# Quantifying EU Strategic Dependence*

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**Abstract**

We develop a Strategic Dependency Index (SDI) to quantify the reliance of European Union (EU) member states on extra-EU imports of goods. Unlike existing empirical indicators based on trade flow data and concentration metrics, the SDI is recovered from a structural model of demand. We obtain trade elasticities, love-for-variety parameters, and country-pair-specific taste shifters from a nested CES framework using highly disaggregated product-level trade data for the EU27 over 2002–2021. These parameters are embedded in a welfare-based index that captures the sensitivity of consumer price indices to source-specific supply shocks. We show that the SDI provides stable and intuitive rankings of strategic dependency across products and sectors. Counterfactuals reveal that tariff-induced shocks generate concentrated welfare losses in chemicals, mining, and selected metals, while intra-EU subsidies disproportionately benefit sectors with high substitutability. The SDI offers a tractable framework for evaluating structural trade exposure and inform strategic autonomy debates.

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# 1 Introduction

Globalization has reshaped the world economy over the past decades, giving rise to highly interconnected global supply chains. However, recent events including natural shocks (e.g. the COVID-19 pandemic) and rising geopolitical tensions have revealed potential vulnerabilities of these global networks, as disruptions in one country can lead to severe shortages or price spikes for goods in others, especially when supply is highly concentrated in a few source countries. In response, most political blocs have promoted various policies aimed at achieving greater strategic autonomy. The European Union (EU) introduced its Open Strategic Autonomy (OSA) agenda in 2020 as its guiding paradigm, which seeks to reduce the EU's dependence on non-EU countries for critical goods and, where feasible, promote domestic production. Since then, several measures have been implemented in sectors of political relevance, such as the Critical Raw Materials Act, the Chips Act, the Net Zero Industrial Act, and the REPower EU plan for energy supplies.

We develop the Strategic Dependency Index (SDI) to evaluate the strategic dependence for goods imported to the EU. Unlike conventional indicators based on observed trade flows and concentration ratios, the SDI is recovered from a structural model of demand, additionally incorporating key structural demand parameters: (i) trade elasticities capturing the ease of substitution across source countries; (ii) love-for-variety elasticities measuring substitutability among similar products; and (iii) taste parameters reflecting persistent consumer preferences for extra-EU goods. A good is then more strategic when it is hard to replace by other countries (low trade elasticity), hard to substitute within the product class (low variety elasticity), and strongly preferred when sourced from extra-EU suppliers (high taste parameter).

We first estimate these structural parameters using a nested CES demand system based on the multi-country and multi-industry model of Lashkaripour and Lugovskyy (2023), applied to rich 8-digit product-level trade data from Eurostat Comext for all EU27 countries from 2002 to 2021. To address the endogeneity between import value and price, we estimate a 2SLS regression with multiple fixed effects where: (a) price is instrumented with the average export price of each source country to extra-EU countries, similar to the approach of Autor et al. (2013), and (b) the product expenditure share is instrumented with two standard count measures, following Khandelwal (2010).

We then construct a cost of living index that evaluates the impact of price shocks for particular varieties on the welfare of consumers in each of the EU countries. The index incorporates traditional import shares with the different demand parameters to obtain a measure that can vary at the product-country-pair level. The index can be used both as a measurement device to evaluate the strategic dependency for individual goods in each EU member state, as well as for welfare analysis with counterfactual scenarios, such as simulated policy shocks or supply disruptions.

We simulate two counterfactual scenarios: a 10% EU-wide tariff on imports from non-EU countries, and a 10% production subsidy for intra-EU sourcing. The results reveal which goods are plausibly strategic: those for which consumers face large welfare losses under import price shocks. In particular, in response to tariff shocks, the welfare cost is higher for specific chemicals, such as explosives, inorganic chemicals and fertilizers, mining products, petroleum and mineral fuels, and some basic metals, especially lead and raw materials. The most affected goods identified from the SDI differ from those flagged by traditional indicators, which include mining, wood, and textiles. In the subsidies scenario, lower EU prices generate a welfare gain or cost saving. The welfare gain is larger for basic metals, particularly lead and zinc, photographic goods, chemicals including cosmetics and explosives, and wood products. These products generally display a low preference for extra-EU imports and high substitutability.

Existing indicators typically assess strategic dependency using concentration measures like the Herfindahl-Hirschman Index (HHI) of import flows, often coupled with ad hoc thresholds to define strategic goods (European Commission (2021); Guinea and Sharma (2022); Jaravel and Méjean (2022); Baur and Flach (2022); Berthou et al. (2024)). These measures do not identify product substitutability or preferences for particular goods. Moreover, many strategic products identified through these methods turn out to reside in industries with high substitution elasticities, such as food, mining, textiles, and N.E.C. manufacturing (see, e.g., Imbs and Méjean (2015) and Fontagné et al. (2022)). Hence, while potentially highly concentrated, it would be relatively easy to substitute away from them in response to a shock. Finally, empirical measures are highly sensitive to short-run fluctuations: many products are considered strategic in one year but no longer in following years (Vicard and Wibaux (2023)), due to changes in trade flows and whether or not they cross chosen thresholds. Such volatility is at odds with the potential structural strategic nature of individual goods.

This paper develops a model-based index of strategic dependency that overcomes those difficulties, while allowing for counterfactual analysis. The use of a model allows us to retrieve structural demand parameters that measure substitutability across source countries and product varieties, as well as consumer preferences for products from a given country. Since these parameters are estimated over a long time period and are time-independent, our index captures the persistent strategic dependency of products.

## 2 Data and descriptive statistics

### 2.1 Data sources and construction

We construct a panel dataset of detailed product-level trade flows between all EU27 member states and their global partners for the years 2002-2021 by combining three data sources: Eurostat's Comext, CEPII's BACI, and the International Trade and Production Database (ITPD-S) at the US International Trade Commission. The resulting dataset comprises nearly 48 million observations with yearly information on trade values, quantities, prices, and domestic expenditures. It serves as the basis for calculating empirical concentration indices (Section 3), estimating model parameters (Section 4.4), and the construction of our Strategic Dependency Index (Section 5).

We use the Comext database to obtain harmonized annual import and export flows at the CN8 product level for all EU27 countries and their trading partners. Each EU country reports monthly import and export values and quantities with each trade partner at the 8-digit Combined Nomenclature (CN8) level, covering around 7,800 unique products.[1] Export values are reported free on board (FOB), while import values include costs, insurance, and freight (CIF), all in current euros. We first aggregate monthly observations to yearly values. Next, to address changes in product codes over time, we follow Pierce and Schott (2012) and Van Beveren et al. (2012), and construct stable CN8+ codes using product concordances from CIRCABC.[2] Unit values - defined as values over quantities - are calculated

[1]Countries in Comext are defined as UN recognized sovereign countries, non-sovereign territories, and customs territories and regions. We exclude the customs territories and regions, as well as any aggregates.

[2]CN8 codes extend the global 6-digit Harmonized System (HS6) classification by two digits. HS product codes can change due to statistical reclassifications of products over time, coordinated by the World Customs Organization, which are adopted in the CN8 product codes used by EU member states. Changes in codes are not always one-to-one, but may be one-to-many, many-to-one, or many-to-many.

as standard proxies for prices.

Next, we use the CEPII BACI dataset with information on annual product-level trade flows at the HS6 level across all countries between 2002 and 2021. We extract export flows from all countries to extra-EU countries to construct instrumental variables for the regressions in Section 4. To avoid aggregation mismatches, we restrict the sample to CN8 products that map cleanly to stable HS6 codes, excluding CN8+ codes for the construction of the instruments.

Finally, we add domestic production and trade data from the ITPD-S database, covering the years 2002–2019 (currently the latest year available). These data report domestic trade flows across 170 ITPD industries and allow us to measure domestic absorption, calculated as domestic production minus gross exports, at the industry-country level. We map ITPD industries to ISIC Rev.3 4-digit industries, and subsequently to HS codes using the World Bank's World Integrated Trade Solutions (WITS) concordance tables. Domestic absorption is then aggregated to the HS2 product level and matched to the Comext data to obtain import and domestic expenditure shares for the construction of the Strategic Dependency Index.

### 2.2 Descriptive statistics

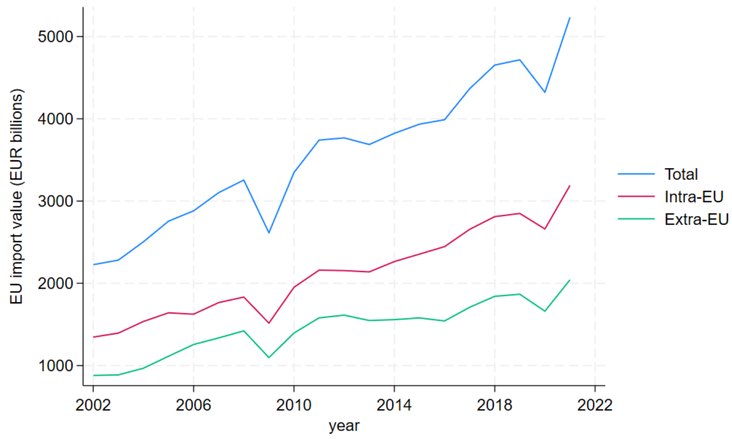
We begin by summarizing the key variables used in our analysis in Table 5 in the Appendix. Import values are highly right-skewed: the yearly mean import value is 1.5 million euro, while the median is only 21,000 euro. This also holds in real terms for import quantities, with a mean of 1,223 tonnes and a median of just 2 tonnes. This skewness remains also in relative terms: while the median import share of products, within a given origin-destination-sector, is 0.2%, the mean is 6%, with shares above 13% at the 90th percentile. By contrast, the number of origin countries for a given destination-product-year and the number of imported products by origin-destination-sector-year are less dispersed, with mean values of 13 and 16, respectively. These patterns already suggest a substantial degree of import concentration in EU trade relationships.

