BANCA D'ITALIA
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INPUTS IN GEOPOLITICAL DISTRESS: A RISK ASSESSMENT BASED ON MICRO DATA

by Alessandro Borin*, Gianmarco Cariola**, Elena Gentili**, Andrea Linarello*, Michele Mancini*, Tullia Padellini*, Ludovic Panon* and Enrico Sette*

Abstract

Using customs and balance sheet data for Italy, we identify foreign-dependent products (FDPs) and quantify the effect of any disruptions to those products. Our framework allows us to assess how geoeconomic fragmentation affects value added at different levels of aggregation. Our baseline calibration suggests that a reduction in the imports of FDPs from high geopolitical risk countries would result in a 2 per cent drop in GDP, with sizable heterogeneity across firms, regions, and sectors. Our findings highlight that the short-term costs of supply disruptions for critical inputs can be substantial, especially when firms cannot easily substitute away from those products.

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1 Introduction[1]

After decades of increasing economic integration across nations and regions through the rise of global value chains, the unprecedented events of the COVID-19 pandemic and the Russian invasion of Ukraine have highlighted the vulnerabilities associated with excessive reliance on foreign inputs.[2] Subsequently, supply disruptions and demand shocks have significantly disrupted international production networks. All these events triggered a major geopolitical rift, further increasing the risk of a reversal of international economic integration, referred to as "geoeconomic fragmentation" (Aiyar et al., 2023).

In many advanced countries, policymakers and enterprises took actions to mitigate exposure to critical dependencies, with a focus on strategic sectors and relationships with geopolitically vulnerable nations. Public initiatives aimed at diversifying global supply chains and enhancing their resilience included tax incentives, subsidies, and public loans to support new investments, as well as encouraging "on-shoring" and "reshoring" of multinational corporations' foreign activities.[3] Export restrictions on specific strategic products have also been implemented.[4] This increased "weaponization" of supply interdependencies could trigger sharp economic losses and inflationary pressures.

In this context, the identification of foreign-dependent products (FDPs) —i.e. vulnerable inputs —becomes key to assessing the potential impact of decoupling scenarios on economic activity.[5] In this paper, we use firm-level data to calibrate a tractable yet parsimonious model of supply disruptions. We use it to assess how disruptions generated by a sudden cut in imports of FDPs would affect the economy at different levels of aggregation.

First, we provide motivating evidence that Italian firms report a strong dependence from foreign critical inputs. To this aim, we rely on a unique survey dataset from the Bank of Italy that focuses on firms' exposure to critical inputs from China.[6]

[1]The views expressed in this paper are solely those of the authors and do not necessarily reflect those of the Bank of Italy. We thank Antoine Berthou, Francesco Paolo Conteduca, and seminar participants at the ESCB Trade Expert Network, and ECB-Bank of Canada conference on Global trade integration and shifting geopolitics for their insightful comments.

[2]While the pandemic vividly demonstrated the challenge of accessing essential goods such as medical protective devices and equipment, the Russian invasion of Ukraine and the ensuing energy crisis stressed the excessive dependency on key raw materials.

[3]See for instance the "CHIPS and Science Act" and the "Inflation Reduction Act" in the US and the "InvestEU", "REPowerEU" and the "Green Deal Industrial Plan" in the European Union.

[4]For instance, China's export restrictions on rare-earth minerals used in semiconductor and electric vehicle production followed those on semiconductor sales enforced by the US, Japan and Netherlands. See the FT article, "China imposes export curbs on chipmaking metals", 3 July 2023.

[5]We use vulnerable inputs and FDPs interchangeably. We prefer the latter label, however, to stress the dependence on sourcing from foreign countries.

[6]This is the Survey of Industrial and Service Firms run by the Bank of Italy since the early 80s.

Indeed, 15% of Italian firms report being exposed to China through the sourcing of critical inputs, accounting for around 25% of Italian value-added and employment in manufacturing. Importantly, firms that account for 7% of manufacturing value-added and employment are particularly exposed to China: they source critical inputs from China that are hard to substitute —as assessed by the firms themselves —and have no immediate plans to decrease their exposure.

Second, motivated by this evidence and with the goal of providing a more complete picture of foreign dependence that goes beyond China, we subsequently identify FDPs sourced by firms using customs data from Italy.[7] We recover a list of 515 FDPs defined at the HS8 level and for which the computers, electronic and optical products industry accounts for 20% of extra-EU imports.[8] Matching our list of FDPs to balance-sheet data on the universe of Italian firms, we unravel stylized facts on importers of specific inputs: FDPs account for a modest share of firms' total purchases; diversification of sourcing is limited for FDPs; importers of FDPs account for a sizable share of the economy and are larger and more productive than other firms within narrowly defined industries.

Third, we build a framework in which firms combine labor, capital and intermediates in a Cobb-Douglas fashion to produce an output good. Importantly, intermediates are produced using FDPs and non-FDPs in a constant-elasticity of substitution (CES) fashion.[9] Our baseline scenario consists of a stress test in which the supply of FDPs from high-geopolitical-risk countries is halved.[10] The benefit of using granular data is that this aggregate shock can be combined with firms' heterogeneous exposure to FDPs to generate idiosyncratic shocks. These shift-share shocks are then fed into our model to assess how geoeconomic fragmentation might affect firms, regions, sectors and the economy. As our model features a CES production function, the impact of firm-level supply disruptions arising from decoupling is governed by the elasticity of substitution across FDPs and non-FDPs. We offer a range of estimates that are contingent on the value of this parameter,[11] to account for uncertainty surrounding its underlying value. Other parameter values needed to calibrate the model —sectoral expenditure shares on capital and labor, firms' ex-

[7]Our methodology extends that highlighted by the European Commission. The Commission identifies vulnerable inputs thanks to three criteria. Inputs for which there are few suppliers, that are mostly imported from extra-EU countries and that are hard to substitute classify as vulnerable. On top of these criteria, we rely on more disaggregated data and focus on intermediate products whose trade flows are larger than a certain threshold value so as to capture relevant flows.

[8]China is a major supplier, but the share of other countries is non-trivial.

[9]A similar approach has been recently adopted by Bachmann et al. (2022) to analyze the potential impact of a Russian oil embargo on value-added at the aggregate level.

[10]We follow Javorcik et al. (2022) and define high-geopolitical-risk countries as those with a different political stance than Italy at the UN general assembly.

[11]As detailed below, we simply constrain this elasticity to be smaller than 0.2, which is consistent with recent evidence (Barrot and Sauvagnat, 2016; Atalay, 2017; Boehm et al., 2019).

penditure shares on FDPs —have a direct counterpart in our micro data. We view our framework as appropriate to study *short-run* effects of fragmentation scenarios, as factors of production other than FDPs are held constant and that the elasticity of substitution between intermediates is assumed to be smaller than one (Peter and Ruane, 2023).

We find that the impact of geoeconomic fragmentation is heterogeneous both in the degree of substitution and across firms. Specifically, the median drop in firm's value-added is -35% among exposed firms —about 8,000 firms —when the production function is Leontief in FDPs. However, the median decrease is smaller, reaching -1.8% when the elasticity of substitution across FDPs and non-FDPs equals 0.2. Aggregating these firm-level effects using value-added weights, we find that the Italian economy could experience a drop in GDP of 2% when FDPs and non-FDPs are perfect complements.[12] This reduced impact at the aggregate level is reminiscent of the argument that firms may have Leontief technologies while the aggregate production function is Cobb-Douglas (Houthakker, 1955; Jones, 2005).

We have stressed that our model is tractable in that it can be easily calibrated using microdata to account for firms' actual exposure to vulnerable inputs and study how different decoupling scenarios may affect the economy at different levels of aggregation in the short-run. It is, however, parsimonious in that it is partial equilibrium and thus does not account for the possibility that factors of production may adjust. For this reason, we view our contribution and that of Baqaee and Farhi (2023) as complementary.[13]

Finally, we show that relying on industry-level data —rather than firm-level data —may severely overestimate the impact of geoeconomic fragmentation if the assumed value of the elasticity of substitution is low enough. In other words, production function complementarities are more costly at the aggregate than at the firm-level because exposure to supply shocks is amplified at the aggregate level. This highlights the importance of using micro data to monitor supply exposures and vulnerabilities. Institutions should therefore foster the collection and availability of micro data for research purposes.

Related literature. The European Commission has been very active in proposing methods to analyze vulnerabilities and identify FDPs. More specifically, the Commission has proposed a data-driven, bottom-up approach, complemented by the discretionary judgment of experts, to retrieve a list of strategic products to be closely monitored (European Commission, 2021; Arjona et al., 2023). Recently, Ioannou

[12]Moreover, the effect of geopolitical fragmentation varies substantially across sectors between -11% and 0% —and regions —ranging from -5% to 0%.

[13]Their general equilibrium framework can be used to study how decoupling scenarios affect the economy at a more aggregate level. See related literature.

et al. (2023) apply the bottom-up procedure defined by the Commission to provide an overview of EU dependencies. We contribute to this literature by leveraging on our foreign transaction dataset to map vulnerabilities at the firm level.[14] We further assess how a decrease in the supply of these products coming from fragmentation would affect the economy.

In parallel, a growing literature focuses on the economic impact of geoeconomic fragmentation. Attinasi et al. (2023) exploit Baqaee and Farhi (2023)'s model to quantify the economic effect of a global trade fragmentation scenario.[15] Despite the richness of these general equilibrium models, they are ill-suited to evaluate firms' exposure to specific supply disruptions —e.g. restrictions imposed by selected high-risk countries on the exports of strategic inputs —and to assess the impact on specific firms or regions. Our contribution is thus to propose an alternative framework aiming to shed light on the short-run micro costs associated with decoupling.

The rest of the paper is organized as follows. In Section 2, we report survey-based evidence on the exposure to sourcing critical inputs from China. In Section 3, we show how to identify FDPs and introduce our stylized facts. Section 4 presents our framework and results. Section 5 concludes.

2 Exposure to China: evidence from survey data

In this Section, we resort to survey data collected by the Bank of Italy to shed light on the exposure of firms to critical inputs sourced from China and to provide a first assessment on the associated economic risk.[16] The Spring 2023 wave of the survey included questions regarding how Italian firms assess their exposure to critical inputs sourced from China and their strategies to increase the resilience of their supply chain.[17]

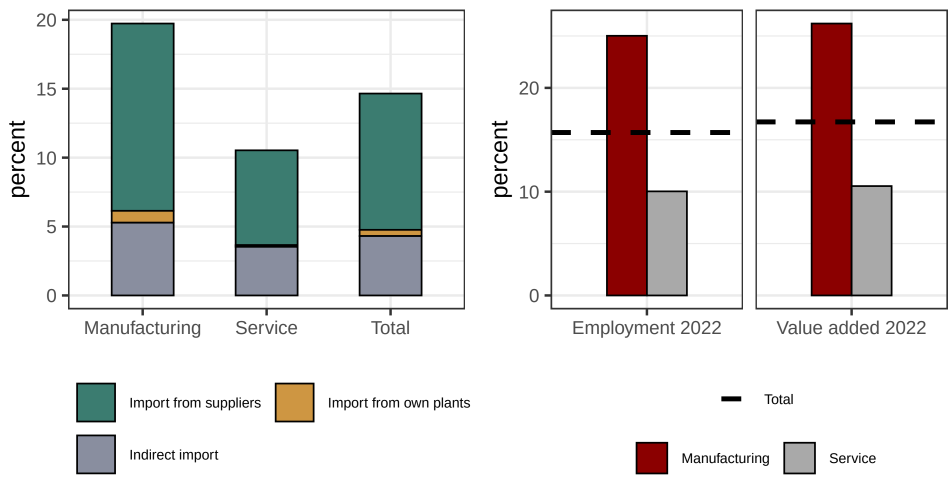
[14]See Jaravel and Méjean (2020) for a notable exception using different criteria on French customs data.

