Economics School of Louvain - ESL

Rare-Earth Dependence, Cost Pressure, and Material-Cost Shares

Evidence from Five European Manufacturing Economies

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Abstract

This paper studies how measured industry dependence on rare-earth inputs shapes firms' responses to country-specific rare-earth import unit-value movements. I combine Orbis accounting data for 2016–2024 with country-year rare-earth import unit-value indices and a fixed NACE4 total-requirement measure capturing both direct rare-earth use and rare-earth content embodied in upstream inputs. A benchmark production-and-pricing model implies that the material-cost share satisfies $\mathrm{MS} = \alpha_s^M c/p$, so a positive response is consistent with unit costs rising by more than output prices. The empirical design interacts fixed industry exposure with country-year rare-earth unit values and includes firm, country-year, and NACE4-year fixed effects. In the preferred M4 specification, which adds empirically motivated controls for broader price and factor-cost channels, the coefficient is 0.00888 with a country–NACE4 clustered standard error of 0.00424. Restricting the outcome period to 2018–2024 while keeping industry intensities fixed using 2016–2017 data leaves the estimate essentially unchanged. The evidence is nevertheless sensitive to inference, weighting, product composition, and treatment of the outcome tail. NACE4-only clustering and a country-sequence permutation diagnostic are more conservative; equalizing country weights weakens the estimate; and product-level results show that the positive aggregate association is concentrated in HS 284690, the dominant component of the import basket in most sample countries. I therefore interpret the estimates as suggestive reduced-form evidence rather than as a structural pass-through elasticity or a causal effect of exogenous changes in rare-earth transaction prices.

Keywords: rare earths; input costs; incomplete pass-through; production networks; material-cost shares.

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1 Introduction

Rare-earth inputs enter manufacturing both directly and through upstream intermediate goods. This makes rare-earth dependence a production-network object: firms facing the same country-level rare-earth import unit-value movement may experience different cost pressure because their industries rely on rare-earth-intensive inputs to different degrees. The effect of that pressure also depends on pricing. If output prices adjust proportionally to unit costs, the ratio of material expenditure to revenue need not change; if output prices adjust less than proportionally, the material-cost share rises.

This paper asks whether firms in industries with greater measured rare-earth dependence exhibit stronger material-cost-share responses when country-specific rare-earth import unit values rise. Rare-earth dependence itself is part of the object of interest rather than merely a device for estimating a generic pass-through parameter. The empirical question is therefore how a production-network measure of dependence maps country-specific import unit-value movements into downstream accounting responses.

The main outcome is

$$\log \mathrm{MS}_{isct} = \log \left(\frac{\mathrm{MaterialCosts}_{isct}}{\mathrm{OperatingRevenue}_{isct}} \right), \tag{1}$$

where i indexes firms, s NACE4 industries, c countries, and t years. Under the benchmark developed below,

$$\mathrm{MS}_{isct} = \alpha_s^M \frac{c_{isct}}{p_{isct}}, \tag{2}$$

so quantity cancels from material expenditure and operating revenue. If $\rho_{isct} = d \log p_{isct} / d \log c_{isct}$ denotes local output-price pass-through,

$$d \log \mathrm{MS}_{isct} = (1 - \rho_{isct}) d \log c_{isct}. \tag{3}$$

The material-cost share is therefore informative about the relative adjustment of unit costs and output prices, although the empirical coefficient remains reduced-form because unit costs, firm-product output prices, and firms' effective rare-earth input shares are not separately observed.

The analysis combines three data sources. Orbis provides firm-level accounting data for manufacturing firms in Belgium, Germany, Spain, France, and Italy over 2016–2024. Eurostat trade data provide country-year import values and quantities for HS 280530, HS 284610, and HS 284690, from which I construct a fixed-weight rare-earth import unit-value index. Industry dependence is measured using a mapped version of the rare-earth total-requirement measure developed by Alfaro et al. (2026), which captures both direct requirements and rare-earth content embodied in upstream inputs. The resulting NACE4 exposure is fixed over time and interpreted as a proxy for relative production-network dependence rather than as a directly observed European input share.