We next examine the evolution of EU imports over time. Figure 1 plots the total value and quantity of imports from intra-EU and extra-EU origins between 2002 and 2021. The overall import value of EU27 countries (panel a) more than doubled during this period, from approximately 2 trillion euro in 2002 to over 5 trillion euro in 2021. Intra-EU imports account for around 60% of this total and has grown more rapidly than extra-EU imports since the 2008 global financial crisis. In real terms (panel b), total import quantities exhibit a flatter trend, reaching over 3 billion tonnes in 2021. Initially, extra-EU import volumes exceeded those from within the EU, but this gap narrowed substantially after 2008. These dynamics are consistent with evidence of a slowdown in globalization during the post-crisis period (Constantinescu et al. (2015); Baldwin (2016); Antràs (2020)). Yet, extra-EU imports remain significant, representing about 40% of total import value and nearly half of total import quantity as of 2021.

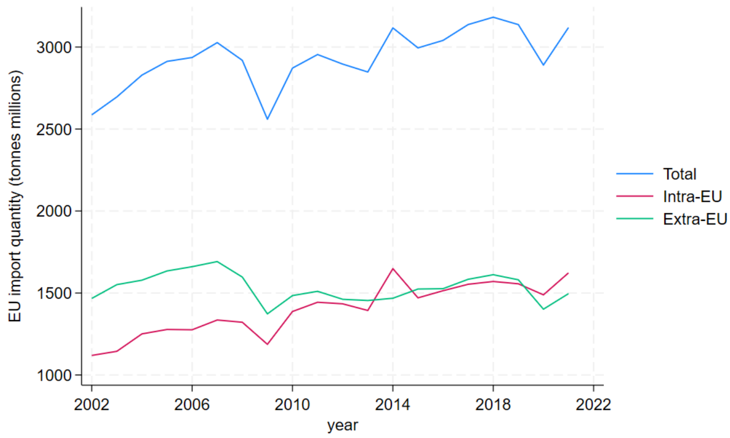
Figure 2 provides further detail on the composition of extra-EU imports by plotting the share of import value attributable to the top five non-EU trading partners over time. These top countries consistently account for more than half of total extra-EU import value. The composition, however, has changed dramatically. In 2002, the United States was the EU's largest extra-EU supplier, accounting for 15% of import value. By 2021, its share had declined to 11%, while China's share rose steadily from 8% to 23%. This shift highlights the increasing dependence of the EU on individual supplying countries, with a significant increase of Chinese imports over the past decade.

Taken together, these descriptive statistics point to structural patterns in EU trade: a small number of supplying countries dominate many trade relationships, with a high and increasing concentration in various goods, signaling potential dependence of the EU on particular third countries for such products.

Figure 1: EU imports by EU and extra-EU origin countries over 2002-2021

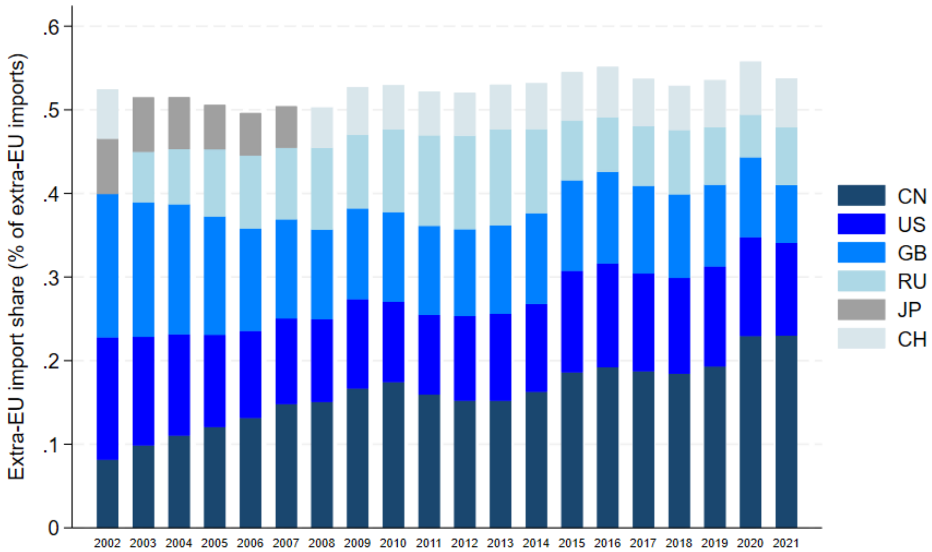



(a) Import value




(b) Import quantity

Figure 2: EU imports from top-5 extra-EU countries over 2002-2021




# 3 Empirical indicators of strategic dependence

## 3.1 Existing indicators

There are by now several empirical indicators used to assess the EU's dependence on imports from third countries (see, e.g., Vicard and Wibaux (2023) for an overview). For example, the European Commission (2021) identifies three sub-indicators for strategic dependence at the product level. A product is considered strategic if all three exceed chosen thresholds. In particular:

1. Herfindal-Hirschman Index (HHI) of concentration of EU imports across extra-EU countries: $I_1 = \sum_{i \in EX} s_i^2 > 0.4$, where $s_i$ is the market share of extra-EU country $i$ in EU imports from all extra-EU countries;

2. Share of EU imports from extra-EU countries: $I_2 = \frac{\text{Extra-EU Imports}}{\text{Total Imports}} > 0.5$;

3. Ratio of extra-EU imports over EU total exports: $I_3 = \frac{\text{Extra-EU Imports}}{\text{Total Exports}} > 1$.

The last sub-indicator serves as a proxy for EU domestic production, for which data is not available at this level of granularity. Berthou et al. (2024) consider two product-level measures of concentration to study the import vulnerability of OECD countries: (i) the HHI of OECD imports across origin countries (similar to the first criterion above), and (ii) the HHI of global exports across supplying countries. The EU Critical Raw Materials Act (European Union, 2024) also specifies four diversification benchmarks to diversify the supply chains of strategic raw materials: (i) at least 10% of the EU's annual consumption for extraction should be sourced domestically, (ii) at least 40% of its consumption for processing should be done within the EU, (iii) at least 25% for recycling, and (iv) no more than 65% of a strategic raw material should be sourced from a single third country.

## 3.2 Concentration and import share metrics

We calculate several metrics of concentration and the share of extra-EU imports for CN 8-digit products in our panel. Table 1 summarizes two concentration measures. Column 3 reports the median HHI of extra-EU import values across all products within an industry, averaged over our sample period. Overall, the median HHI is relatively high at 0.35. The most concentrated products tend to be within Food (0.54); Petroleum, coal, mineral fuels (0.42); Agriculture (0.39); Chemicals (0.38); and N.E.C. and recycling (0.38). The least concentrated products tend to be within Rubber and plastics (0.26); Non-metallic minerals (0.28); Machinery (0.28); and Electrical Equipment (0.28). Column 4 shows the import share of the source country with the largest import share to the EU. The median share of the first extra-EU source country across all products is 0.51. This share tends to be largely higher for products in the same industries: Food (0.70); Petroleum, coal, mineral fuels (0.57); N.E.C. and recycling (0.57); and Agriculture (0.55), and lower in Rubber and plastics (0.41); Machinery (0.43); Electrical Equipment (0.44); and Non-metallic minerals (0.45).

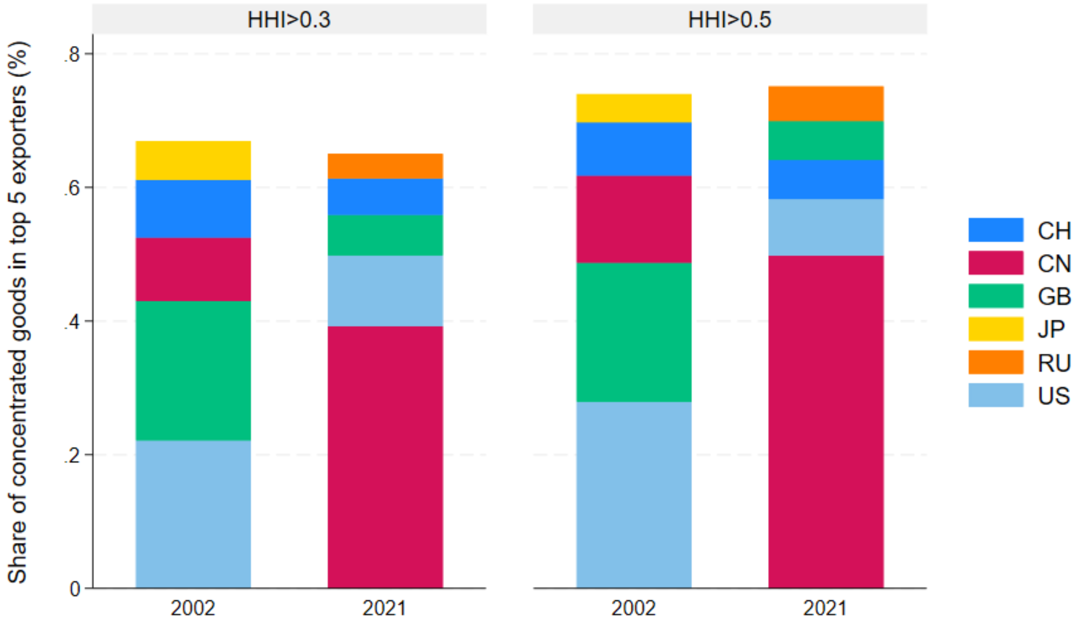
Figure 3 shows the subsets of concentrated goods ($HHI > 0.3$) and highly concentrated goods ($HHI > 0.5$) for the years 2002 and 2021. The top-5 countries export around two-thirds of concentrated goods and around 75% of highly concentrated goods to the EU. These shares are quite persistent over time, while their composition across source countries changes significantly. In 2002, the USA is the first exporter of concentrated (20%) and highly concentrated goods (25%), while China becomes the first exporter of concentrated goods (40%) and very concentrated goods (50%) in 2021. Moreover, China's shares of concentrated goods are much higher than its 23% overall export share (Figure 2), while the other top-5 exporters show similar export shares for concentrated goods and the whole set of goods. This suggests that EU imports from China involve particularly concentrated goods compared to the other top-5 exporters.