[15]Javorcik et al. (2022) further build on Baqaee and Farhi (2023)'s work to investigate the costs of friend-shoring. Other works rely on multi-country multi-sector models a la Caliendo and Parro (2015) and Antràs and Chor (2022), such as Eppinger et al. (2021), Góes and Bekker (2022) and Felbermayr et al. (2023). Other studies use different frameworks, as large macroeconomic models (the METRO model in OECD (2020) and the World Bank ENVISAGE model in Chepeliev et al. (2022)), Hypothetical Extraction Method (Wu et al., 2021; Giammetti et al., 2021), or CGE models (Lim et al., 2021).

[16]These data come from the 2023 Survey of Industrial and Service Firms (INVIND hereafter). INVIND covers a representative sample of firms operating in the industrial and services sector. Around 4,000 companies are surveyed each year.

[17]Critical inputs are defined as those whose shortage would lead to a reduction in the quality of the good or service produced, or without which a significant part of the production process would not be completed or would cause considerable delays.

Figure 1: Critical Inputs in the Economy



Notes: Left panel: Firms sourcing critical inputs from China (share of total firms). Right panel: Exposure to China (share of total employment and value-added). Source: own elaboration on INVIND data.

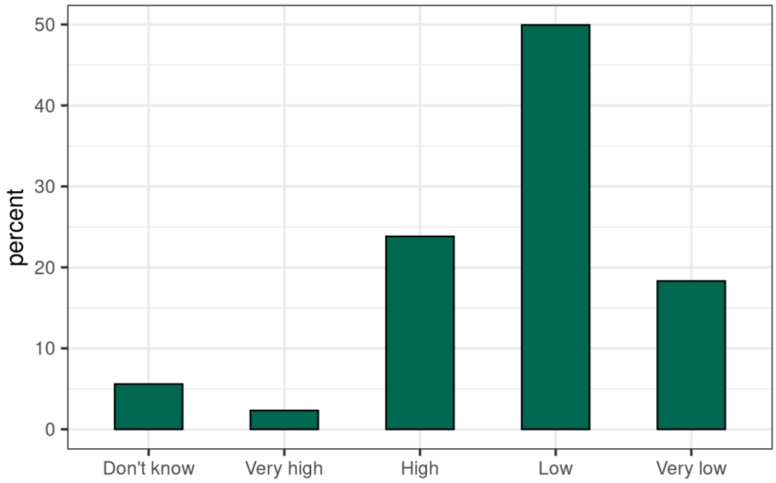
Exposure to critical inputs. Almost 15% of Italian firms rely on inputs from China they deem critical for their activity, as shown in the left panel of Figure 1. About two-thirds of these firms import such inputs directly from companies located in China, while slightly less than a third buys it indirectly through a foreign or domestic distributor. Intra-group imports, on the other hand, are modest. Perhaps not surprisingly given the importance of China in manufacturing, the share of firms importing critical inputs from China is much higher in manufacturing than in services (20% and 10%, respectively).

Manufacturing firms importing critical inputs from China account for around 25% of Italian manufacturing value-added and employment. Instead, the exposure in services —mostly driven by the wholesale sector —is much lower: it represents 10% for both value-added and employment, as displayed in the right panel of fig. 1. For this reason, we now focus only on manufacturing companies in the rest of the section.[18]

Subtitutability of critical inputs. We further asked firms how difficult replacing their critical inputs from China would be, as this important piece of information cannot be inferred from granular trade data. Figure 2 shows that the degree of substitution associated with sourcing critical inputs from China is either low or very low for almost 70% of manufacturing firms. Only 25% of firms consider it to

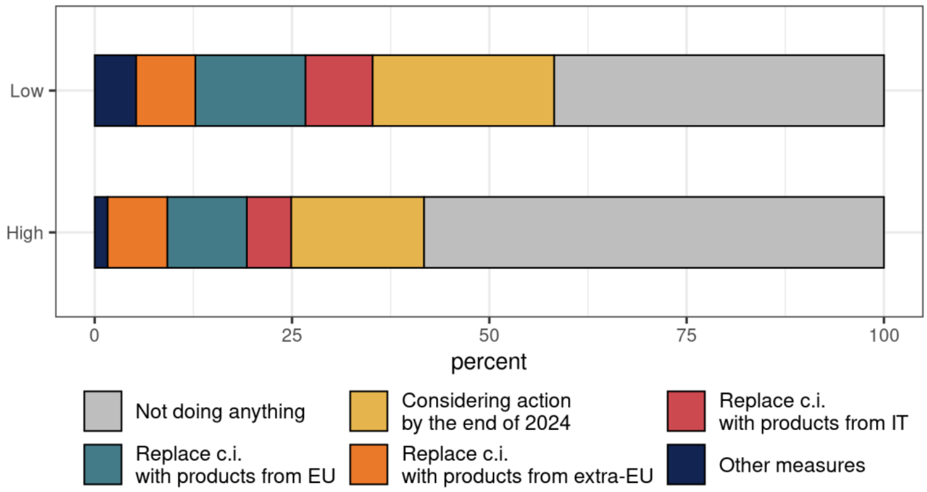
[18]The level of exposure is highly heterogeneous across sectors, even within manufacturing. Figure A1 shows that the basic metals and engineering industry is the most exposed one (close to 35% in terms of value-added and employment), followed closely by textile, clothing, leather and footwear. The food industry and non-metallic minerals, on the other hand, appears to be much less exposed, with shares of value-added and employment comparable to those of services.

Figure 2: Substitutability of Critical Inputs from China



Notes: The bars refer to the extent to which critical inputs sourced from China (share of manufacturing firms sourcing critical inputs from China) can be substituted. Source: own elaboration on INVIND data.

Figure 3: Supply Chain Strategies by degree of substitution of critical inputs

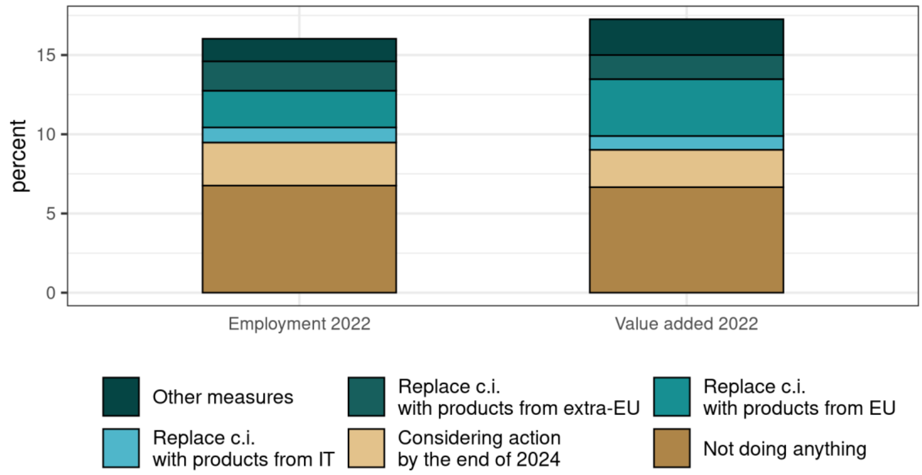


Notes: This figure displays the strategies to reduce exposure to sourcing from China (share of firms sourcing critical inputs from China; high/low substitutability). Source: own elaboration on INVIND data.

be at least high or very high.

Supply chain reorganization. How are Italian companies reorganizing their supply chains to cope with increasing geopolitical risks? De-risking strategies are more frequent for users of Chinese inputs that are difficult to substitute. Firms exposed to China were specifically asked about their strategies to reduce purchases of critical inputs from China. Firms stating that they would face challenges in finding alternative inputs for critical Chinese components are trying to reduce more their exposure on Chinese inputs – or are considering doing so by the end of 2024 – compared to firms with a higher degree of input substitutability (almost 60% vs 40%,

Figure 4: Exposure to China



Notes: The figure displays the exposure to China for firms with limited input substitutability (share of total employment and value-added accounted for by firms that buy Chinese inputs with low substitutability). Own elaboration on INVIND data.

respectively, Figure 3). Firms would rather regionalize their supply chain (substituting Chinese suppliers with EU ones), than reshoring their suppliers to Italy or sourcing from non-Chinese suppliers outside the EU.

Even if de-risking is on the way, a relevant share of manufacturing activity remains highly exposed to fragmentation risks. Around 40% of firms with limited substitution possibilities are neither implementing, nor planning, any action to reduce their exposure to China, possibly because their sourcing from China has no viable alternative. Notably, Figure 4 shows that these firms represent almost 7% of total employment and value-added in manufacturing, which suggests a relevant exposure of the Italian economy to trade disruptions and fragmentation risks.

Overall, amidst growing geopolitical tensions, China represents a key source of vulnerability.

3 Identifying foreign-dependent products

Given the exposure of firms to China, we detail the methodology used to identify vulnerable inputs and discuss our key findings.

3.1 Data

Our analysis makes use of three datasets: i) Italian customs data from the Italian National Institute of Statistics (ISTAT) and the Italian Customs and Monopolies Agency; ii) balance-sheet data from Cerved; iii) international trade data from CEPII BACI. We use data for 2019, the last year before the Covid pandemic.

Customs data. The key information behind the vulnerability indices is contained in the Italian import data from the ISTAT data warehouse for international trade statistics, which is based in turn on the microdata of the Italian Customs and Monopolies Agency (CMA) and is available at the exporting country-product-year level. Italian firms are required to report to the CMA all transactions with extra-EU counterparts, indicating the products they trade, the date, the quantity and value of the transaction, as well as the specific product —at the CN8 level, and country of origin or destination. Intra-EU trade flows include the same information, but the frequency of the reporting is either monthly or quarterly depending on the total traded value.[19] Product codes are defined at the 8-digit level of the 2019 Combined Nomenclature (CN), the European counterpart of the Harmonized System nomenclature (HS). Unique firm tax identifiers are reported in the customs data, which allows us to merge the identity of the importing firm with other firm-level datasets.

Balance-sheet and other sectoral data. Our balance-sheet data come from the Cerved Group. This database provides reclassified balance sheet variables and indicators for all Italian limited liability companies starting from 1995, excluding companies operating in the financial and real estate sectors, and companies with no revenues or assets.

Cerved also includes information on the firm's sector of economic activity, according to the 2-digit ATECO 2007 classification, which is equivalent to the first two digits of ISIC Rev. 4. We complement this database with the information contained in Infocamere, which is the Official Business Register of Italian Chambers of Commerce and includes demographic information also for non limited liability companies. Lastly, we collect sectoral data from the Frame SBS database provided by ISTAT.[20]

CEPII BACI trade data. International trade data are recovered through the CEPII-BACI dataset, which provides data on bilateral trade flows for 200 countries at the HS-6 level.

3.2 Methodology

To identify foreign-dependent products, we build on the methodology originally developed by the European Commission (European Commission, 2021) and used also in Ioannou et al. (2023). The idea behind this methodology is that a product is

[19] In our case, the frequency of the reporting does not affect the analysis, because the data are aggregated at the year level.

[20] This database complements administrative data on business units with survey and balance-sheet data and is one of the major sources for national accounts statistics.

foreign-dependent if imports of that product are highly concentrated, its availability within the EU is scarce, and it is difficult to substitute. To do so, we compute a concentration index, a scarcity index, and a substitutability index for each HS8 product imported by Italy. In this section, we provide a brief overview of these indices.

Concentration index. Concentration of imports from extra-EU countries is measured through an Herfindahl index:

$$\mathrm{HHI}_{jp} = \sum_{i=1}^{N_{jp}} \left(\omega_{ijp}\right)^2 \tag{1}$$

where i are extra-EU countries, ω_{ijp} is country i's export share of product p to country j in country j's total imports of product p from extra-EU countries, i.e., $\omega_{ijp} := X_{ijp} / \sum_i X_{ijp}$, and N_{jp} is the total number of countries exporting product p to country j.[21] If $\mathrm{HHI}_{jp} = 1$, this means that country j depends solely on one extra-EU supplier. In our paper, j denotes Italy.

