

It is between the two extremes of the input share that the elasticity makes a marked difference, as shown by the different curves in figure 3. For a low elasticity of 0.1, which may be a reasonable value in the short term after a shock hits, an input share of 20% already leads to a drop in imports of over 40%, as varieties of p from different suppliers cannot easily be substituted. In comparison, an elasticity of 0.5 (which is far lower than common medium- to long-term product-level estimates; cf. Fontagné *et al.* (2022)) attenuates the drop in imports to less than 20% for the same input share. This again highlights the importance of elasticities in all three stages of the model. Moving to higher values of ε, the curves become far closer. As goods become perfectly substitutable and ε approaches infinity, the curve becomes a 45-degree line where shocks are transmitted exactly proportional to input shares.

Using this intuition on how parameters and observed input shares play into the equations, we now illustrate the transmission of shocks through all three stages of the model. Figures 4 and 5 present a numerical example, tracing a 50% drop in supplies of one product from one supplying country-sector. Whereas figure 4 summarizes the results of each stage of the model, figure 5 illustrates in more detail what drives these results. Input shares are chosen arbitrarily and elasticities are set to values which could be considered reasonable in the short term. Introducing the shock in the first stage of the model, the parameterization chosen here leads to an almost one-to-one drop in imports of the affected good. This is due to the importer, at baseline, sourcing 60% of its imports of the affected good from the shocked supplier ($\omega_{ijps} = 0.6$) and the relatively low elasticity of substitution between suppliers ($\varepsilon = 0.1$), visible in figure 5 from the highly convex curve for stage 1. Feeding the first stage results into stage 2, the effect of the shock is attenuated significantly. Although total imports of the shocked product decrease by close to 50%, total intermediate input use only decreases by around 25%. Again, this is driven by the specific parameterization: Although the elasticity of substitution between intermediate inputs is chosen to be relatively small, suggesting a strong effect of the shock, the input share of the shocked product is set to only 20%, limiting the shock's impact on total intermediate input use. Finally, output in the example drop by around 20%, only slightly less than intermediate input use. Figure 5 confirms that this is primarily due to the large share of intermediate inputs in production, resulting in a strong pass-through of the shock from stage 2 to stage 3. The stark differences in results between the three stages highlight that the model can not only simulate output losses at the sector level, it can also identify where in the production process these output losses arise.

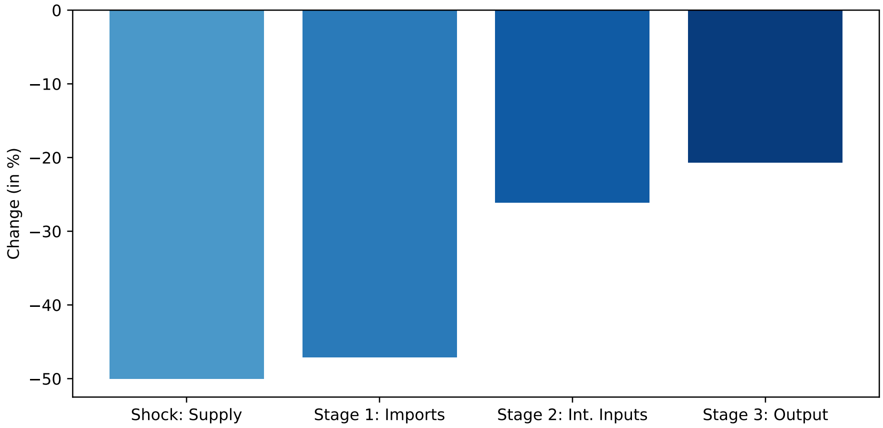

Figure 4: Effects of a supply shock propagating through the nested CES structure. The first bar represents the shock size, each subsequent bar shows the result obtained in one stage of the model.
Parameter values: $\varepsilon = 0.1; \sigma = 0.2; \mu = 0.3$ and *input shares:* $\omega_{ijps} = 0.6; \alpha_{jps} = 0.2; \rho_{js} = 0.7$
Source: own calculations.

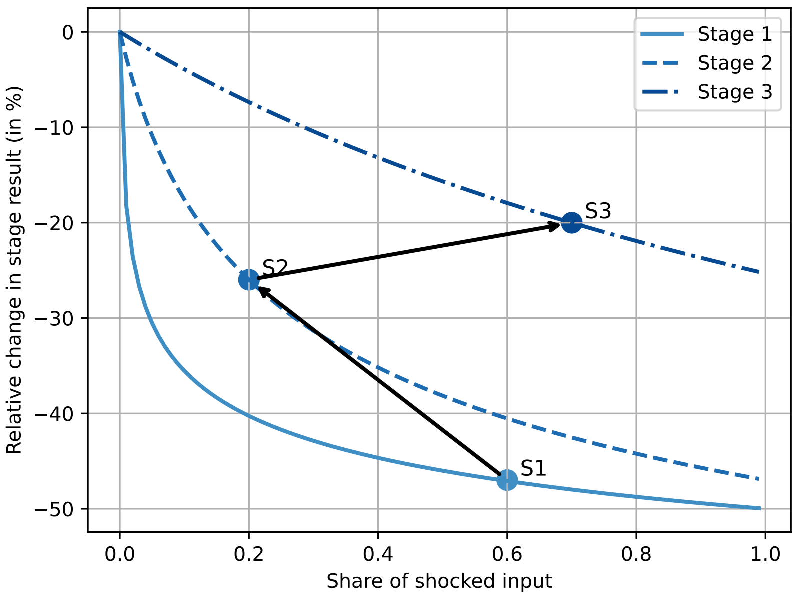

Figure 5: Effects of a supply shock propagating through the nested CES structure. Each curve represents one stage of the model. Labeled points correspond to the results of each stage of the CES structure (y-axis) for the chosen input shares (x-axis).
Parameter values: $\varepsilon = 0.1; \sigma = 0.2; \mu = 0.3$ and *input shares:* $\omega_{ijps} = 0.6; \alpha_{jps} = 0.2; \rho_{js} = 0.7$
Source: own calculations.

6 Conclusion

This report presents a methodology for (*i*) constructing a dataset of global trade flows between country-sectors at the product level, (*ii*) identifying product-level vulnerabilities of importing sectors in this dataset, and (*iii*) simulating how supply disruptions affect the output of downstream sectors.

The first step, constructing the dataset, can be done using any data on product-level trade flows and international input-ouptut tables including information on value added. Depending on the data sources, the resulting dataset will have very different coverage and level of detail, making it suitable to a wide range of applications. Similarly, in identifying vulnerabilities and simulating the effects of supply disruptions, researchers are left free reign within the limitations of their dataset. This flexibility makes the presented methodology a useful tool for policy-makers: it can easily be applied to investigate any country, sector, or product of interest, providing descriptive information along with a framework to simulate supply shocks. Going forward, we intend to apply this methodology to the case of Belgium by constructing a dataset with global coverage, identifying vulnerabilities of Belgian sectors in their imports of intermediate goods, and quantifying the risk these vulnerabilities pose by simulating a series of possible supply disruptions.

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