Table 1: Measures of concentration of extra-EU imports by ISIC industry

| Sector | ISIC4 codes | HHI | 1st source-country share |
|---|---|---|---|
| Agriculture | 100-999 | 0.39 | 0.55 |
| Mining | 1000-1499 | 0.34 | 0.51 |
| Food | 1500-1699 | 0.54 | 0.70 |
| Textiles | 1700-1999 | 0.30 | 0.46 |
| Wood | 2000-2099 | 0.34 | 0.51 |
| Paper | 2100-2299 | 0.35 | 0.51 |
| Petroleum, mineral fuels | 2300-2399 | 0.42 | 0.57 |
| Chemicals | 2400-2499 | 0.38 | 0.53 |
| Rubber and plastics | 2500-2599 | 0.26 | 0.41 |
| Non-metallic minerals | 2600-2699 | 0.28 | 0.45 |
| Basic metals | 2700-2799 | 0.34 | 0.49 |
| Fabricated metals | 2800-2899 | 0.28 | 0.44 |
| Machinery | 2900-3099 | 0.28 | 0.43 |
| Electrical equipment | 3100-3399 | 0.28 | 0.44 |
| Transport equipment | 3400-3599 | 0.34 | 0.49 |
| N.E.C. and recycling | 3600-3800 | 0.38 | 0.57 |
| Total | | 0.35 | 0.51 |

Next, Table 2 reports three variants of extra-EU import shares into the EU. Column 3 shows the extra-EU share in total EU imports, again reported as the median value of CN8 products within industries over the panel. In total, extra-EU imports account for 41% of total EU imports. This share is particularly high in the sectors of Petroleum and mineral fuels (75%); Mining (64%); Textiles (50%); and Electrical equipment (46%). The overall ratio of extra-EU imports over EU exports of the same product

Figure 3: Concentrated goods in top 5 extra-EU countries in 2002 and 2021




(column 5) is 0.97, i.e. EU exports slightly outweigh extra-EU imports overall.[3] This ratio provides similar results for the most dependent sectors, especially Petroleum, coal, mineral fuels (4.68) and Mining (4.09), for which extra-EU imports are hardly replaced with EU domestic production. We also provide a measure of extra-EU imports in total EU domestic absorption in column 5. Since detailed data on product-level production is not available, we aggregate CN8 products to HS2 chapters for which we do observe EU domestic production. The total extra-EU import share amounts to 13% of EU domestic absorption, and the same sectors turn out to be highly concentrated as a share of EU demand. Hence, while accounting for total demand largely reduces the share of less concentrated sectors (e.g. agriculture, food, and non-metallic minerals) EU domestic production does not overturn import concentration of goods in highly concentrated sectors.

[3]Note that EU exports are FOB values, while extra-EU imports are CIF values in Comext. Therefore, the ratio is likely to be generally biased upwards.

Table 2: Measures on the share of extra-EU imports by ISIC industry

| Sector | ISIC4 codes | Extra-EU/ total imports | Extra-EU/ total exports | Extra-EU/ total demand |
|---|---|---|---|---|
| Agriculture | 100-999 | 0.25 | 1.10 | 0.06 |
| Mining | 1000-1499 | 0.44 | 2.22 | 0.21 |
| Food | 1500-1699 | 0.16 | 0.74 | 0.05 |
| Textiles | 1700-1999 | 0.44 | 1.22 | 0.18 |
| Wood | 2000-2099 | 0.29 | 1.16 | 0.06 |
| Paper | 2100-2299 | 0.19 | 0.53 | 0.05 |
| Petroleum, mineral fuels | 2300-2399 | 0.38 | 2.55 | 0.42 |
| Chemicals | 2400-2499 | 0.33 | 0.87 | 0.14 |
| Rubber and plastics | 2500-2599 | 0.24 | 0.69 | 0.07 |
| Non-metallic minerals | 2600-2699 | 0.28 | 0.60 | 0.04 |
| Basic metals | 2700-2799 | 0.24 | 0.85 | 0.09 |
| Fabricated metals | 2800-2899 | 0.30 | 0.72 | 0.09 |
| Machinery | 2900-3099 | 0.30 | 0.34 | 0.15 |
| Electrical equipment | 3100-3399 | 0.45 | 0.86 | 0.21 |
| Transport equipment | 3400-3599 | 0.26 | 0.50 | 0.11 |
| N.E.C. and recycling | 3600-3800 | 0.51 | 1.44 | 0.07 |
| Total | | 0.31 | 0.78 | 0.13 |

### 3.3 Strategic goods

We now compute the strategic dependence indicator using the methodology of European Commission (2021), applied to the more granular Comext data at CN8 level than the HS6 products of the Commission. We identify 831 CN8 products as strategic in 2002, and 891 products in 2021. Strategic goods account for around 11% of CN8 goods in any given year.[4]

In the cross-section, strategic goods concentrate in N.E.C. manufacturing and recycling (29%), such as umbrellas (HS2=66), feathers and related articles (HS2=67), and toys and sport equipment (HS2=95); Mining products (19%); Wood (17%), particularly straw and plaiting materials (HS2=46); Petroleum and mineral fuels (15%); and Textiles (15%), such as leather (HS2=42), silk (HS2=50), and headgear (HS2=65). However, many of these sectors, such as mining, wood, and textiles, turn out to have high elasticities of substitution (e.g., Imbs and Méjean (2015) and Fontagné et al. (2022)).

When evaluating strategic dependence over time, many products are considered strategic in one year but no longer in following years. For example, only 47% of strategic goods in 2002 remain strategic after five years, and only 32% after ten years. This is due to the volatility of sub-indicators crossing or not crossing thresholds over time. For example, 8% of observations for sub-indicator 1, and 10% and 15% for sub-indicators 2 and 3 respectively, exhibit growth rates above 100% from year to year. It is unclear whether these changes stem from volatility in trade flows or structural changes in strategic dependence over time.

[4]The European Commission identifies around 400 strategic goods at the HS6 level in 2019 (the latest year available), versus 860 in the CN8 data. This difference is attributed to the different granularity of product codes, as well as different harmonization of product codes over time as we employ CN8+ codes.

# 4 A structural framework for dependency

In this section, we provide a structural framework that allows us to recover key demand parameters, such as substitution elasticities and taste shifters, which are not directly observable in the data. We build on the multi-country, multi-industry model of Lashkaripour and Lugovskyy (2023), focusing on the demand side implications. We then estimate the different demand parameters for all industries $k$, which serve as inputs for the Strategic Dependency Index in Section 5.

## 4.1 Preferences and demand

Consider an endowment economy with multiple countries $i, j \in C$, industries $k \in K$, and time indexed by $t$. A representative consumer in country $i$ maximizes homothetic preferences by choosing a bundle of industry $k$ goods in $t$:

$$\max_{Q_{i,1t},\dots,Q_{i,Kt}} U_i(Q_{i,1t}, \dots, Q_{i,Kt})$$

subject to her budget constraint

$$\sum_{k=1}^{K} P_{i,kt} Q_{i,kt} = Y_{i,t}$$

where $Q_{i,kt}$ is the quantity consumed of industry $k$ goods in country $i$ at time $t$, $P_{i,kt}$ is the respective ideal price index, and $Y_{i,t}$ is total expenditures. Since there are no production choices, expenditures are exogenous. Each $Q_{i,kt}$ is a CES aggregator of goods sourced across supplying countries $j$:

$$Q_{i,kt} = \left[ \sum_{j \in C} \alpha_{ji,kt}^{\frac{1}{\sigma_k}} Q_{ji,kt}^{\frac{\sigma_k - 1}{\sigma_k}} \right]^{\frac{\sigma_k}{\sigma_k - 1}} \tag{1}$$

where $Q_{ji,kt}$ represent industry $k$ goods produced in country $j$ and consumed in country $i$ at time $t$, $\sigma_k > 1$ is the elasticity of substitution across origin countries for industry $k$ goods, and $\alpha_{ji,kt}$ is a time-varying preference shifter, capturing consumers' $i$ taste for goods $k$ from a specific source country $j$. This taste shifter captures non-price factors such as reputation, perceived quality, geopolitical ties, or supply chain stickiness. A higher value of $\alpha_{ji,kt}$ implies stronger preferences for goods from origin $j$ and leads to a higher demand conditional on prices. In turn, $Q_{ji,kt}$ aggregates the demand for varieties of goods within a country-pair-sector:

$$Q_{ji,kt} = \left[ \int_{\omega \in \Omega_{ji,kt}} \phi_{ji,kt}(\omega)^{\frac{1}{\gamma_k}} q_{ji,kt}(\omega)^{\frac{\gamma_k - 1}{\gamma_k}} d\omega \right]^{\frac{\gamma_k}{\gamma_k - 1}} \tag{2}$$

where $q_{ji,kt}(\omega)$ is the quantity consumed of variety $\omega$ within industry $k$ goods produced in $j$ and consumed in $i$ at time $t$, $\gamma_k \geq \sigma_k > 1$ is the elasticity of substitution across varieties in industry $k$, and $\phi_{ji,kt}(\omega)$ is a variety-specific taste shifter.

The demand for each individual variety is then given by:

$$q_{ji,kt}(\omega) = \phi_{ji,kt}(\omega) \left[ \frac{p_{ji,kt}(\omega)}{P_{ji,kt}} \right]^{-\gamma_k} \alpha_{ji,kt} \left[ \frac{P_{ji,kt}}{P_{i,kt}} \right]^{-\sigma_k} Q_{i,kt} \tag{3}$$

where $p_{ji,kt}(\omega)$ is the price of variety $\omega$ of industry $k$ produced in $j$ and consumed in $i$, $P_{ji,kt} =$

$\left[\int_{\omega\in\Omega_{ji,kt}} \phi_{ji,kt}(\omega)p_{ji,kt}(\omega)^{1-\gamma_k}\right]^{\frac{1}{1-\gamma_k}}$ is the ideal price index related to $Q_{ji,kt}$, and $P_{i,kt} = \left(\sum_{j=1}^{C} \alpha_{ji,kt} P_{ji,kt}^{1-\sigma_k}\right)^{\frac{1}{1-\sigma_k}}$ is the price index for sector $k$ goods consumed in $i$ at $t$.

This nested CES formulation offers a tractable yet flexible framework to capture key margins of trade-related strategic dependence. It allows us to identify three parameters of interest: $\sigma_k$, which governs the substitutability across source countries and corresponds to the elasticity of trade with respect to trade costs (the 'trade elasticity' $\sigma_k - 1$), $\gamma_k$, which measures the substitutability across varieties within industry and reflects consumers' love for variety, and $\alpha_{ji,kt}$, which embeds consumers' taste for goods from specific origin countries. Together, these parameters determine how consumers reallocate demand in response to price changes, and they form the basis for our structural measure of strategic dependency.