Scarcity index. The EC further uses a "scarcity" indicator (European Commission, 2021) ,[22] which is defined as:

$$\mathrm{Scarce}_{j,p} = \frac{M_{j,p}^{\mathrm{Extra}}}{M_{j,p}^{\mathrm{Extra}} + M_{j,p}^{\mathrm{Intra}}} \tag{2}$$

This index ranges from 0 to 1 and is equal to 0 if country j does not import product p from extra-EU suppliers. Therefore, the index will be low if imports from other EU members are high compared to those from outside the EU.[23]

Subtitutability index. The last criterion used to identify FDPs aims to measure the substitutability of extra EU imports with a country's production. It is defined as the ratio of extra-EU imports to total exports for a given product p:[24]

$$\mathrm{Substitute}_{jp} = \frac{M_{jp}^{\mathrm{Extra}}}{X_{jp}^{\mathrm{Extra}} + X_{jp}^{\mathrm{Intra}}} \tag{3}$$

[21] Let us note that HHI_{jp} varies across products and destination countries.

[22] The European Commission refers to it as the "importance of extra EU imports in total demand".

[23] With some abuse of notation, we label this measure a scarcity index. Indeed, Italian firms may import relatively more from extra-EU countries because they find it cheaper to do so. The index, however, aims at identifying products whose demand from the point of view of Italian firms is mainly met through imports from extra-EU countries.

[24] While domestic production would be needed, the European Commission notes that PRODCOM contains too many missing values at the 6-digit level.

This measure's goal is to assess whether a country's production would be sufficient to replace extra-EU imports in the event of an input disruption. The higher the index, the harder it might be to substitute away from extra-EU countries.[25]

This measure does not account for the network structure and how central suppliers of specific products might be —and thus how easy it may be to substitute away from specific suppliers. We address this limitation in Section 3.4.2.

Criteria. To operationalize the identification of FDPs, one needs to take a stance on threshold values for the criteria defined above. The European Commission fixes the following thresholds to pin down foreign dependencies (European Commission, 2021), which we follow:

$$\begin{aligned} \text{HHI}_{jp} &> 0.4 \\ \text{Scarce}_{jp} &> 0.5 \\ \text{Substitute}_{jp} &> 1 \end{aligned}$$

While we rely on these three criteria to recover a list of foreign-dependent inputs, we add two other criteria. First, the value of imports has to be larger than one million euros for a product to be classified as foreign-dependent, thereby allowing us to focus on quantitatively relevant flows. Second, we focus on intermediate goods according to the Broad Economic Categories (BEC) classification and thus exclude final goods and energy commodities. This last criterion permits focusing on intermediate goods, which account for two-thirds of international trade (Johnson and Noguera, 2017).

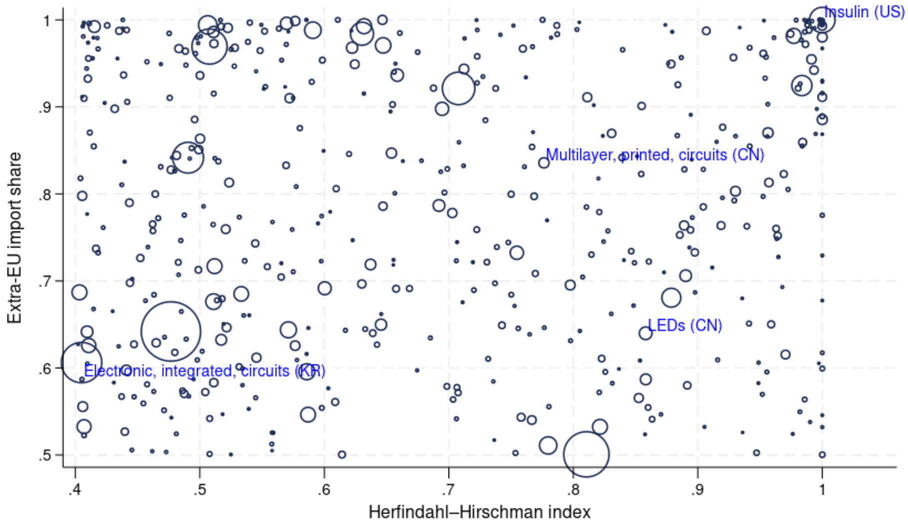
3.3 Stylized facts

3.3.1 Foreign-dependent products

Using the criteria described above, we identify 515 FDPs. As highlighted in Figure 5, half of these FDP have a HHI above 67% while the median for the extra-EU import share is 80%. Our methdology allows us to define vulnerable produts at a very high level of granularity. For instance, Electronic, integrated, circuits (HS code 85423919) or Insulin and its salts (HS code 29371200) for which South Korea and the US are the most important foreign exporters to Italy, respectively. Reassuringly, some of these products —for instance, LEDs, Data, processing, machines from China —overlap with some HS6 codes identified by the European Central

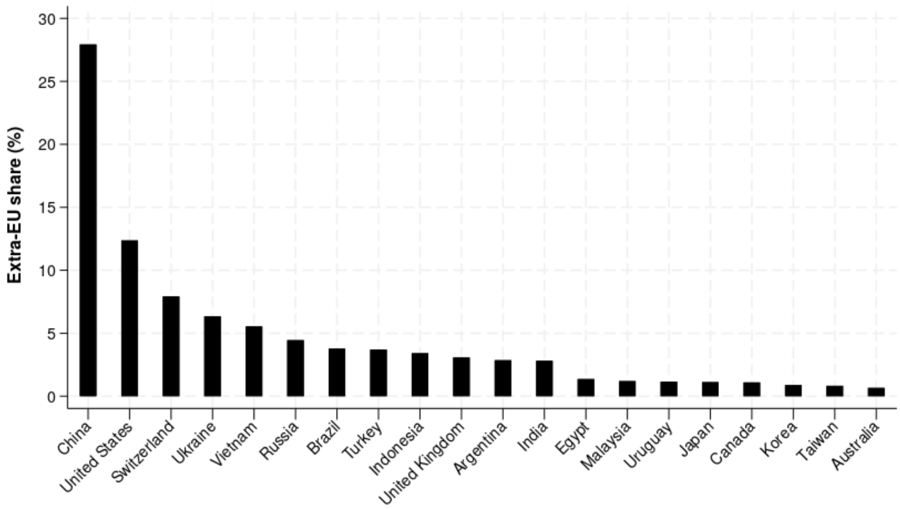
[25]Following the EC, we rely on imports from extra-EU suppliers while exports include both intra- and extra-EU flows. Given our focus on a particular EU country, this means that we implicitly assume that in the case of a disruption, exports to both EU and non-EU countries could be repurposed.

Figure 5: Concentration and Extra-EU Import Share of FDPs



Notes: The figure displays the values of the extra-EU import share (y-axis) and HHI (x-axis) of foreign dependent products (FDPs). The size of the markers represents the import value of each FDP.

Figure 6: Extra-EU Import Share of FDPs by Country



Notes: The bars represent the share of each extra-EU country's exports of foreign dependent products (FDPs) in Italian imports of FDPs from all extra-EU countries.

Bank in their recent report (Ioannou et al., 2023). We then investigate the distribution of main exporters of foreign-dependent products. As is evident in Figure A2, this distribution is very skewed. Indeed, while China is the main exporter of FDPs for about 40% of these goods (194 FDPs out of 515), the United States are the second most important supplier of 53 FDPs while Turkey follows closely with 42 products.

Finally, we explore the country and sectoral import shares of FDPs in extra-EU imports. As Figure 6 shows, China represents 28% of extra-EU imports of FDPs and is thus ranked as the most important extra-EU supplier of FDPs to Italy. The

US follow with a share of 12% while Switzerland's share is lower, at 8%. These three countries account for roughly 50% of imports of FDPs from extra-EU countries while other countries such as Ukraine or Russia account for 6% and 4%, respectively. In terms of sectoral composition, computers, electronic and optical products is the sector with the highest import share of FDPs in extra-EU imports as highlighted in Figure A3. While this share reaches 21% for that sector, metallurgy and chemicals represent the two other most relevant sectors with shares reaching 16% and 11%, respectively.

3.3.2 Firms and FDPs

We now rely on balance-sheet data to provide four stylized facts on the characteristics of firms importing foreign-dependent products. In our data, there are 17,385 importers of FDPs, i.e. about 2% of the firms in the balance sheet data.

Firms importing FDPs account for 31% (51%) of total Italian (manufacturing) value-added. On the other hand, firms importing FDPs from high-risk countries account for 15% (24%) of total Italian (manufacturing) value-added.[26]

As shown in the previous section, China is by far the most relevant source of FDPs. In fact, the value-added produced by firms importing FDPs from China corresponds to 11% of total Italian value-added, while this figure reaches 20% in the manufacturing sector. Interestingly, these figures are very close to those coming from the Bank of Italy business survey despite the methodological differences.[27]

Fact 1: *Firms importing FDPs account for a sizable share of the economy.*

To understand the importance of FDPs for firms, we compute the share of imports of FPDs in firms' total purchases of goods and services. These statistics are described in Table 1. As can be seen in the first row, on average FDPs account for about 5% of firms' total purchases. However, this reflects substantial heterogeneity as the median is 0.5% and the 90th percentile is 13%. From the point of view of Italy, however, diplomatic ties with Switzerland and the U.S. are stronger than those with other countries, e.g. China, or even Russia. The risk of supply disruption are higher when countries have weaker ties and different political stances on key

[26] These firms span various industries and 50% of these firms can be found in four different sectors: 34% of these firms can be found in the wholesale industry, 6% operate in the manufacture of machinery and equipment, while 6% and 5% mainly produce computers, and electronic and optical products, and textiles, respectively. Moreover, as Figure A4 shows, a larger share of firms importing FDPs is located in Northern Italy, consistent with the well documented North-South economic divide (Boeri et al., 2021).

[27] Indeed, firms directly importing inputs deemed as critical for the production process from China through arm's length relations or via intra-firm trade account for 11% of total Italian value-added —17.4% for manufacturing firms. The survey (customs) data refer to 2022 (2019).

Table 1: Summary Statistics for FDP Importers

	Mean	p10	p50	p90	SD	Obs.
FDPs, share of firms' total purchases	4.81	0.01	0.53	13.10	14.60	17,385
FDPs from low-risk countries, share of firm's total purchases	3.25	0.00	0.26	8.11	9.29	12,489
FDPs from high-risk countries, share of firm's total purchases	5.09	0.04	0.88	14.17	11.29	8,102

Notes: The table displays summary statistics for firms importing foreign dependent products in 2019. The variables are expressed in percentage points. Intermediate goods refer to expenditures on goods and services.

Table 2: Summary Statistics for FDPs

	Mean	Min	p10	p50	p90	p99	max	Obs.
# FDPs for each firm	2.46	1	1	1	5	15	110	17,385
# Non-FDPs for each firm	15.77	1	1	3	39	194	1,380	65,403
# source countries, FDP × firm	1.34	1	1	1	2	5	60	42,753
# source countries, # Non-FDPs × firm	1.42	1	1	1	2	7	46	1,031,683

Notes: The table displays summary statistics for foreign dependent products imports in 2019.

issues. To take this dimension into account, we further distinguish between "high-risk" and "low-risk" countries. The next two rows of Table 1 show that the FDP share from high-risk and low-risk countries averages 5% and 3%, respectively.[28,29]

Fact 2: *FDPs, on average, account for a modest share of firms' total purchases.*

We then dig deeper into firms' sourcing strategies. Firms purchase few FDPs, 2.5 on average, compared to 16 non-FDPs. Table 2 shows that these figures are higher in the right tail of the distribution, reaching a maximum of 110 for FDPs. The median number of sourcing countries for each firm-FDP pair is 1, while around 10% of firms purchase the same FDP from at least 2 different countries. These figures are similar to those observed for non-FDPs.[30]

Fact 3: *Diversification of sourcing is limited for FDPs.*

To assess whether there are differences between importers of FDPs and non-

[28] The number of firms reported in the second and third row need not add up to that reported on the first row as firms import from both friends and enemies. For 19 observations out of 17,385, the shares exceed 100% and we thus winsorize them at 100%.

[29] Following Javorcik et al. (2022), high-risk countries are defined as those that on the UN General Assembly resolution of 23 February 2023 on peace in Ukraine voted differently from the main Western countries, including Italy. We note that the average ratio of imports of FDPs from high-risk countries to total imports of FDPs is sizable (38%), but its distribution is bimodal and heavily concentrated as shown in Figure A5. This suggests that sourcing is not diversified.