The treatment variable is

$$Z_{sct} = 1000 \times \text{Exposure}_s^{\text{REE}} \times \log P_{ct}^{\text{REE}}. \tag{4}$$

The empirical design includes firm, country-year, and NACE4-year fixed effects. Identification comes from whether industries with different fixed exposure exhibit different material-cost-share responses across countries experiencing different rare-earth import unit-value movements. The preferred M4 specification additionally controls for a broader industry PPI and allows national labor- and capital-cost conditions to load differently across industries according to fixed NACE4 production-structure proxies.

The coefficient is positive in all four sequential specifications, ranging from 0.00448 to 0.00888. M4 yields 0.00888 with a country–NACE4 clustered standard error of 0.00424. A timing check that estimates the outcome equation only over 2018–2024, while retaining intensities constructed from 2016–2017 data, gives 0.00965 with a standard error of 0.00429. The baseline evidence is nevertheless sensitive along economically important dimensions. NACE4-only clustering gives a p-value of 0.101 and the country-sequence permutation diagnostic 0.133. Equal country weighting reduces the coefficient to 0.00328, and an unweighted country–NACE4–year cell estimator is close to zero. Product-level exercises show that the positive aggregate association is concentrated in HS 284690. Outcome-tail treatment also attenuates the estimate: excluding observations whose revenue falls below 1 percent of the firm's own median leaves 0.00628 ($p = 0.107$).

The contribution is threefold. First, the paper connects the pass-through literature to an accounting outcome available when firm-product output prices are not observed. Second, it brings a production-network measure of total rare-earth requirements into firm-level analysis, making indirect upstream exposure part of the treatment. Third, it applies insights from exposure-based empirical designs by making explicit how the estimand and statistical evidence depend on a small number of national unit-value paths, unequal country weights, and alternative inference procedures. The paper's main contribution is therefore empirical rather than methodological: it documents how measured rare-earth production-network dependence is associated with downstream material-cost-share responses while making the limits of the identifying variation transparent.

2 Related Literature

2.1 Input-cost pass-through

Pass-through is not mechanically one-for-one. Under imperfect competition it depends on demand curvature, conduct, and market conditions (Weyl and Fabinger, 2013). Empirical work similarly finds substantial heterogeneity. Nakamura and Zerom (2010) show that local costs and markup adjustment contribute importantly to incomplete pass-through in coffee, while Fabra and Reguant (2014) and Pless and van Benthem (2019) document settings with much higher pass-through. The closest manufacturing benchmark is Ganapati et al. (2020), who interact predetermined fuel-use shares with national fuel-price movements and estimate energy-cost pass-through using direct output-price and quantity information. The present paper shares the exposure-by-price architecture but not the estimand: Orbis provides broad firm coverage without firm-product output prices, so I study the material-cost-share response rather than estimate a structural pass-through elasticity.

2.2 Production networks and rare-earth dependence

Production-network research shows that upstream shocks can propagate through indirect input linkages. Acemoglu et al. (2012) provide the foundational network logic; Barrot and Sauvagnat (2016) and Carvalho et al. (2021) show that supplier disruptions propagate to downstream firms, particularly when inputs are difficult to substitute. Dhyne et al. (2021) further demonstrate that direct importing can substantially understate firms' total foreign-input exposure because imported content is embodied in domestic intermediate purchases. These results motivate a total-requirement measure rather than direct rare-earth imports.

Alfaro et al. (2026) provide the measurement foundation used here by embedding detailed rare-earth use in a supply-use framework and using the Leontief inverse to construct total rare-earth requirements. Related work studies the upstream market environment and downstream adjustment. Chinese rare-earth policy and international price transmission are examined by Zhang et al. (2015), Müller et al. (2016), Proelss et al. (2018), and Seiler (2021). Alfaro et al. (2025) show that the 2010 export restrictions induced innovation toward rare-earth efficiency and affected export performance, while Bogmans et al. (2026) quantify heterogeneous macroeconomic effects of rare-earth supply-chain disruptions. These studies motivate rare-earth dependence as economically relevant, but they do not imply that the country-specific unit values used here are clean exogenous prices.