### 4.2 Parameter estimation

We derive an estimable version of the product-level demand equation to obtain a specification that allows us to estimate the key parameters of interest. Log-linearizing eq(3):

$$\ln x_{ji,kt}(\omega) = (1-\sigma_k)\ln p_{ji,kt}(\omega) + \left(1 - \frac{\sigma_k - 1}{\gamma_k - 1}\right)\ln \lambda_{ji,kt}(\omega) + \ln \delta_{i,kt} + \ln \alpha_{ji,kt} + \ln \phi_{ji,kt}(\omega) \tag{4}$$

where $x_{ji,kt}(\omega) = p_{ji,kt}(\omega)q_{ji,kt}(\omega)$ is the import value of variety $\omega$, $p_{ji,kt}(\omega)$ is its import price, and $\lambda_{ji,kt}(\omega)$ is the expenditure share on variety $\omega$ within industry $k$ goods imported from country $j$ at time $t$. We derive $\lambda_{ji,kt}(\omega)$ from the product-level CES structure by rewriting the quantity demand in value terms, and then normalizing by the total value of imports from origin $j$ to destination $i$ in sector $k$ in $t$, so that:

$$\lambda_{ji,kt}(\omega) \equiv \frac{x_{ji,kt}(\omega)}{\sum_{\omega\in\Omega_{ji,kt}} x_{ji,kt}} = p_{ji,kt}(\omega)\phi_{ji,kt}(\omega)\left[\frac{p_{ji,kt}(\omega)}{P_{ji,kt}}\right]^{1-\gamma_k}$$

Next, $\delta_{i,kt} \equiv P_{i,kt}^{\sigma_k} Q_{i,kt}$ includes industry-level expenditures and is estimated with destination country-sector-year fixed effects. We assume that the origin-destination-sector taste shifter $\alpha_{ji,kt}$ can be decomposed into a time-invariant component $\alpha_{ji,k}$ and a time-varying component $\alpha_{ji,kt}$. We are interested in $\alpha_{ji,k}$, as it represents the persistent preferences for goods in the destination country from a specific source country over time, and will be estimated as origin-destination-sector fixed effects.[5] Similarly, we assume that the variety-level taste shifter $\phi_{ji,kt}(\omega)$ can be decomposed into a time-invariant component $\phi_{ji,k}(\omega)$ and a time-variant element $\phi_{ji,kt}(\omega)$. We control for $\phi_{ji,k}(\omega)$ with origin-destination-sector-product fixed effects. The time-varying $\phi_{ji,kt}(\omega)$, which includes changes in consumers' taste for a specific good and other unobserved variables that might explain the demand change for that variety, is the error term. Hence, we estimate the following demand equation in logs with three sets of fixed effects:

$$\ln x_{ji,kt}(\omega) = (1-\sigma_k)\ln p_{ji,kt}(\omega) + \left(1 - \frac{\sigma_k - 1}{\gamma_k - 1}\right)\ln \lambda_{ji,kt}(\omega) + \ln \delta_{i,kt} + \ln \alpha_{ji,k} + \ln \phi_{ji,k}(\omega) + \ln \phi_{ji,kt}(\omega) \tag{5}$$

We define product varieties as is standard in the literature (e.g., Feenstra (1994), Broda and Weinstein (2006), Caliendo and Parro (2015)): a variety $\omega$ is identified at the product (CN8) level, sourced

[5] We do not separately identify $\alpha_{ji,kt}$, as it would be perfectly collinear with the other fixed effects at the destination-sector-year and origin-destination-sector levels.

from any origin country $j$ to any EU destination country $i$ in sector $k$ and year $t$. These are the units of observation in the Comext database. The industry $k$ index is assigned to HS 2-digit aggregate products. Then, $x_{ji,kt}(\omega)$ and $p_{ji,kt}(\omega)$ are directly observable in the data, and $\lambda_{ji,kt}(\omega)$ is calculated from country-pair-sector imports.

### 4.3 Identification strategy

The estimation of demand elasticities from trade data is subject to well-known endogeneity concerns. In particular, both prices and expenditure shares are likely to be endogenous to unobserved demand shocks. Higher demand for a given variety may raise its observed import price and increase its expenditure share, leading to biased estimates of substitution elasticities if these variables are treated as exogenous. To address this, we adopt an instrumental variables strategy that isolates exogenous variation in both prices and expenditure shares, allowing us to identify the demand parameters of interest.

We first address the endogeneity of prices. Unobserved demand shocks may lead to both higher import quantities and higher prices, inducing a positive correlation between the observed import price $p_{ji,kt}(\omega)$ and the error term in the demand equation, biasing estimates of the trade elasticity $\sigma_k - 1$. To address this, we employ an approach similar to Autor et al. (2013) and construct an instrument based on the average export price of variety $\omega$ from origin country $j$ to non-EU destinations at time $t$:

$$p^e_{j,kt}(\omega) = \sum_{i \in EX} \frac{x_{ji,kt}(\omega)}{x_{j,kt}(\omega)} p^e_{ji,kt}(\omega) \tag{6}$$

where $p^e_{ji,kt}(\omega)$ is the export price from country $j$ to each extra-EU country $i$, and the weights $\frac{x_{ji,kt}(\omega)}{x_{j,kt}(\omega)}$ reflect the share of exports to that destination. By excluding EU destinations from the construction of the instrument, we isolate supply-driven components of export prices, such as cost shocks, productivity, or quality differences, that are common across extra-EU countries and plausibly exogenous to EU-specific demand shocks.

A remaining concern is the presence of aggregate demand shocks that are correlated across EU and extra-EU countries. In such cases, export prices to extra-EU destinations may be affected by unobserved demand shocks that also affect EU imports, potentially violating the exclusion restriction. To mitigate this concern, we include destination-sector-year, origin-destination-sector, and sector-product fixed effects in the first-stage regression, thereby absorbing common demand shocks across markets. See, e.g., Wooldridge (2010) for a discussion of fixed effects in first versus second stages.[6]

Data on export prices at the CN8 product level from the Comext database are only available for EU origin countries. To obtain export prices for all global origin countries, we therefore use the CEPII BACI database, which reports prices at the HS6 level. We restrict our analysis to HS6 products that can be mapped consistently to CN8 codes over time. While HS6 prices are more aggregated than CN8 prices, this allows us to construct a consistent instrument across all countries. To assess whether this aggregation introduces bias, we conduct a robustness check (see Table 6 in the Appendix) using the average CN8-level export price from EU origin countries to extra-EU destinations from the Comext

[6]While some studies use tariffs as instruments for import prices, this strategy is not viable in our setting. First, tariffs may be endogenous to trade flows, for example, if imposed in response to trade shocks or if firms adjust imports in anticipation of tariff changes. Second, EU tariffs on CN8 products are zero for a large share of trade flows (82% of observations in our data), due to internal EU trade and preferential agreements with many extra-EU partners. Incorporating all zero trade flows would pose computational challenges, particularly in a three-way fixed effects framework, while excluding them would introduce severe selection bias.

data. This more granular instrument yields somewhat higher estimates of trade elasticity for some industries, but the relative ranking across industries remains nearly identical, suggesting that the HS6-based instrument provides a reliable approximation of supply-side price variation, despite its coarser product definition.

To address the endogeneity of expenditure shares, we construct two instrumental variables based on the approaches of Khandelwal (2010) and Lashkaripour and Lugovskyy (2023). The main instrument is the number of origin countries supplying CN8 product $\omega$ to EU country $i$ in year $t$. This count-based measure proxies for exogenous variation in supply-side market access. Because the instrument varies only at the destination-product-year level, including all three fixed effects would absorb nearly all of its identifying variation. We therefore include only destination-sector-year fixed effects in the first stage. As a robustness check (see Table 7 in the Appendix), we alternatively use the number of CN8 products imported from country $j$ to EU country $i$ within industry $k$ in year $t$. This measure is mechanically correlated with product expenditure shares: the more products a country supplies, the smaller the share of any one product on average. Unlike the main instrument, it varies at the origin-destination-sector-year level and can be used alongside the full set of fixed effects. However, it may be more directly correlated with unobserved determinants of import demand, such as trade policy shifts or structural market changes, potentially violating the exclusion restriction. We therefore interpret this second instrument as a complementary but imperfect robustness check. It delivers slightly lower but consistent estimates of love for variety elasticity for most industries, with few exceptions, suggesting that the main instrument captures well the exogenous variation of the expenditure share.

### 4.4 Demand parameter estimates

We start with the average effects and then show estimated parameters by industry and by product. Table 3 reports OLS and 2SLS estimates of the pooled model under three different fixed effects specifications. Columns (1) and (2) report results using only destination-sector-year and origin-destination-sector fixed effects. The OLS estimates are statistically significant and have the expected signs, but the coefficients are clearly biased: the price coefficient is almost zero, and the expenditure share coefficient tends to one. The 2SLS estimates in column (2) correct for this bias, and the trade elasticity increases in magnitude to -0.6, while the expenditure share coefficient falls to 0.8. The instruments are highly relevant, as evidenced by a Kleibergen-Paap Wald F-statistic well above conventional thresholds. These estimates do not account for differences in product-specific patterns.

Columns (3) and (4) add origin-destination-sector-product fixed effects, allowing for fine-grained control of product-specific demand shocks. While the OLS estimates remain biased, the 2SLS estimates in column (4) reveal a stronger trade elasticity of -1.1 and a much lower expenditure share coefficient of 0.2. The low expenditure share elasticity likely reflects the fact that much of the variation is now absorbed by the granular fixed effects, leading to weaker identification, as $\phi_{jik\omega}$ absorbs a large part of the variation in prices and expenditure shares. Still, the weak identification test comfortably passes standard thresholds.

Columns (5) and (6) replace the most granular fixed effect with a sector-product fixed effect, which controls for product heterogeneity across all countries without oversaturating the model. The 2SLS estimate in column (6) suggests a trade elasticity of -2.3, implying that a 1% increase in the price of a good reduces EU imports from a given source by 2.3%. The coefficient on the expenditure share is 0.38, indicating moderate love for variety within sectors: a 1% increase in the expenditure share of one variety increases its imports, on average, by about 0.4%. Next, we obtain the taste parameter $\alpha_{jik}$ from the origin-destination-industry fixed effects, which we normalize so that $\sum_j \alpha_{jik} = 1$. This is done to identify $\alpha_{jik}$ uniquely and make it interpretable across all origin countries.