[30] As shown in Table A1, firms tend to source more FDPs from low-risk countries only (66%, vs 27% from high-risk countries only), while a very modest share is sourced from both country groups (7.5%). Even if this latter share seems rather modest, it is higher than the one for non-FDPs products (5%). However, the value of FDPs sourced both from low- and high-risk countries accounts for almost half of the total value of purchased FDPs by Italian firms (47%).

importers of such products, we estimate the following regression:

$$\log y_i = \gamma + \beta \text{Foreign Dependent}_i + \delta_s + \varepsilon_i \tag{4}$$

where i is a firm, y_i is employment, turnover, wages or labor productivity measured as the ratio of value-added to the number of employees. Foreign Dependent$_i$ is a dummy variable equal to one if firm i imports foreign-dependent products. We further control for differences in demand or supply that could explain size differences across firms as well as the fact that firms in specific industries may need FDPs for their production process by including four-digit industry fixed effects δ_s.

Table 3 presents our results. As shown in Panel A, firms importing foreign-dependent products are larger than non-importers of FDPs. To fix ideas, column 1 shows that importers of FDPs have 470% more employment, 2400% more turnover, give 70% higher wages and are 80% more productive than non-importers of such products.[31] These size differences remain even when comparing firms within narrowly defined industries. A concern, however, is that these premia mostly reflect size differences across importers and non-importers (Bernard et al., 2007). To address this concern, Panel B focuses on size differences across firms importing from extra-EU countries —these firms are arguably larger than other types of importers since fixed costs associated with sourcing from outside the EU may be larger. While the point estimates are smaller, they remain highly significant and the size differences remain important: column 8, for instance, shows that importers of FDPs are 20% more productive than non-importers of FDPs conditional on sourcing from extra-EU partners.[32]

Fact 4: *Firms importing FDPs are larger and more productive.*

3.4 Discussion

3.4.1 Level of aggregation

To better understand the importance of identifying FDPs using granular data, we use our methodology at the HS6 product code level instead.[33] In column 1 of Table 4, we report the number of FDPs identified at the HS8 level for the sake of

[31] This is calculated as $(\exp(X) - 1) * 100$ where X is the point estimate reported in Table 3.

[32] In a more demanding specification, we include a control for the number of imported products to account for the fact that firms importing FDPs may be larger because they need more foreign goods to operate. Table A2 shows that the results remain positive in all specifications but one. The point estimates, however, are not significant for wages but are significant at the 10% level for labor productivity within narrowly defined industries as shown in column 8.

[33] As there is a one-to-one mapping from HS8 codes to HS6 codes, we rely on our customs data and compute all the criteria discussed in Section 3.2 at the HS6 level.

Table 3: FDP Premia

	log Employment		log Turnover		log Wages		log Labor Productivity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A. All firms				
Import FDP	1.736***	1.551***	3.205***	2.545***	0.512***	0.336***	0.596***	0.383***
	(0.013)	(0.012)	(0.014)	(0.014)	(0.003)	(0.004)	(0.006)	(0.006)
Obs.	552,620	552,598	753,461	753,429	549,452	549,430	528,004	527,986
				Panel B. Extra-EU importers				
Import FDP	0.870***	0.950***	1.270***	1.283***	0.163***	0.167***	0.183***	0.180***
	(0.015)	(0.014)	(0.017)	(0.016)	(0.004)	(0.004)	(0.007)	(0.007)
Obs.	58,152	58,107	63,035	62,991	58,082	58,036	56,309	56,263
4-digit industry FE	No	Yes	No	Yes	No	Yes	No	Yes

Notes: The table reports estimates from eq. (4) in the text. Standard errors clustered at the firm level. * significant at 10%, ** significant at 5%, *** significant at 1%.

Table 4: Vulnerabilities at Different Levels of Aggregation

	FDPs (HS8)	FDPs with HS6 Data	FDPs from HS6 Data	FDPs from HS8 Data	Merged HS8 Codes
Number	515	500	139	154	361

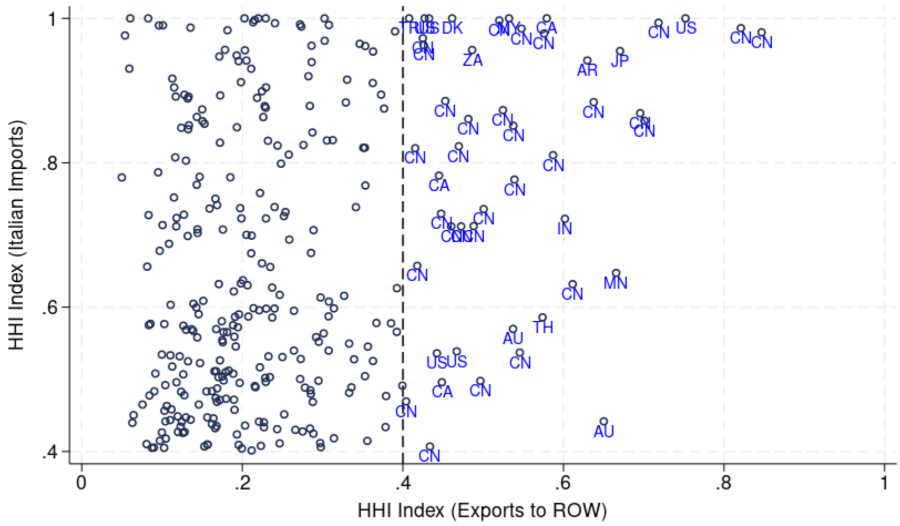
Notes: This table displays the number of foreign dependent products (FDPs) identified using trade data at different levels of aggregation. Column 1 reports the number of FDPs identified through our baseline procedure. Column 2 reports the number of HS8 product codes recovered from the 324 vulnerable HS6 product codes identified using more aggregate data (HS6 level). Columns 3-4 and 5 report the number of HS8 codes unmatched and matched, respectively.

comparison. In column 2, we rely on the 324 HS6 codes identified using more aggregate data and map them to all corresponding HS8 product codes. This results in 500 FDPs identified when we conduct our analysis at a lower level of aggregation. We then proceed to merging the list of FDPs identified in the first two columns. The resulting merge is reported in the last three columns. Columns 3 and 4 show that 139 and 154 FDPs are identified using HS6 and HS8 data and these product codes do not perfectly overlap. Importantly, some key FDPs such as semiconductors (HS4 code 8542) are not identified when using HS6 data to identify FDPs. The last column shows that 361 HS8 codes can be matched. Overall, this lends further support to the importance of relying on granular data to identify import vulnerabilities (Jaravel and Méjean, 2020).

3.4.2 Granularity of demand or granularity of supply?

Our methodology identifies foreign-dependent products from the point of view of Italian demand. Other authors, on the other hand, have put forth the importance of considering the supply-side (Korniyenko et al., 2017). The idea is that some goods that we identify as FDPs for Italy may not be FDPs for other countries as this depends on their own sourcing strategies.

Figure 7: Granularity of Supply



Notes: The figure displays the values of the HHI constructed using Italian imports at the HS6 level (y-axis) and of the HHI constructed using exports of each country to the rest of the world (x-axis).

While our approach is best-suited as we are interested in understanding Italian vulnerabilities, we further consider how accounting for the concentration of suppliers of each product could affect our list of FDPs. To do so, we aggregate data at the HS6 level, as this is the only level of aggregation available using harmonized data across countries. We thus rely on BACI (Gaulier and Zignago, 2010) and measure export concentration for each HS6 product.

We identify 324 FDPs when using data at the HS6 level. Figure 7 shows that out of these 324 FDPs, 49 products are heavily concentrated on the export-side as the HHI index associated with the export-side is larger than 40%. Out of these 49 products (82 HS8 codes), 30 are mostly exported by China while the US are the main exporter for 5 of these FDPs.

This finding suggests that our approach, if applied to other countries, may identify common FDPs for which the possibility of diversifying away from specific suppliers may be low.

4 Risk-assessment: supply shortages of FDPs

In this section we adopt a stress-test approach and evaluate the effects of a disruption in the availability of FDPs on value added. We start by outlining our framework before describing our results.

4.1 Model

4.1.1 Environment

Each firm i produces output Y with a Cobb-Douglas technology, by combining labor (L), capital (K), and intermediates goods and services (M):

$$Y_i = A_i K_i^{\alpha_s} L_i^{\beta_s} M_i^{1-\alpha_s-\beta_s} \tag{5}$$

where α_s and β_s are industry-specific expenditure shares on labor and capital while $1-\alpha_s-\beta_s$ is the expenditure share of goods and services purchases.

In turn, intermediate goods and services are combined through a firm-specific CES aggregator:[34]

$$M_i = \left[\gamma_i^{\frac{1}{\sigma}} E_i^{\frac{\sigma-1}{\sigma}} + (1-\gamma_i)^{\frac{1}{\sigma}} X_i^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \tag{6}$$

where γ_i is firms' goods and services expenditure share on FDPs E, whereas X is a bundle of non-foreign-dependent intermediate goods and services. Importantly, σ denotes the elasticity of substitution between FDPs and other intermediates. As usual with this type of production function, FDPs and non-FDPs become perfect complements when $\sigma = 0$, while the function becomes Cobb-Douglas when $\sigma = 1$.

4.1.2 FDP disruption and value-added

We assume a firm-specific shock ε_i reduces the availability of foreign-dependent products E. Normalizing its original endowment to 1, expenditures on FDPs after the shock are thus given by $E_i = 1 - \varepsilon_i$. After some derivations detailed in Appendix A, we obtain:

$$\Delta \text{va}_i = (1-\alpha_s-\beta_s)\left(\frac{\left(\gamma_i^{\frac{1}{\sigma}}(1-\varepsilon_i)^{\frac{\sigma-1}{\sigma}} + (1-\gamma_i)^{\frac{1}{\sigma}}\left(\frac{1-\gamma_i}{\gamma_i}\right)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}}{\left(\gamma_i^{\frac{1}{\sigma}} + (1-\gamma_i)^{\frac{1}{\sigma}}\left(\frac{1-\gamma_i}{\gamma_i}\right)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}} - 1\right) \tag{7}$$

The change in value-added Δva_i depends on the firm-specific shock ε_i, on the elasticity of substitution σ, on the sectoral parameter $1-\alpha_s-\beta_s$ and on the firm-specific parameter γ_i.

Lastly, we aggregate firm-level value-added changes at the industry level s and

[34] This formulation echoes Bachmann et al. (2022)'s approach to studying the effect of cutting energy imports from Russia.

at the aggregate level as follows:

$$\Delta \text{va}_s = \sum_{i \in s} \Delta \text{va}_i \times \omega_{is}^{va} \tag{8}$$

$$\Delta \text{va} = \sum_{i \in s} \Delta \text{va}_i \times \omega_{i}^{va} \tag{9}$$

where ω_{is}^{va} is firm i's sectoral value-added share while ω_{i}^{va} is firm i's value-added share in the economy.

Discussion. Despite its limitations —prices and factors of production other than FDPs are held constant, we find the framework above to be useful for the following reasons. First, the model can easily be calibrated using standard micro data —which are typically available to researchers. Second, considering alternative decoupling scenarios or using alternative elasticity values is computationally convenient as eq. (7) can be readily computed. Third, our framework can be used to recover effects at different levels of aggregation —firms, regions, industries, aggregate. Because of its limitations and advantages, we consider our framework to be complementary to papers relying on Baqaee and Farhi (2023)'s work.[35]

4.2 Calibration

We calibrate our model by combining the customs data at the firm-product level with the balance sheet data for 2019.

In our baseline scenario, we assume that geoeconomic fragmentation would disrupt imports of FDPs sourced from high-risk countries. We thus compute the share of FDPs sourced from high-risk countries in total imports of FDPs (risky share_i) and allow this share to change according to the parameter $\delta \in [0.25, 0.75]$. Therefore, the firm-level shock is:

$$\varepsilon_i = \text{risky share}_i \times \delta \tag{10}$$

In other words, we reduce the total firm-level endowment of foreign-dependent products by a share that is proportional to its imports from risky countries. Our baseline value for δ is 0.5. Let us note that δ not only captures different degrees of disruptions but also the ease of substitution between FDPs from high- and low-risk countries.[36]

[35] They provide a flexible general equilibrium framework calibrated to aggregated input-output tables.