2.3 Exposure-based designs and positioning

The empirical design also shares features with exposure-based designs. Adão et al. (2019) emphasize that common exposure patterns can induce dependence that conventional standard errors miss. Goldsmith-Pinkham et al. (2020) show how Bartik-style identification can be understood through the exposure shares, while Borusyak et al. (2022) formulate a quasi-experimental perspective centered on the exogeneity and effective number of underlying shocks. The present regression is not a standard shift-share IV because the exposure–unit-value interaction enters directly as the regressor. It nevertheless has a similar inferential structure: many firm observations are generated from only a few national unit-value paths. This motivates the alternative clustering, permutation, and weighting exercises below.

Relative to this literature, the paper links measured production-network rare-earth dependence to realized downstream firm-level material-cost responses. It does not estimate a universal pass-through elasticity, validate a uniquely correct exposure measure, or claim a new exposure-design method.

3 Conceptual Framework

Let firm i in industry s, country c, and year t produce with labor, capital, and materials under constant returns. A convenient benchmark unit-cost function is

$$c_{isct} = \frac{\kappa_s}{A_{isct}} w_{ct}^{\alpha_s^L} r_{ct}^{\alpha_s^K} (P_{sct}^M)^{\alpha_s^M}. \tag{5}$$

A local approximation is

$$d \log c_{isct} \approx \lambda_{sct}^{T,eff} d \log P_{ct}^{\text{REE}} + \lambda_{sct}^X d \log P_{sct}^X + \alpha_s^L d \log w_{ct} + \alpha_s^K d \log r_{ct} - d \log A_{isct}, \tag{6}$$

where $\lambda_{sct}^{T,eff}$ is the firm's effective direct and indirect rare-earth requirement. The empirical NACE4 exposure is a proxy for this object rather than a direct observation of the firm's cost share.

Under cost minimization with Cobb–Douglas materials,

$$P_{sct}^M M_{isct} = \alpha_s^M c_{isct} q_{isct}. \tag{7}$$

Since operating revenue is $p_{isct} q_{isct}$,

$$\text{MS}_{isct} = \frac{P_{sct}^M M_{isct}}{p_{isct} q_{isct}} = \alpha_s^M \frac{c_{isct}}{p_{isct}}. \tag{8}$$

Thus,

$$d \log \text{MS}_{isct} = (1 - \rho_{isct}) d \log c_{isct}, \tag{9}$$

where $\rho_{isct} = d \log p_{isct} / d \log c_{isct}$. Combining the equations gives

$$d \log \text{MS}_{isct} \approx (1-\rho_{isct}) \left[\lambda_{sct}^{T,eff} d \log P_{ct}^{\text{REE}} + \lambda_{sct}^X d \log P_{sct}^X + \alpha_s^L d \log w_{ct} + \alpha_s^K d \log r_{ct} - d \log A_{isct} \right]. \tag{10}$$

This expression motivates both the rare-earth exposure–unit-value interaction and the non-REE controls. The country–NACE2–year PPI proxies broader material-price conditions, although it may also reflect output-price conditions. Country-year-specific slopes on fixed NACE4 labor and capital intensities allow national factor-cost conditions to load differently across industries. These variables are empirical proxies, not structural counterparts to P^X, α_s^L, or α_s^K.

The preferred empirical specification is

$$\begin{aligned} \log MS_{isct} = \beta \left(Exposure_s^{REE} \times \log P_{ct}^{REE} \right) + \theta \log PPI_{sct} + \mu_i + \delta_{ct} + \gamma_{st} \\ + \psi_{ct}^L LaborIntensity_s + \psi_{ct}^K CapitalIntensity_s + \varepsilon_{isct}. \end{aligned} \tag{11}$$

A positive β is consistent with rare-earth-related unit costs changing by more than output prices under the benchmark. It cannot be mapped directly into $1 - \rho$ because exposure, price transmission into upstream intermediates, and firm-level pass-through are not separately observed.