Table 3: OLS and 2SLS estimation results.

| Dependent: import value (log) | OLS | 2SLS | OLS | 2SLS | OLS | 2SLS |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Price, $(1-\sigma_k)$ | -0.023*** | -0.619*** | -0.011*** | -1.077*** | -0.023*** | -2.329*** |
| | (0.001) | (0.023) | (0.002) | (0.059) | (0.002) | (0.042) |
| Product expenditure share, $\left(1-\frac{\sigma_k-1}{\gamma_k-1}\right)$ | 0.955*** | 0.759*** | 0.908*** | 0.209*** | 0.946*** | 0.376*** |
| | (0.001) | (0.011) | (0.002) | (0.004) | (0.001) | (0.004) |
| $\delta_{ikt} + \alpha_{jik}$ FE | YES | YES | - | - | - | - |
| $\delta_{ikt} + \alpha_{jik} + \phi_{jik\omega}$ FE | - | - | YES | YES | - | - |
| $\delta_{ikt} + \alpha_{jik} + \phi_{k\omega}$ FE | - | - | - | - | YES | YES |
| N. of HS2-year clusters | 1,920 | 1,920 | 1,920 | 1,920 | 1,920 | 1,920 |
| Weak identification test | - | 15,278 | - | 1,645 | - | 5,553 |
| Within-$R^2$ | 0.92 | - | 0.83 | - | 0.90 | - |
| Obs. | 43,177,933 | 29,712,807 | 41,643,081 | 28,714,391 | 43,177,933 | 29,712,806 |

*Note:* Log-linearized structural demand equation eq(5). The estimation is conducted with different fixed effects specifications. Robust standard errors in parentheses are clustered at the HS2-year-level. The weak identification test statistics is the F-statistics from the Kleibergen-Paap Wald test. The test for over-identification is not reported due to the drawbacks of the Sargan-Hansen J test for over-identification in multi-dimensional large datasets (see Angrist et al. (1996)). The reported $R^2$ in the OLS estimations corresponds to within-group goodness of fit. *** p-value<0.01.

We now turn to the industry-specific parameter estimates in Table 4. The trade elasticity (column 3) is large in the industries of Basic metals (4.3); Petroleum and mineral fuels (3.8); and Rubber and plastics (3.6), while Transport equipment (1.3); Electrical equipment (1.6); and N.E.C and recycling (1.6) are less substitutable across source countries. Similarly, the love for variety elasticity (column 5) is high in Basic metals (9.5); Paper (7.6); and Petroleum and mineral fuels (7.2), while it is low in Transport equipment (3.0); Electrical equipment (3.5); and N.E.C. and recycling (3.7). These results are not surprising as the two elasticities are correlated by construction (column 4).[7]

Column 6 reports the estimated taste for extra-EU imports, $\sum_{j\in EX} \alpha_{ji,k}$, averaged across EU destinations. High values of $\alpha_{ji,k}$ reflect a strong and persistent relative consumer preference for sourcing specific goods from outside the EU, capturing the various non-price elements of demand. The taste shifter suggests a strong preference for extra-EU imports of Petroleum, coal and mineral fuels (0.85) and Mining products (0.72). Fabricated metals (0.27); Paper (0.30); and Non-metallic minerals (0.32) from extra-EU countries are relatively less attractive to EU consumers. We also report the weak identification test statistic for each separate estimation in column 8.

These elasticities offer an interpretable ranking of industries by their vulnerability to price shocks and substitutability of foreign inputs. Sectors with low substitutability (low $\sigma_k$ and $\gamma_k$) and a high preference for extra-EU imports ($\alpha_{ji,k}$ are candidates for strategic sectors, including Transport equipment; Electrical equipment; and Mining. Industries like Paper; Rubber and plastics; and Wood combine high substitutability with low extra-EU dependence, suggesting lower strategic vulnerability. In contrast, a classical dependency candidate like Petroleum, coal, mineral fuels, has a very high extra-EU taste shifter, but also exhibits high elasticities of substitution. This suggests that there is a high relative preference for exta-EU imports of this sector, due to the low production within the EU, but that

[7] These estimated trade and love of variety elasticities are similar to estimations in other datasets (e.g., Lashkaripour and Lugovskyy (2023) for Columbia).

it is easy to substitute away towards other supplying countries and/or varieties in response to a shock. Overall, these results underscore the importance of jointly considering price elasticity, variety substitution, and persistent taste parameters when evaluating strategic trade exposure.

Table 4: Estimated parameters by ISIC industry.

| Sector | ISIC4 codes | $\sigma_k - 1$ | $\frac{\sigma_k - 1}{\gamma_k - 1}$ | $\gamma_k$ | $\sum_{j \in EX} \alpha_{jik}$ | Obs. | Weak Ident. test |
|---|---|---|---|---|---|---|---|
| Agriculture | 100-999 | 2.126 | 0.623 | 4.411 | 0.556 | 1,204,836 | 624.7 |
| | | (0.128) | (0.009) | | | | |
| Mining | 1000-1499 | 2.489 | 0.411 | 7.050 | 0.723 | 286,835 | 158.4 |
| | | (0.217) | (0.024) | | | | |
| Food | 1500-1699 | 2.976 | 0.668 | 5.454 | 0.461 | 2,762,006 | 1,335.4 |
| | | (0.107) | (0.014) | | | | |
| Textiles | 1700-1999 | 1.971 | 0.650 | 4.030 | 0.438 | 6,350,635 | 5,354.9 |
| | | (0.093) | (0.009) | | | | |
| Wood | 2000-2099 | 2.884 | 0.536 | 6.386 | 0.368 | 316,247 | 220.0 |
| | | (0.316) | (0.015) | | | | |
| Paper | 2100-2299 | 3.546 | 0.534 | 7.637 | 0.303 | 909,676 | 216.1 |
| | | (0.292) | (0.016) | | | | |
| Petroleum, mineral fuels | 2300-2399 | 3.778 | 0.613 | 7.165 | 0.852 | 117,685 | 74.0 |
| | | (0.290) | (0.023) | | | | |
| Chemicals | 2400-2499 | 2.148 | 0.646 | 4.327 | 0.420 | 2,620,733 | 3,312.2 |
| | | (0.042) | (0.007) | | | | |
| Rubber and plastics | 2500-2599 | 3.583 | 0.644 | 6.564 | 0.377 | 1,660,561 | 1,593.6 |
| | | (0.057) | (0.015) | | | | |
| Non-metallic minerals | 2600-2699 | 2.308 | 0.583 | 4.959 | 0.317 | 977,489 | 897.4 |
| | | (0.083) | (0.011) | | | | |
| Basic metals | 2700-2799 | 4.326 | 0.512 | 9.450 | 0.524 | 1,197,876 | 315.9 |
| | | (0.203) | (0.008) | | | | |
| Fabricated metals | 2800-2899 | 2.471 | 0.544 | 5.539 | 0.267 | 2,021,799 | 1,543.0 |
| | | (0.130) | (0.012) | | | | |
| Machinery | 2900-3099 | 1.891 | 0.661 | 3.863 | 0.362 | 2,955,171 | 203.7 |
| | | (0.129) | (0.015) | | | | |
| Electrical equipment | 3100-3399 | 1.619 | 0.645 | 3.508 | 0.384 | 2,881,042 | 1,140.3 |
| | | (0.100) | (0.018) | | | | |
| Transport equipment | 3400-3599 | 1.291 | 0.659 | 2.957 | 0.419 | 669,707 | 152.1 |
| | | (0.143) | (0.016) | | | | |
| N.E.C. and recycling | 3600-3800 | 1.636 | 0.613 | 3.669 | 0.431 | 1,626,183 | 541.4 |
| | | (0.103) | (0.014) | | | | |

*Note:* The estimation is conducted separately for each ISIC industry with destination-HS2 product-year, origin-destination-HS2 product, and CN8 product-HS2 product fixed effects. Parameter $\sum_{j \in EX} \alpha_{ji,k}$ is the average preference weight on extra-EU countries, normalized such that $\sum_j \alpha_{ji,k} = 1$. Standard errors in parentheses are robust to clustering within HS2 product-year. The weak identification test statistics is the F-statistics from the Kleibergen-Paap Wald test. The test for over-identification is not reported due to the drawbacks of the Sargan-Hansen J test for over-identification in multi-dimensional large datasets (see Angrist et al. (1996)).

While parameters at the ISIC industry level provide a broad view of substitution and dependence patterns, substantial heterogeneity may still exist at the product level. We therefore estimate $\sigma_k$, $\gamma_k$, and $\alpha_{ji,k}$ at the HS2 level to further explore within-sector variation. Figures 4-6 summarize these parameters across HS2 products, highlighting examples of both high and low substitutability and dependence. The product-level parameters show very heterogeneous results within broader industries. In particular, products classified under Agriculture; Food; Chemicals; and Basic metals display very different parameters from their sector averages. For instance, in the agriculture and food sectors, the trade elasticity is almost -6 for cereals (HS2=10) and -4.2 for cocoa products (HS2=18), whereas it ranges from about 0 to -1 for live animals (HS2=1), meat (HS2=2) and fish (HS2=3). For basic metals, iron and steel (HS2=72), tin (HS2=79), and zinc (HS2=80) products are highly substitutable, while nickel (HS2=75) and raw materials (HS2=81) are less substitutable. In Figure 6, the taste parameter for extra-EU imports is very heterogeneous for food, agriculture, and chemical products. For example, EU consumers prefer animal originated products (HS2=5), vegetables (HS2=7), and fruit and nuts (HS2=8) sourced from extra-EU countries, compared to dairy products (HS2=4) and plants (HS2=6). Some chemicals from extra-EU countries, such as inorganic (HS2=28) and organic chemicals (HS2=29), are also more attractive to EU consumers than others, like pharmaceuticals (HS2=30) and cosmetic products (HS2=33,34). Other sectors like wood, electrical equipment, and transport equipment show more homogeneous parameters across products.