[36] For instance, $\delta = -0.5$ could result from either a 100% drop in the supply of FDPs, partially mitigated by substituting 50% of this supply, or from a 50% drop in the supply of FDPs without any substitution.

Table 5: FDP Disruptions and Value-Added Change (in %)

	Mean	SD	p1	p10	p50	p90	p99	Obs.
σ=0.00	-33.12	15.08	-50.00	-50.00	-35.40	-6.52	-0.13	8,102
σ=0.02	-29.13	14.89	-49.27	-46.34	-31.54	-1.37	-0.00	8,102
σ=0.05	-22.86	13.75	-48.12	-40.40	-24.50	-0.30	-0.00	8,102
σ=0.10	-12.93	12.17	-46.07	-31.05	-9.83	-0.11	-0.00	8,102
σ=0.15	-8.10	10.44	-43.91	-23.81	-3.31	-0.07	-0.00	8,102
σ=0.20	-6.01	9.18	-41.73	-18.91	-1.78	-0.05	-0.00	8,102
σ=1.00	-2.69	5.84	-30.67	-7.55	-0.47	-0.02	-0.00	8,102

Notes: The table reports the value-added change (in %) induced by a 50% cut in foreign-dependent inputs from high-risk countries. We include all firms importing FDPs from high-risk countries.

Finally, given the central role of σ —see footnote 43 —and to reflect the uncertainty about its value, we allow this parameter to vary from 0 to 1. However, since our focus is on the *short-run* effects of decoupling, the elasticity of substitution between intermediates is arguably closer to zero (Barrot and Sauvagnat, 2016; Atalay, 2017; Boehm et al., 2019).[37]

4.3 Results

4.3.1 Heterogeneous effects across firms

In Table 5, we report the firm-level changes in value-added following a 50% cut in FDPs from high-risk countries for selected levels of σ. Around 8,000 firms are exposed to this shock. The impact varies widely across firms conditioning on σ and for different values of σ. Indeed, the median impact ranges from -35% when the intermediate bundle is obtained with a Leontief function ($\sigma = 0$), to -0.5% in the Cobb-Douglas case ($\sigma = 1$). Moreover, when $\sigma = 0.1$, the drop ranges from 46% for firms in the bottom percentile to 0.1% for firms in the ninetieth percentile.

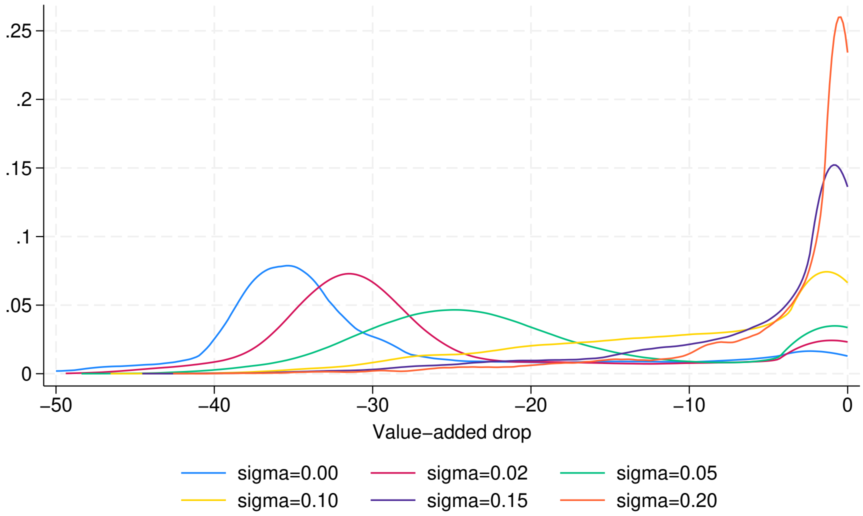
We visually inspect these results by focusing on manufacturing firms only (about 4,300), in Figure 8. It is clear that when σ approaches zero, the distribution tends to be more concentrated towards more negative values, while as σ increases the mass flattens out and then moves towards zero.

4.3.2 Aggregate effects

We aggregate our firm-level results using eq. (9) and plot them in Figure 9. In the case where FDPs cannot be substituted with non-FDP inputs, a 75% cut in the sup-

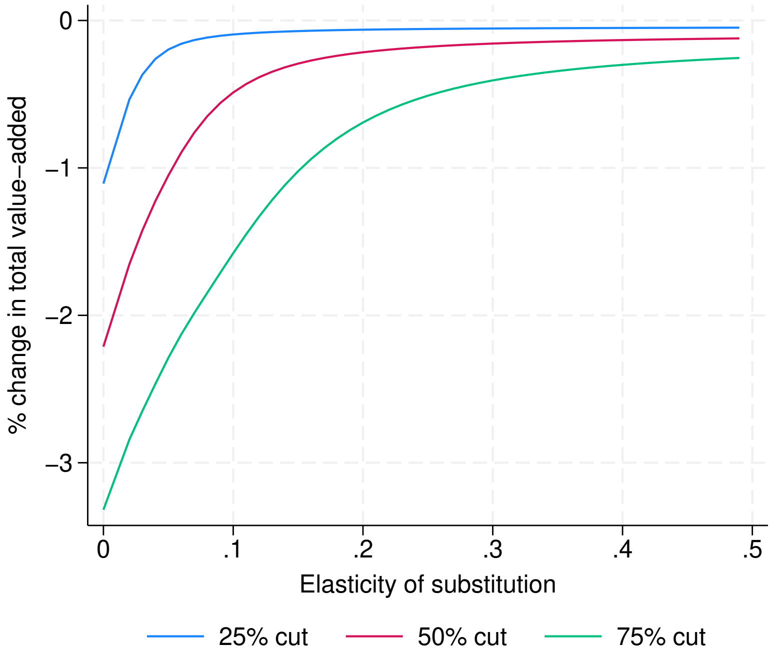
[37] Peter and Ruane (2023) find values for the elasticity of substitution between intermediates consistently higher than one. Their estimates, however, are long-run ones in that they focus on India's trade liberalization episode.

Figure 8: Distribution of Value-Added Change (in %)



Notes: The figure reports the distribution of value-added changes (in %) due to a 50% cut in FDPs from high-risk countries. We include manufacturing firms only.

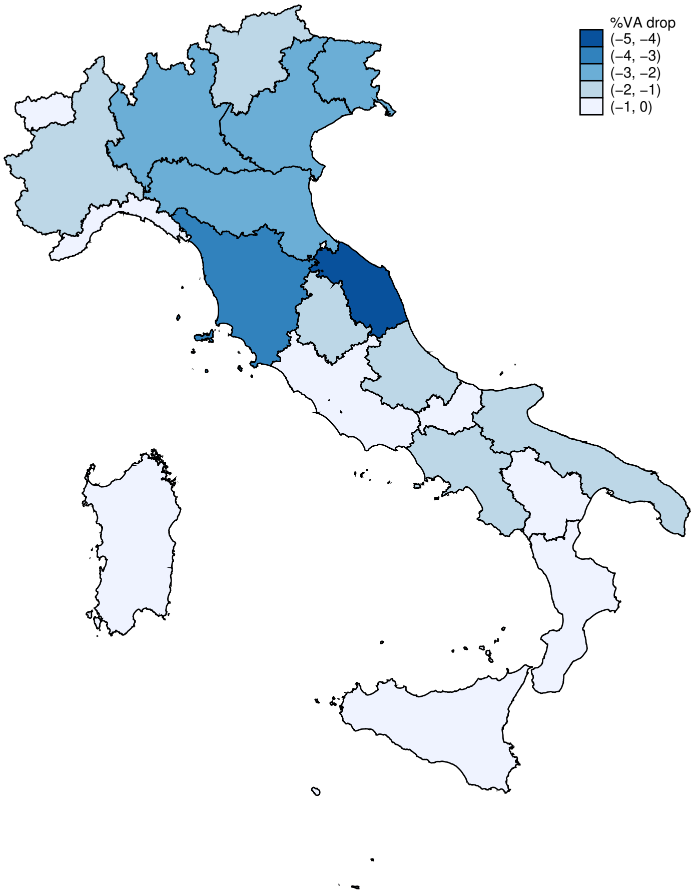
Figure 9: Aggregate Value-Added Change (in %) across Scenarios



ply of FDPs from high-risk countries is associated with a drop in total Italian value-added of more than 3%. On the other hand, halving the supply of FDPs from these countries would generate a drop in value-added up of 2%. A small drop of 25% would lead to a one percent drop in value-added.

Regional- and sectoral-level impacts vary substantially. First, even if most of the firms exposed to a cut in the supply of FDPs from high-risk countries are found in

Figure 10: Aggregate Value-Added Change (in %) across Regions



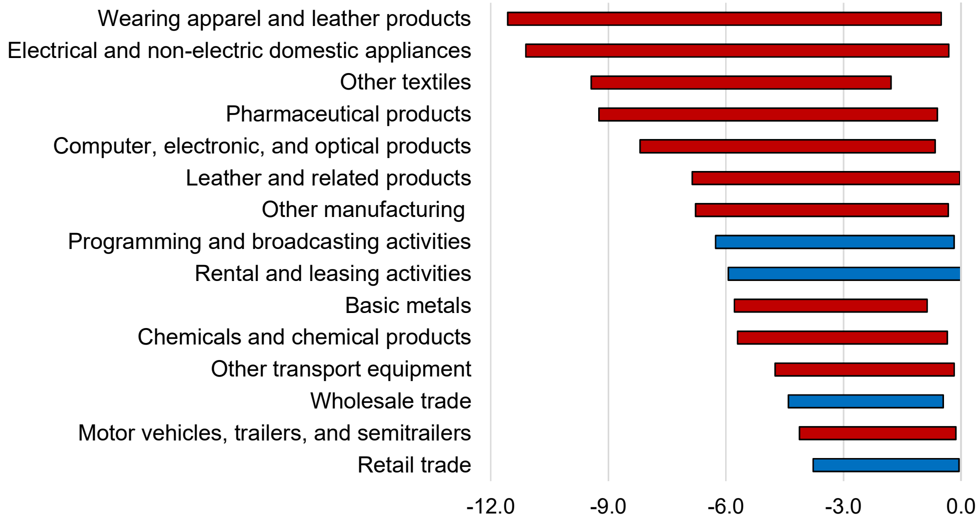
Notes: The figure reports the value-added change (in %) across regions coming from a 50% drop in FDP supply from high-risk countries ($\sigma = 0$).

the Northern regions (Figure A6), the potential impact of the shock on two Central regions – Marche and Tuscany – is the highest (Figure 10).[38] This suggests that focusing solely on customs data and on the location of firms would provide an inaccurate perspective of the relative regional exposure. Instead, it is crucial to take into account firms' characteristics obtained from balance sheet data.

Second, there is even more heterogeneity across sectors than across regions. Figure 11 shows that the impact of the shock in the Leontief case would exceed 11% for the wearing apparel and leather products and electrical and non-electric domestic appliances industries, and would be higher than 8% for the other textiles, pharmaceutical products and computers, electronic and optical products industries. These effects are considerably higher than the result obtained for the entire economy (2.2%), reflecting the higher share of FDPs from high-risk countries used by these industries.

[38]We present results in the Leontief case where $\sigma = 0$, for the sake of simplicity. Results for alternative values of σ are available upon request.

Figure 11: Aggregate Value-Added Change (in %) across Sectors



Notes: The figure reports the value-added change (in %) across the most exposed sectors from a 50% drop in FDP supply from high-risk countries. Red (blue) bars refer to manufacturing (services) industries. σ ranges from 0 (lower bound of the impact reported in the chart) to 0.5 (upper bound of the impact reported in the chart).

4.4 Additional results

4.4.1 Disruptions of FDPs coming from different countries

We consider other scenarios in Figure A7. Halving the supply of FDPs from low-risk countries outside the EU would have a higher impact on the Italian economy. Instead, halving the supply of FDPs from China would imply a drop in value-added close to that obtained when reducing the entire supply of FDPs from high-risk economies. This can be explained by the central role of China as a supplier of these products. We consider a more extreme scenario —75% shock on manufacturing firms —in Figure A8. The decrease in value-added from a cut in the supply from China would amount to 4.5% in the Leontief case.[39]

4.4.2 Aggregation level and aggregate effects

Lastly, we investigate how relying on more aggregated data (at the HS6-level) would affect our quantitative results. To do so, we assess the impact of a cut in the supply of the 500 FDPs identified in Section 3.4.1. It turns out that the aggregate impact is close to what we previously estimated (Figure A9). This, however, masks heterogeneity across sectors. As reported in Figure A10, the exposure of two industries —leasing and rental services, other transport equipment —is overstated by

[39]Interestingly, this figure is close to what we documented using the firm-level survey. Indeed, almost 5% of total manufacturing value-added is highly exposed to disruptions, i.e., manufacturing firms directly sourcing from China inputs they deem critical for their activity with limited substitution possibilities that they are neither implementing nor planning.

more than 1 p.p., while those of five industries are understated by the same magnitude.[40,41]

The bias is more substantial if we instead consider 3-digit sectors rather than firms. Overall, conditional on σ, aggregate data overstate the exposure to supply shocks. For instance, in the case of a 50% cut in the supply of FDPs, the results obtained with aggregated data would be 7 p.p. higher in the Leontief case compared to the estimate obtained with firm-level data (Figure A12). This bias decreases as σ increases and becomes almost negligible for $\sigma > 0.2$.[42]

5 Conclusion

In this paper, we identify foreign-dependent products for the Italian economy and exploit micro data to provide a risk-based assessment of potential supply disruptions from high-risk countries. In doing so, we propose a framework to obtain quantitative estimates of the impact of supply disruptions of foreign dependent products on value added at different levels of aggregation. We find that firms, sectors, and regions are highly exposed to this supply shock. We also document that the impact on value added is highly heterogeneous. We argue that microdata are crucial for these exercises, especially when complementarities in production are strong.

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[40]These are the tobacco industry, programming and broadcasting activities, other textiles, furniture, paper and paper products.

[41]We also proceed to simulate a cut in the supply of FDPs for which supply is concentrated at the global level —in the spirit of Section 3.4. Figure A11 shows that the estimates closely align with our baseline results, indicating that a concentrated global supply poses a significant concern for the most relevant FDPs.

[42]For $\sigma = 0.05$, the impact doubles in size for aggregated data compared to firm-level data, while in the Leontief case it is almost five-fold Figure A13).

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Appendix

A Derivations

The CES aggregator combining intermediate goods and services given by

$$M_i = \left[\gamma_i^{\frac{1}{\sigma}} E_i^{\frac{\sigma-1}{\sigma}} + (1-\gamma_i)^{\frac{1}{\sigma}} X_i^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$$

gives us the following cost-minimization problem:

$$\begin{aligned} &\min_{E_i, X_i} p_E E_i + P_X X_i \\ \text{s.t.} \quad &\left[\gamma_i^{\frac{1}{\sigma}} E_i^{\frac{\sigma-1}{\sigma}} + (1-\gamma_i)^{\frac{1}{\sigma}} X_i^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \geq M_i \end{aligned}$$

The first-order conditions yield:

$$p_E = \lambda \gamma_i^{\frac{1}{\sigma}} E_i^{\frac{-1}{\sigma}} M_i^{\frac{1}{\sigma}} \tag{11}$$

and

$$p_X = \lambda (1-\gamma_i)^{\frac{1}{\sigma}} X_i^{\frac{-1}{\sigma}} M_i^{\frac{1}{\sigma}} \tag{12}$$

where λ is the associated Lagrange multiplier. Taking the ratio of the two first-order conditions, one gets:

$$\frac{p_E}{p_X} = \left(\frac{\gamma_i}{1-\gamma_i}\right)^{\frac{1}{\sigma}} \left(\frac{E_i}{X_i}\right)^{\frac{-1}{\sigma}} \tag{13}$$

Solving for FDPs yields:

$$X_i = \left(\frac{p_E}{p_X}\right)^{\sigma} \frac{1-\gamma_i}{\gamma_i} E_i \tag{14}$$

We take a partial equilibrium point of view in that relative prices are normalized to one and so is the supply of non-FDPs E_i. The supply of FDPs is then pinned down by the expenditures shares γ_i.

Plugging this term and the fact that E_i is normalized to one prior to the shock yields:

$$M_i = \left[\gamma_i^{\frac{1}{\sigma}} + (1-\gamma_i)^{\frac{1}{\sigma}} \left(\frac{1-\gamma_i}{\gamma_i}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$$

Given that expenditures on FDPs are given by $(1-\varepsilon_i)$ after the shock, the change in M is:[43]

$$\frac{\Delta M_i}{M_i} = \frac{\left[\gamma_i^{\frac{1}{\sigma}}(1-\varepsilon_i)^{\frac{\sigma-1}{\sigma}} + (1-\gamma_i)^{\frac{1}{\sigma}}\left(\frac{1-\gamma_i}{\gamma_i}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}}{\left[\gamma_i^{\frac{1}{\sigma}} + (1-\gamma_i)^{\frac{1}{\sigma}}\left(\frac{1-\gamma_i}{\gamma_i}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}} - 1 \tag{15}$$

We assume that K and L are fixed in the short-run. Proxying Δm with $\frac{\Delta M}{M}$, the log change in production can be recovered from eq. (5):

$$\Delta y_i = (1-\alpha_s-\beta_s)\Delta m_i \tag{16}$$

From the Cobb-Douglas production function specified in eq. (5), expenditure shares on goods and services are pinned down by the Cobb-Douglas exponents, i.e., $p_M M_i / p_Y Y_i = (1-\alpha_s-\beta_s)$. Value-added can thus be expressed as $\text{VA}_i = p_Y Y_i - p_M M_i = p_Y Y_i - (1-\alpha_s-\beta_s) p_Y Y_i$. Normalizing the price of the output good to unity, we obtain:

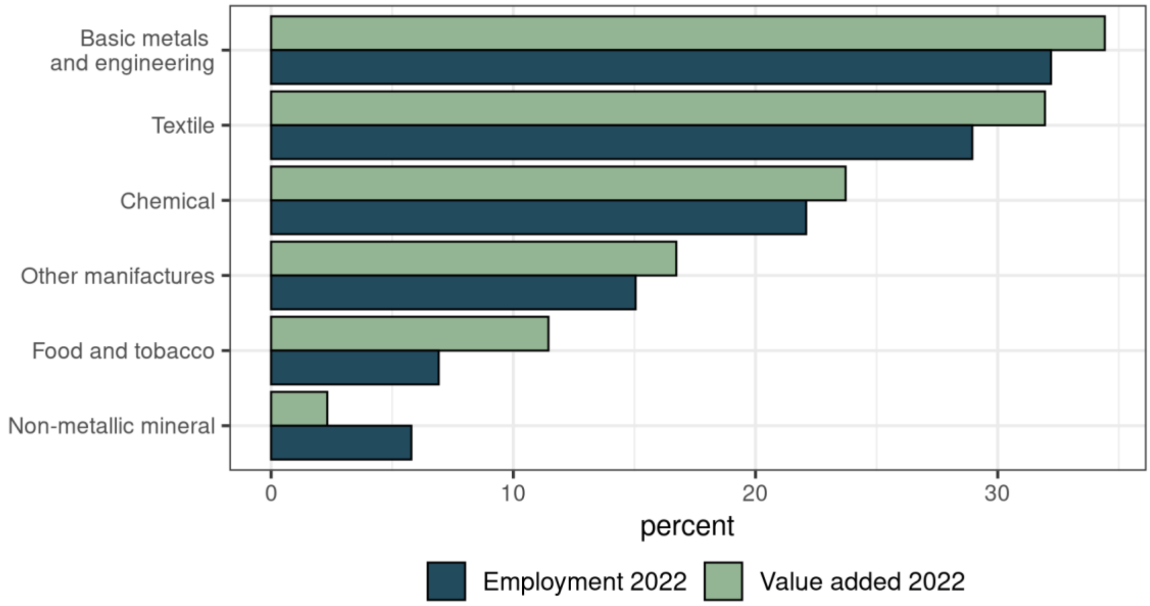
$$\Delta \text{va}_i = \Delta y_i \tag{17}$$

Combining eq. (15), eq. (16), and eq. (17) yields the firm-level impact of a reduction in FDPs on value-added given by eq. (7) in the text.

[43]When $\sigma = 0$, $\frac{\Delta M_i}{M_i} = -\varepsilon_i$. Conversely, when $\sigma = 1$, $\frac{\Delta M_i}{M_i} = \frac{\frac{1-\gamma}{\gamma}^{1-\gamma_i}(1-\varepsilon_i)^{\gamma_i}}{\frac{1-\gamma}{\gamma}^{1-\gamma_i}} - 1$.

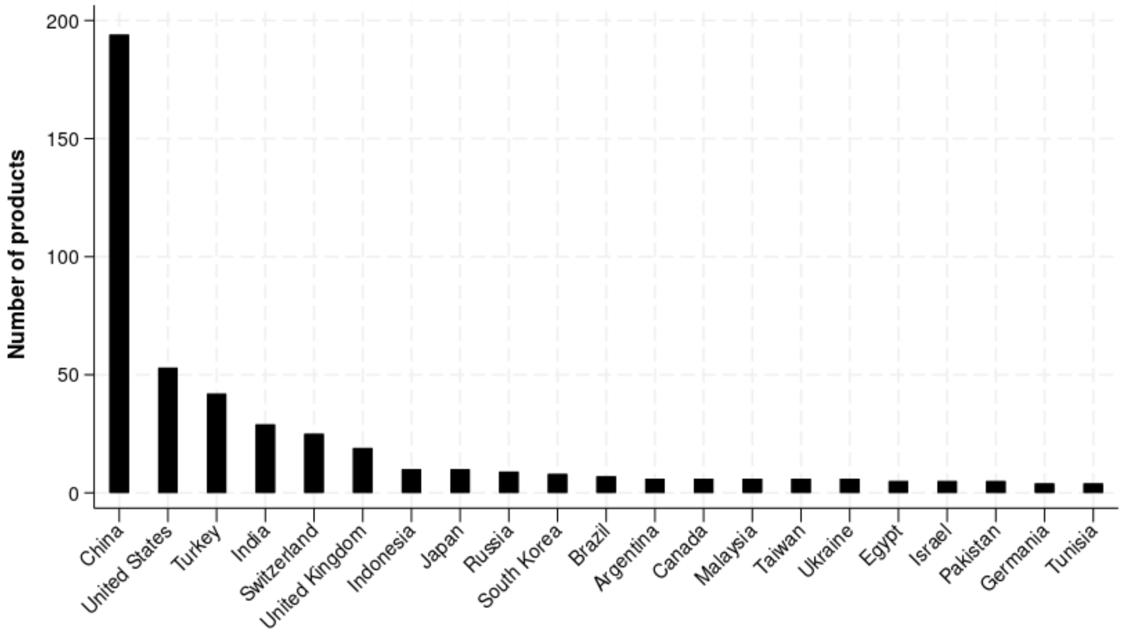
B Additional Figures

Figure A1: Exposure to China, by sector (share of sectoral employment and value-added)



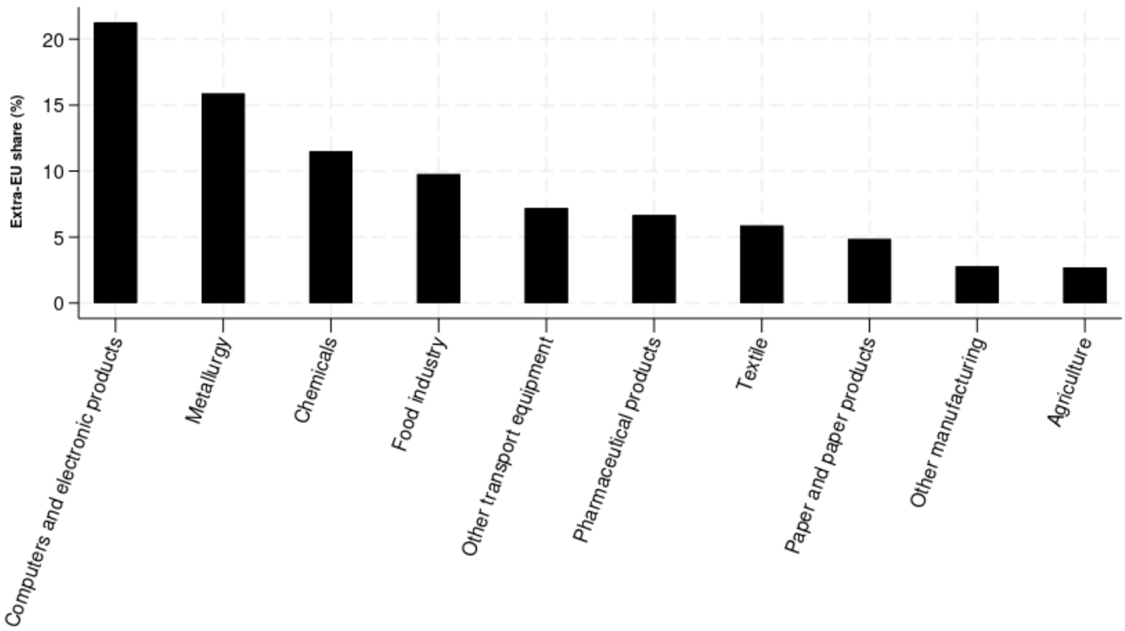
Notes: own elaboration on INVIND data.