Figure 4: Trade elasticity by HS2 product category

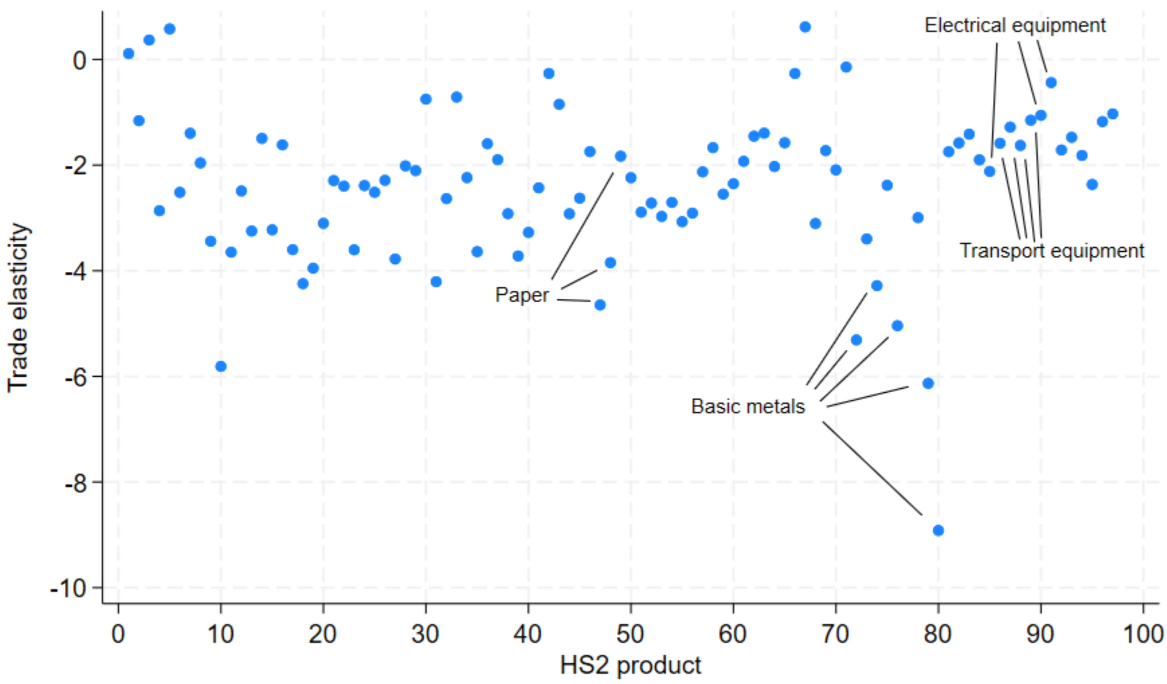


Figure 5: Love for variety elasticity by HS2 product category

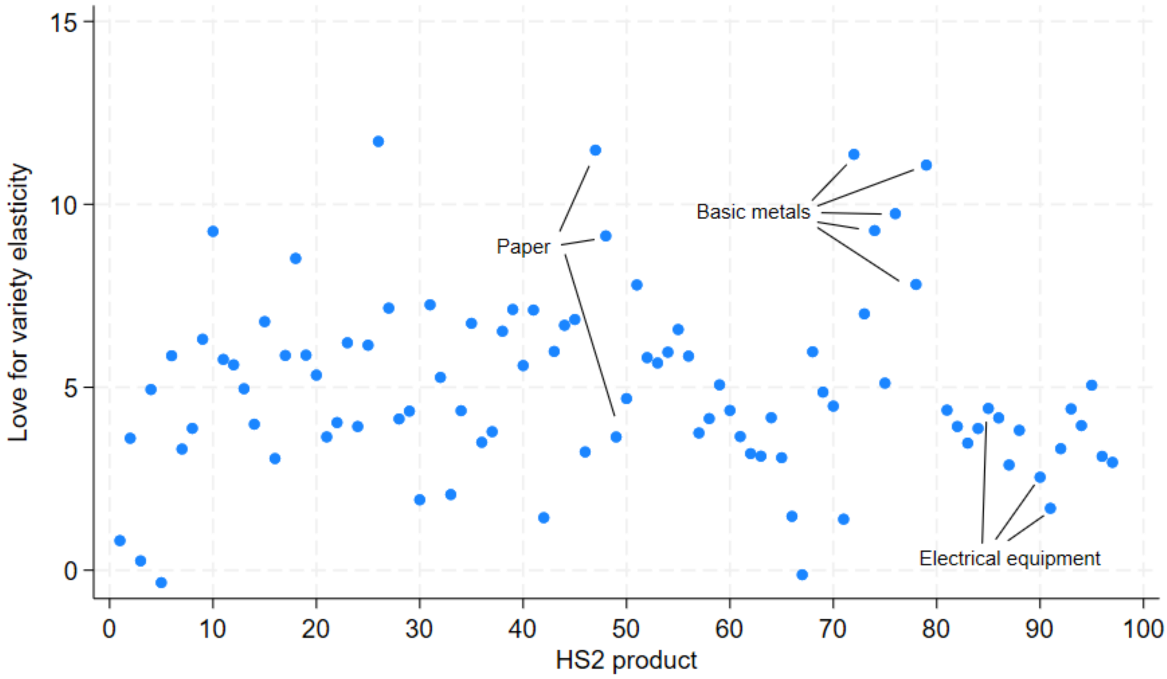
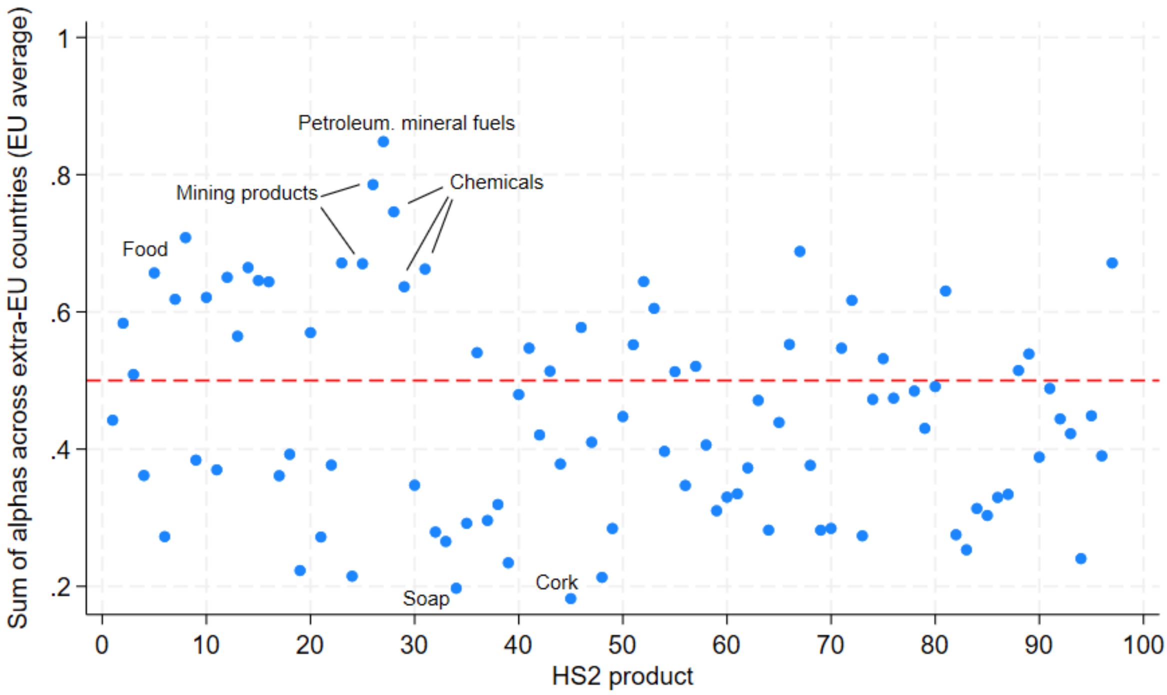



Figure 6: Taste parameter for extra-EU imports by HS2 product category




## 5 The Strategic Dependency Index

We construct a product-level index of the EU's strategic dependency on imports from extra-EU countries. The index incorporates the three demand parameters into a welfare-based measure, together with the traditional notion of import concentration. A product scores higher on the index when it exhibits low trade elasticity, low love-for-variety elasticity, and a strong consumer preference for extra-EU imports. The SDI also enables welfare analysis under alternative natural and policy scenarios.

## 5.1 Index of strategic dependency

The strategic dependency index is constructed as a measure of welfare cost for EU consumers due to a price shock in a given source country. The derivation of the index is provided in the Appendix. The welfare cost for EU country $i$ in HS2 product $k$ from a price shock in source country $j$ is:

$$C_{ji,k} = \sum_{\omega \in \Omega_{ji,k}} \frac{y_{ji,k}(\omega)}{y_{ji,k}} \frac{\partial \ln P_{i,k}}{\partial \ln p_{ji,k}(\omega)} \tag{7}$$

where $\frac{y_{ji,k}(\omega)}{y_{ji,k}}$ is the import share of variety $\omega$ in the total expenditure of country $i$ on product $k$ varieties from country $j$; and $\frac{\partial \ln P_{i,k}}{\partial \ln p_{ji,k}(\omega)}$ is the effect of a price shock to variety $\omega$ imported from source country $j$ on the price index of product $k$ in EU country $i$. Under homothetic preferences, the change in the price index is equal to the welfare cost of a price change. The import shares of varieties are added as weights for the relative importance of each imported variety. Since the product-specific CES price index is $P_{i,k} = \left[\sum_{j \in C} \alpha_{ji,k} P_{ji,k}^{1-\sigma_k}\right]^{\frac{1}{1-\sigma_k}}$ and the origin-specific CES price index is $P_{ji,k} = \left[\sum_{\omega \in \Omega_{ji,k}} \phi_{ji,k}(\omega) p_{ji,k}(\omega)^{1-\gamma_k}\right]^{\frac{1}{1-\gamma_k}}$, the change in the price index due to a price shock in one source country depends on the three estimated parameters: $\sigma_k$,$\gamma_k$, and $\alpha_{ji,k}$. In particular, as $\gamma_k \geq \sigma_k > 1$, the higher the value of $\sigma_k$ and $\gamma_k$, the weaker the effect of the price shock on the price index of product $k$. Hence, a lower substitutability across source countries and across varieties causes a larger change in the price index of a product in a EU country. On the other hand, a higher value of $\alpha_{ji,k}$ generates a stronger effect of the price shock in that source country $j$ on the price index. A higher preference for a product from a specific country increases the price index change for that product in the EU. The variety taste parameter $\phi_{ji,k}(\omega)$ also affects the price index change, as it increases the effect of the price shock of variety $\omega$. It is computed as $1/\Omega_{ji,k}$, that is the reciprocal of the total number of varieties from country $j$ to country $i$ in product $k$.

We then define the aggregate welfare cost for EU country $i$ in product $k$ as follows:

$$C_{i,k} = \sum_{j \in C} \frac{y_{ji,k}}{y_{i,k}} C_{ji,k} \tag{8}$$

where $\frac{y_{ji,k}}{y_{i,k}}$ is the import share of product $k$ from country $j$ in the total expenditure of country $i$ on product $k$ from all countries $j$, including domestic expenditure ($y_{ii,k}$). Hence, $C_{i,k}$ is the welfare cost for consumers of EU country $i$ in product $k$ from a common price shock in all source countries. This functional form of welfare cost allows to focus on specific source-countries. For instance, we can compute the welfare cost for a EU country from a common price shock in extra-EU countries only. To obtain a product-specific measure at EU level, we aggregate the welfare cost of all EU countries for each product $k$:

$$C_k = \sum_{i \in EU} \frac{y_{i,k}}{y_k} C_{i,k} \tag{9}$$

where $\frac{y_{i,k}}{y_k}$ is the expenditure share of EU country $i$ in the total EU expenditure on product $k$. $C_k$ measures the welfare cost for EU consumers from a price shock in any source country for each product. Hence, it allows to build an index of strategic dependency of EU imports on extra-EU countries across all HS2 products. Note that this index identifies which products are more vulnerable or exposed to extra-EU imports. It does not consider the economic relevance of each product in the EU economy.

## 5.2 Counterfactual policies and index results

We compute the strategic dependency index in two counterfactual policy scenarios: (i) a change in the EU trade policy toward extra-EU countries; and (ii) a change in the industrial policy of EU countries. First, we consider an increase in EU tariffs by 10% on imports from all extra-EU countries. As tariffs are direct price shifters, we simulate the effect of a 10% price increase for each variety, within a certain category of products, imported from extra-EU countries. These price shocks affect the price index of EU countries for each product, and hence generate a welfare cost for consumers. The impact of tariffs on the EU welfare cost is calculated for each HS2 product and each year. Figure 7 reports the strategic dependency index by HS2 product in 2019 (last year available for data on domestic expenditure). It shows that the welfare cost for EU consumers is higher for some chemicals, such as explosives (HS2=36), inorganic chemicals (HS2=28) and fertilizers (HS2=31), mining products (HS2=26), petroleum and mineral fuels (HS2=27), and some basic metals, such as lead (HS2=78) and raw materials (HS2=81). These strategic products are either harder to substitute or highly demanded from extra-EU countries. In particular, most of them show a high preference for extra-EU imports, but only some of them have low substitution elasticities, for example explosives and inorganic chemicals, mining products, and raw materials. Therefore, the origin-specific taste parameter is driving the index more than the substitution elasticities for these goods. The results of the strategic dependency index are consistent over time (see Figure 9 in the Appendix). The most strategic products are roughly the same ones and their ranking is quasi-maintained between 2002 and 2019. Interestingly, the index is higher in 2019 for most of these goods, except for mining products and inorganic chemicals.

In the second scenario, we consider the introduction of a production subsidy in the EU countries, which has the effect of reducing the price of imports from other EU countries by 10%. Hence, we simulate the effect of a 10% price reduction of all goods sourced from EU countries. This time, a lower price reduces the price index of the importing EU country for each product and generates a welfare gain or cost saving for consumers. Figure 8 reports the strategic dependency index with a subsidy by HS2 product in 2019. The welfare cost reduction for EU consumers is stronger for basic metals, such as lead (HS2=78) and zinc (HS2=79), photographic goods (HS2=37), some chemicals, such as cosmetics (HS2=34) and explosives (HS2=36), and wood products (HS2=45,46). These products are quite different from the ones identified under the tariffs scenario, expect lead and explosive products. Moreover, they show a low preference for extra-EU imports and quite high elasticities with few exceptions. This suggests that these products are generally more traded between EU countries and more substitutable. Consequently, they are sensitively different from strategic products sourced from extra-EU countries.

While some strategic products identified by our index under the tariffs scenario are similar to the ones identified from the European Commission methodology in Section 3.1, many are not. First, some chemicals (inorganic chemicals, explosives, fertilizers) and basic metals (lead and raw materials) have a high SDI value, whereas they are not revealed from the European Commission indicator. Most of these products display a low substitution and high preference for extra-EU imports, which raise the SDI values. Second, while many products in N.E.C. manufacturing and recycling (umbrellas, feathers and related articles, toys and sport equipment) are labeled as strategic by the European Commission, they are not signaled by our index. This is due to the import shares weights in our index, which weigh the imports from extra-EU countries by domestic and intra-EU expenditures, correcting the impact on the welfare cost for these products. On the other hand, wood (straw and plaiting materials) and some textiles (leather, silk, headgear) are strategic for both indicators, but to a lower extent in our index.

Mining and petroleum products are strategic for both indicators, but to a greater extent in our case.

Figure 7: Strategic dependency index with tariffs, 2019

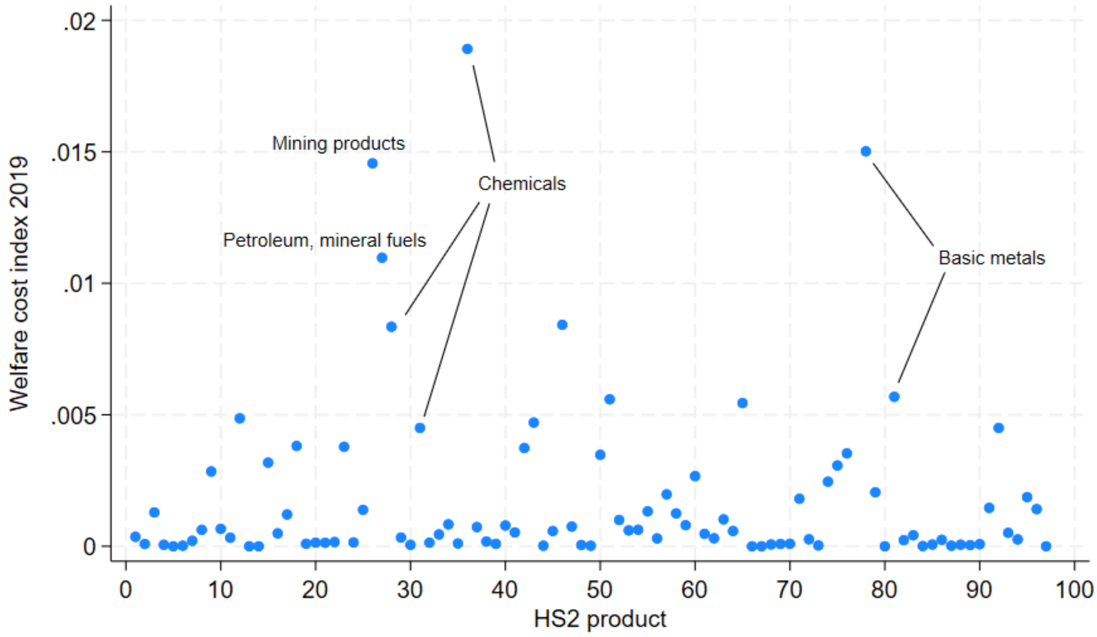
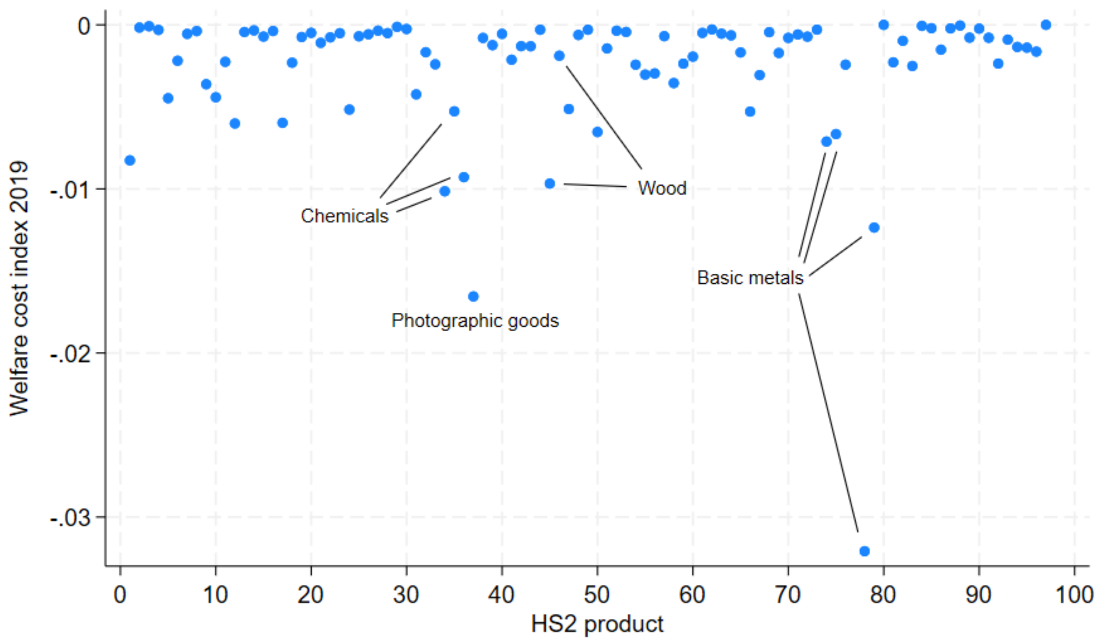



Figure 8: Strategic dependency index with subsidy, 2019




## 6 Conclusions

This paper proposes the Strategic Dependency Index (SDI) as a novel measure to evaluate the dependency of EU countries on third countries as suppliers of particular goods. This measure not only accounts for the concentration of imported goods across supplying countries, but also incorporates the ease of substitution across source countries and across close varieties, as well as intrinsic preferences for particular suppliers of these goods. The index can be used both as a measurement device to evaluate the EU strategic dependency for particular goods and for welfare analysis with counterfactual scenarios, such as simulated policy shocks or supply disruptions.