Figure A2: Number of foreign-dependent products by country



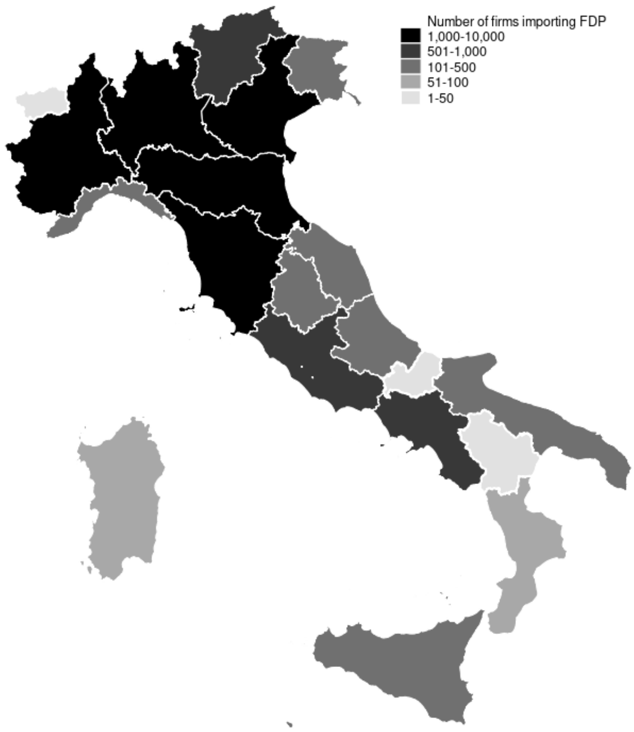
Notes: The bars represent the number of foreign dependent products (FDPs) by country. The x-axis represents the main exporter of each FDP.

Figure A3: Extra-EU Import Share of Foreign-Dependent Products by Sector



Notes: The bars represent the share of each sector's imports of foreign dependent products (FDPs) in Italian imports of FDPs.

Figure A4: Importers of FDPs by Region



Notes: This map represents the number of firms importing foreign dependent products (FDPs) by Italian regions.

Figure A5: Distribution of the ratio of expenditures on FDPs from high-risk countries to total FDP expenditures

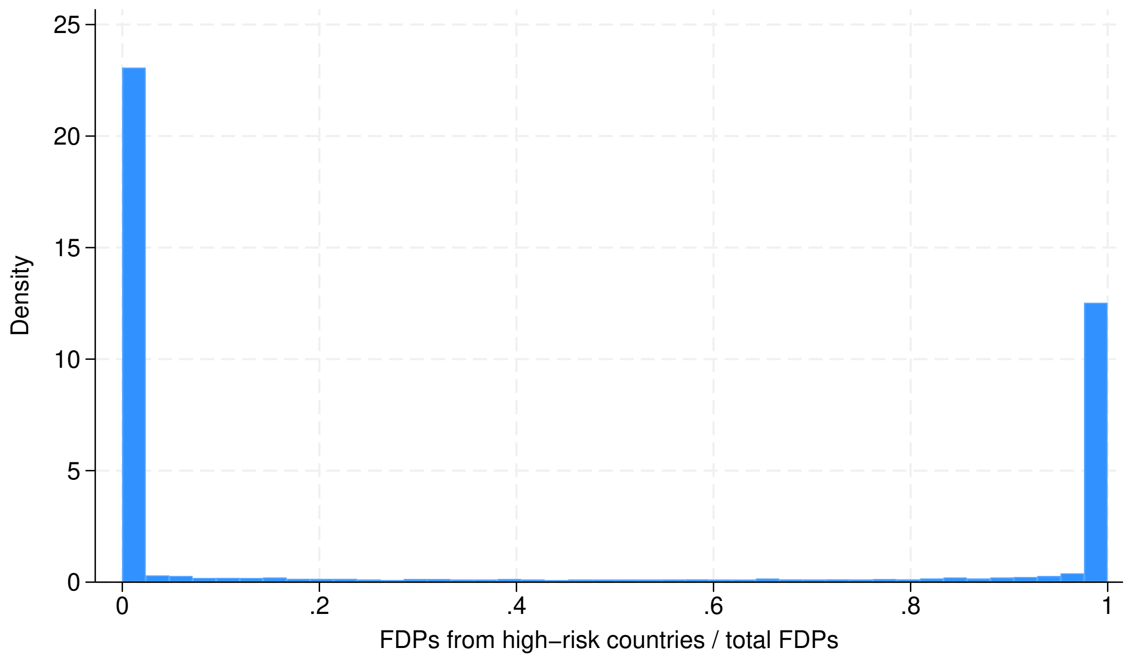


Figure A6: % share of firms exposed to a cut in FDPs supply from high-risk countries

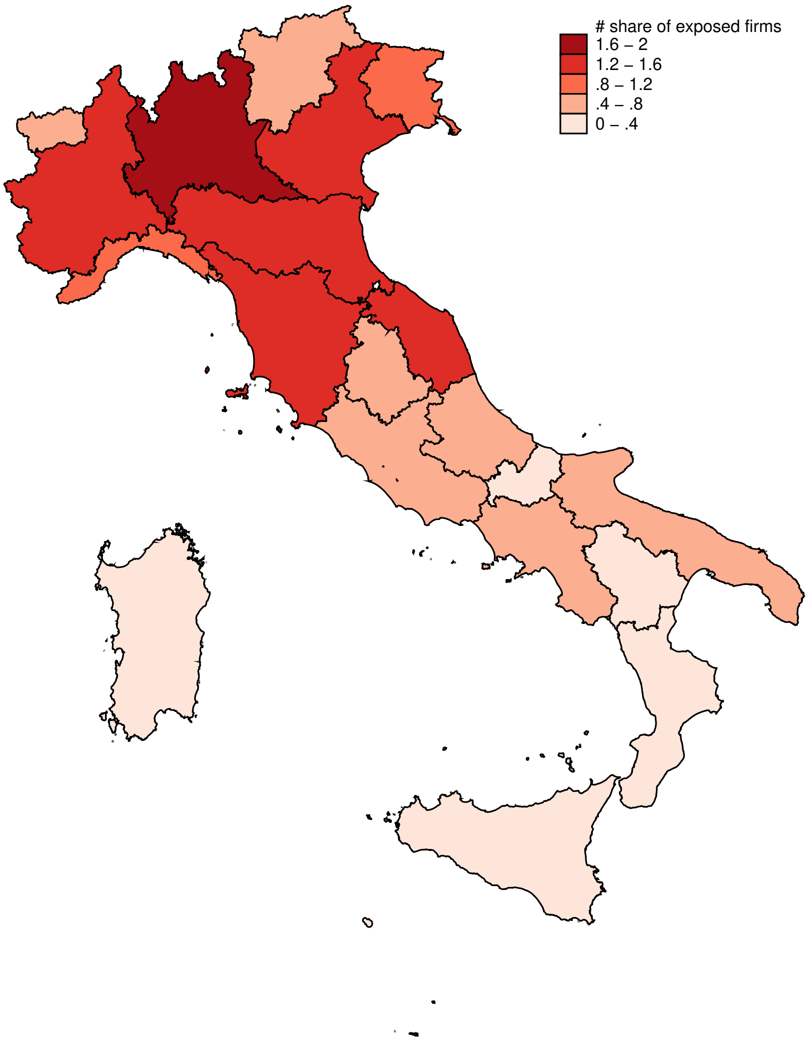


Figure A7: Value-added change (in %) following a disruption of FDPs, 50% cut in supply

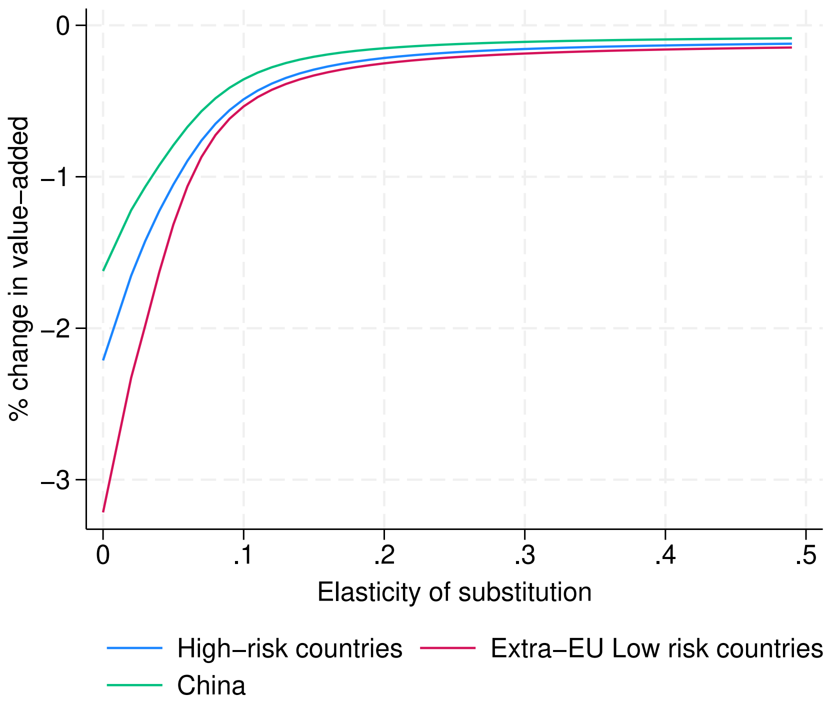


Figure A8: Manufacturing value-added change (in %) following a disruption of FDPs, 75% cut in supply

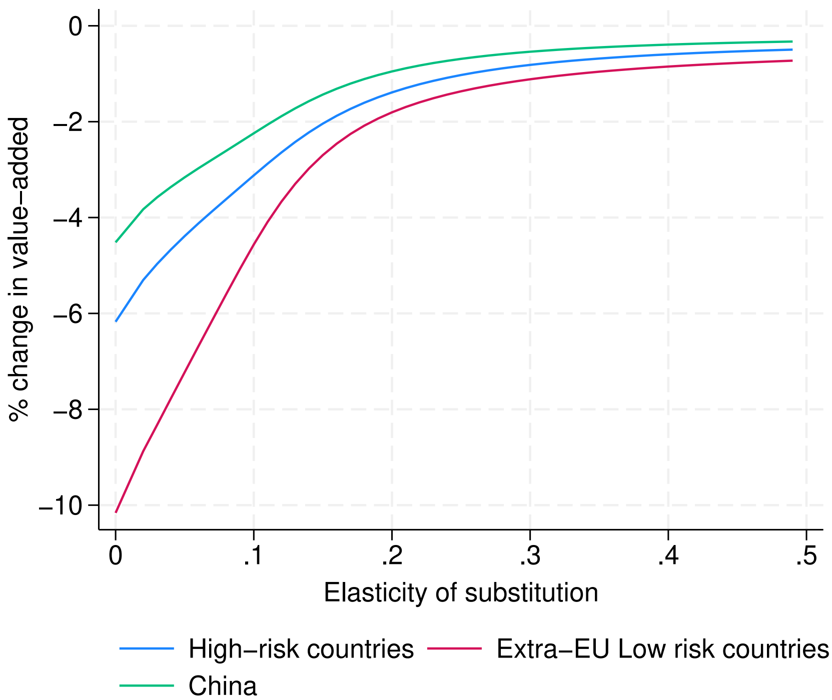


Figure A9: Value-added change (in %) following a 50% cut in FDPs from high-risk countries, baseline vs HS6-digit for different values of σ

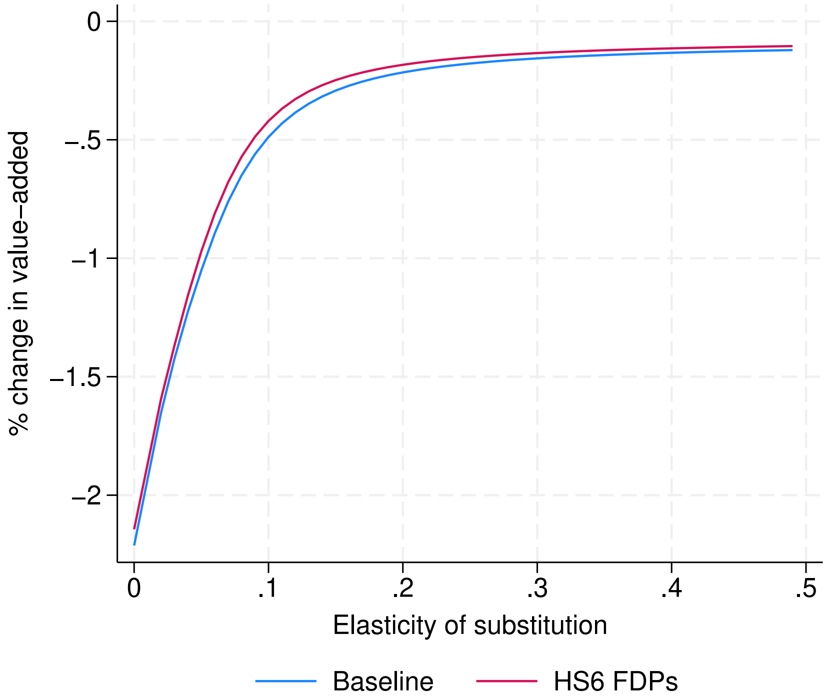


Figure A10: Value-added change (in %) following a 50% cut in FDPs from high-risk countries with $\sigma = 0$, HS8 vs HS6 by sector

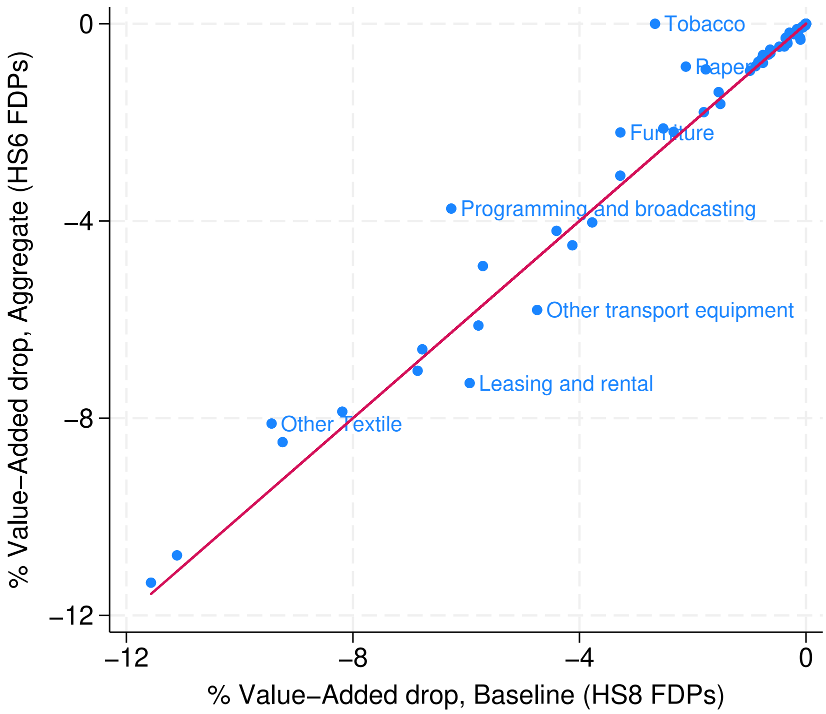


Figure A11: Value-added change (in %) following a 50% cut in supply from high-risk countries, FDPs with high concentration of supply, total economy

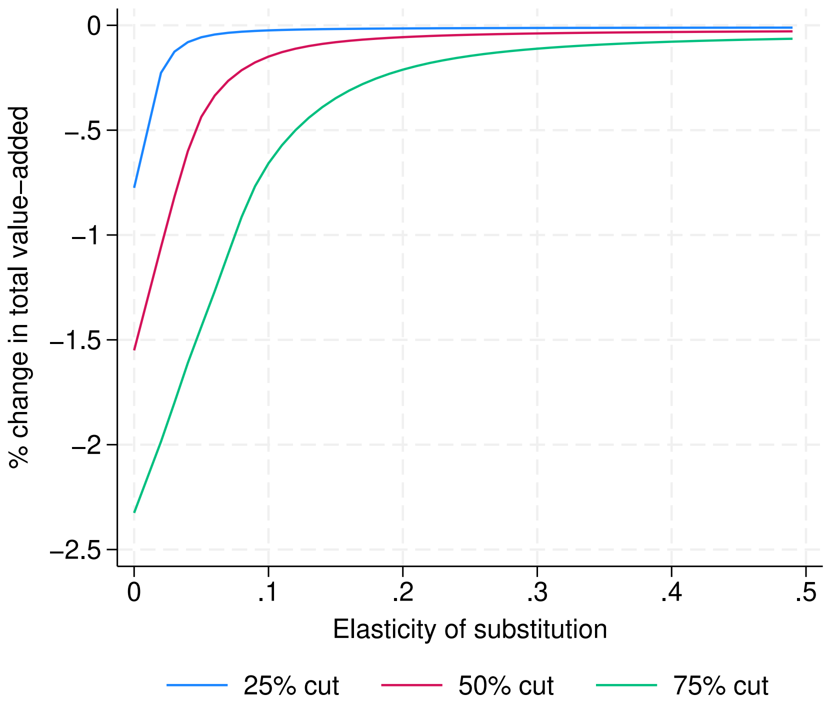


Figure A12: Aggregation bias: % Δ VA from 3-digit industry-level - % Δ VA from firm-level (baseline)

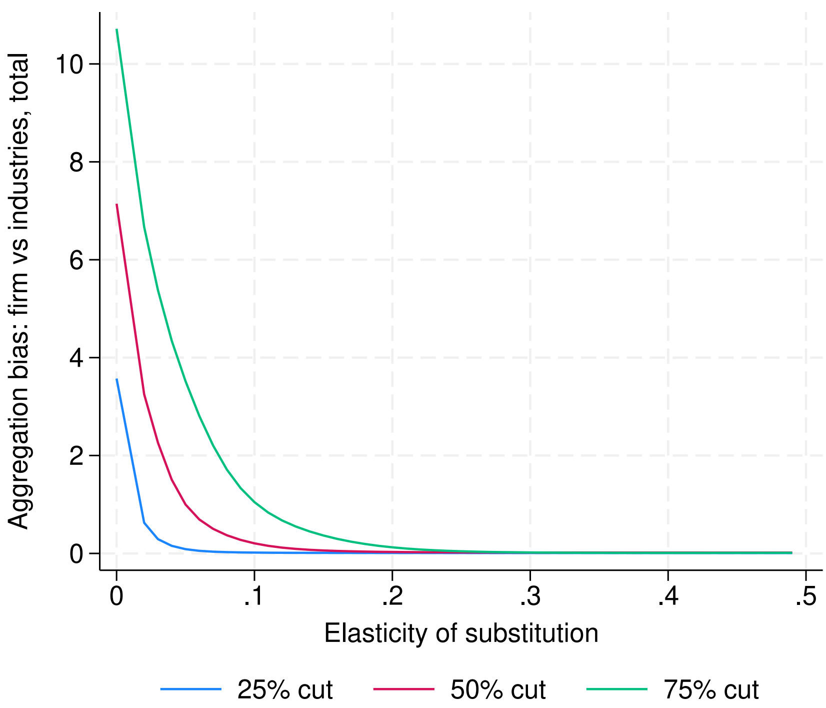
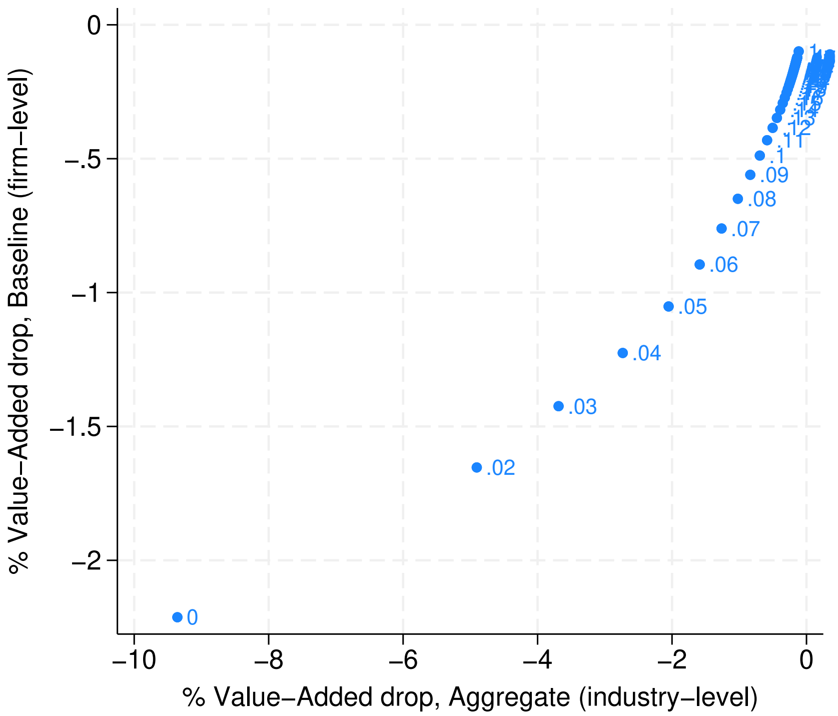


Figure A13: Value-added change (in %) following a 50% cut in FDPs from high-risk countries, firm-level vs industry-level for different values of σ



C Additional Tables

Table A1: Summary Statistics for FDPs sourcing, by country-group

	# of total Firms × Product		Share of total Firms × Product		Share of total imports	
	FDPs	Non-FDPs	FDPs	Non-FDPs	FDPs	Non-FDPs
High-risk only	11,375	817,674	26.61	15.73	9.57	4.68
Low-risk only	28,175	162,239	65.90	79.26	43.13	61.36
Low-risk and High-Risk	3,203	51,770	7.49	5.02	47.30	33.96
Total	42,753	1,031,683	100.00	100.00	100.00	100.00

Notes: The table displays summary statistics for foreign dependent products imports in 2019.

Table A2: FDP Premia: Additional Robustness

	log Employment		log Turnover		log Wages		log Labor Productivity	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Import FDP	0.026*	0.054***	-0.056***	0.039***	0.006	0.002	0.010	0.013*
	(0.015)	(0.013)	(0.015)	(0.014)	(0.005)	(0.004)	(0.008)	(0.008)
Obs.	62,053	62,009	67,125	67,083	61,981	61,936	60,070	60,026
4-digit industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Control for number of imported products	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports estimates from eq. (4) in the text. Standard errors clustered at the firm level. * significant at 10%, ** significant at 5%, *** significant at 1%. All columns include a control for the log of the number of imported products by each firm.