The products indicated by the index as strategic for EU countries can be particularly informative for policymakers in designing new policies. For instance, the introduction of EU tariffs would increase the welfare cost for EU consumers more for products such as petroleum, mining products, and specific chemicals and basic metals. As petroleum and most basic metals are relatively highly substitutable across source countries, EU policies could promote a diversification of extra-EU imports to reduce strategic dependency on these goods. Instead, mining, chemicals, and raw materials are hardly substitutable, underlining their strategic dependency nature.

The SDI views strategic dependency as the exposure or vulnerability of final demand to foreign shocks. A natural extension is to incorporate the production of firms in the model and examine the exposure of EU value chains. This requires both trade and production data at a very granular level. Another possible extension is to consider dependency in digital and services markets, which might be very concentrated and strategic as well as goods. Detailed data beyond trade statistics are necessary to make progress here.

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# Appendix

Table 5: Summary statistics of main variables.

| Variable | N | mean | stdev | percentiles p10 | p25 | p50 | p75 | p90 |
|---|---|---|---|---|---|---|---|---|
| Import value (th. EUR) | 47,968,504 | 1,485 | 35,605 | 0.3 | 2.2 | 20.8 | 182.5 | 1,171 |
| Import quantity (tonnes) | 47,968,504 | 1,223 | 71,295 | 0.0 | 0.1 | 2.0 | 28.2 | 270.2 |
| Import price (th. EUR/tonnes) | 47,968,504 | 229.1 | 97,659 | 1.1 | 3.0 | 9.9 | 32.8 | 102.2 |
| Product import share (%) | 47,968,504 | 6.2 | 0.2 | 0.0 | 0.0 | 0.2 | 2.0 | 13.6 |
| N. of origin countries (units) | 3,715,005 | 12.9 | 12.6 | 2 | 4 | 9 | 18 | 29 |
| N. of products (units) | 2,992,682 | 16.0 | 35.1 | 1 | 2 | 4 | 15 | 40 |
| Origin-country export price (th. EUR/tonnes) | 3,410,899 | 558.9 | 80,985 | 0.7 | 2.1 | 6.5 | 20.8 | 60.2 |
| Domestic expenditure (mil. EUR) | 46,170 | 1,140 | 5,080 | 0.3 | 3.9 | 54.8 | 431.2 | 2,202 |

*Note:* All statistics are pooled over 2002-2021. Monetary values are expressed in current euros.

Figure 9: Strategic dependency index with tariffs, 2002

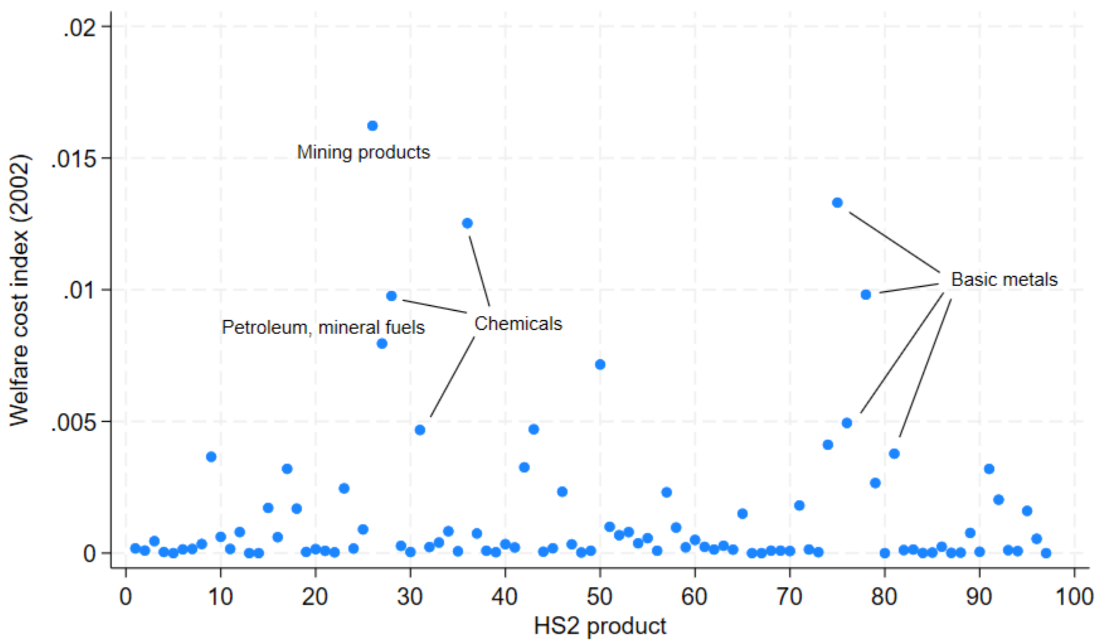

Table 6: Estimated trade elasticity with CN8-level EU export price by ISIC industry.

| Sector | ISIC4 codes | $\sigma_k - 1$ | Obs. | Weak Ident. test |
|---|---|---|---|---|
| Agriculture | 100-999 | 1.827 | 1,035,166 | 673 |
| | | (0.108) | | |
| Mining | 1000-1499 | 2.575 | 193,932 | 463 |
| | | (0.117) | | |
| Food | 1500-1699 | 2.653 | 2,366,319 | 1,790 |
| | | (0.098) | | |
| Textiles | 1700-1999 | 2.105 | 3,781,132 | 1,627 |
| | | (0.079) | | |
| Wood | 2000-2099 | 3.617 | 362,886 | 349 |
| | | (0.110) | | |
| Paper | 2100-2299 | 3.983 | 651,826 | 416 |
| | | (0.276) | | |
| Petroleum, mineral fuels | 2300-2399 | 3.600 | 117,201 | 326 |
| | | (0.201) | | |
| Chemicals | 2400-2499 | 2.075 | 2,020,299 | 3,511 |
| | | (0.037) | | |
| Rubber and plastics | 2500-2599 | 4.012 | 1,270,434 | 1,082 |
| | | (0.083) | | |
| Non-metallic minerals | 2600-2699 | 2.543 | 738,803 | 1,028 |
| | | (0.053) | | |
| Basic metals | 2700-2799 | 4.162 | 1,022,469 | 417 |
| | | (0.203) | | |
| Fabricated metals | 2800-2899 | 2.566 | 1,556,970 | 1,321 |
| | | (0.101) | | |
| Machinery | 2900-3099 | 2.058 | 2,470,163 | 580 |
| | | (0.081) | | |
| Electrical equipment | 3100-3399 | 1.660 | 2,492,555 | 1,379 |
| | | (0.101) | | |
| Transport equipment | 3400-3599 | 1.073 | 591,104 | 346 |
| | | (0.081) | | |
| N.E.C. and recycling | 3600-3800 | 1.814 | 1,127,135 | 424 |
| | | (0.156) | | |

*Note:* The estimation is conducted separately for each ISIC industry with destination-HS2 product-year, origin-destination-HS2 product, and CN8 product-HS2 product fixed effects. Standard errors in parentheses are robust to clustering within HS2 product-year. The weak identification test statistics is the F-statistics from the Kleibergen-Paap Wald test. The test for over-identification is not reported due to the drawbacks of the Sargan-Hansen J test for over-identification in multi-dimensional large datasets (see Angrist et al. (1996)).

Table 7: Estimated love for variety elasticity with number of CN8 products by ISIC industry.

| Sector | ISIC4 codes | $\frac{\sigma_k - 1}{\gamma_k - 1}$ | $\gamma_k$ | Obs. | Weak Ident. test |
|---|---|---|---|---|---|
| Agriculture | 100-999 | 0.661 | 3.760 | 1,246,737 | 712 |
| | | (0.016) | | | |
| Mining | 1000-1499 | 0.590 | 5.142 | 286,835 | 158 |
| | | (0.015) | | | |
| Food | 1500-1699 | 0.687 | 5.228 | 2,762,006 | 1,335 |
| | | (0.011) | | | |
| Textiles | 1700-1999 | 0.797 | 3.468 | 6,350,635 | 5,354 |
| | | (0.079) | | | |
| Wood | 2000-2099 | 0.961 | 3.847 | 362,886 | 349 |
| | | (0.027) | | | |
| Paper | 2100-2299 | 0.913 | 4.850 | 909,676 | 216 |
| | | (0.038) | | | |
| Petroleum, mineral fuels | 2300-2399 | 0.579 | 7.268 | 117,685 | 74 |
| | | (0.025) | | | |
| Chemicals | 2400-2499 | 0.709 | 3.992 | 2,620,733 | 3,312 |
| | | (0.024) | | | |
| Rubber and plastics | 2500-2599 | 0.835 | 5.259 | 1,660,561 | 1,594 |
| | | (0.052) | | | |
| Non-metallic minerals | 2600-2699 | 0.844 | 3.691 | 977,489 | 897 |
| | | (0.019) | | | |
| Basic metals | 2700-2799 | 0.772 | 6.465 | 1,197,876 | 316 |
| | | (0.024) | | | |
| Fabricated metals | 2800-2899 | 0.644 | 4.735 | 2,021,799 | 1,543 |
| | | (0.032) | | | |
| Machinery | 2900-3099 | 0.816 | 3.261 | 2,955,171 | 204 |
| | | (0.064) | | | |
| Electrical equipment | 3100-3399 | 0.779 | 3.076 | 2,881,042 | 1,140 |
| | | (0.053) | | | |
| Transport equipment | 3400-3599 | 0.938 | 2.295 | 669,707 | 152 |
| | | (0.061) | | | |
| N.E.C. and recycling | 3600-3800 | 0.906 | 2.588 | 1,721,466 | 620 |
| | | (0.023) | | | |

*Note:* The estimation is conducted separately for each ISIC industry with destination-HS2 product-year, origin-destination-HS2 product, and CN8 product-HS2 product fixed effects. Standard errors in parentheses are robust to clustering within HS2 product-year. The weak identification test statistics is the F-statistics from the Kleibergen-Paap Wald test. The test for over-identification is not reported due to the drawbacks of the Sargan-Hansen J test for over-identification in multi-dimensional large datasets (see Angrist et al. (1996)).