4 Data and Variable Construction

4.1 Firm data and sample

The initial Orbis panel contains 4,933,503 firm-year observations for 548,167 firms in manufacturing NACE Rev.2 divisions 10–33. The main outcome requires positive material costs and operating revenue. The Netherlands contributes no observations to the complete estimation sample because material-cost information is almost entirely unavailable. The final M4 sample contains 1,044,805 firm-years for 146,171 firms in Belgium, Germany, Spain, France, and Italy.

Table 1: Country Composition of the Final Estimation Sample

Country	Firm-year observations	Share (%)
Belgium	16,346	1.56
Germany	24,580	2.35
Spain	353,476	33.83
France	117,107	11.21
Italy	533,296	51.04
Total	1,044,805	100.00

Italy and Spain jointly account for 84.87 percent of observations, so the baseline is a firm-weighted rather than country-equal estimand.

The raw material-cost share is extremely right-skewed. Table 2 reports the distribution in the exact M4 sample. The median is 0.475, but the maximum is generated by an exceptionally small revenue denominator relative to reported material costs. The logarithm compresses the distribution substantially, although it does not eliminate upper-tail sensitivity.

Table 2: Descriptive Statistics for the Main Outcome

Statistic	Material-cost share	Log material-cost share
Observations	1,044,805	1,044,805
Mean	15.5230	-0.9308
Median	0.47481	-0.74483
95th percentile	0.82576	-0.19145
99th percentile	0.98258	-0.01757
99.5th percentile	1.26465	0.23480
Maximum	3,897,870	15.17594

Notes: Statistics are calculated in the exact M4 estimation sample before outcome-based restrictions.

There are 9,061 firm-years with a raw share above one, 3,138 above two, and 1,738 above five. A denominator diagnostic shows that extreme shares are strongly concentrated in years when operating revenue is unusually low relative to the firm's own typical scale. I retain the untrimmed sample as the reference because it does not condition inclusion on the realized outcome, and report systematic outcome-tail and denominator-quality diagnostics below and in the appendix.

4.2 Rare-earth import unit values

For country c, product h, and year t, the observed unit value is

$$UV_{cht} = \frac{V_{cht}}{Q_{cht}}.$$

using positive import quantities. Each HS series is normalized relative to its country-specific 2013–2015 geometric mean. Fixed product weights are based on 2013–2015 import values, and the country-year index is the weighted average of the normalized log unit values. Missing product-year observations are not set to zero or interpolated. French HS 284610 is unavailable in the source data for 2013–2020, so the French basket is formed from the remaining available categories.

Table 3: Fixed Product Weights in the Rare-Earth Unit-Value Index, 2013–2015

Country	HS 280530	HS 284610	HS 284690
Belgium	20.10	45.41	34.49
Germany	4.92	31.37	63.71
Spain	10.34	11.30	78.35
France	5.77	0.00	94.23
Italy	2.55	19.46	77.99

Notes: Entries are percentages. French HS 284610 is absent because no import value or quantity is reported in the source database for 2013–2020.

The measure is an import unit-value index, not a homogeneous transaction price. Unit values can move because of purity, chemical form, sourcing, supplier composition, contract terms, product mix, or small trade flows. More generally, changes in imported varieties and composition can complicate the interpretation of trade-based price indices (Feenstra, 1994).

Table 4 separates two sources of cross-country variation: fixed HS basket weights and country-specific within-HS paths.

Table 4: Descriptive Price-Index Construction Diagnostics

Index construction	Mean	SD	Corr. with baseline
Baseline country weights and country-HS prices	-0.2056	0.4270	1.000
Common HS weights, country-HS prices	-0.1519	0.6642	0.883
Country HS weights, common HS price paths	-0.1517	0.2975	0.384
Country HS weights, common median price paths	-0.2136	0.2458	0.499

Notes: These are raw country-year index diagnostics, not an additive variance decomposition or a decomposition of the residualized treatment after fixed effects.

Imposing common HS weights leaves the index highly correlated with the baseline (0.883), whereas imposing common within-HS price paths lowers the correlation much more sharply. Country-specific within-HS variation is therefore economically important but also a central measurement concern.

Figure 1 plots the five country-specific rare-earth import unit-value indices over 2016–2024. The figure illustrates both the common movements and the cross-country deviations in the national unit-value paths that underlie the identifying variation.

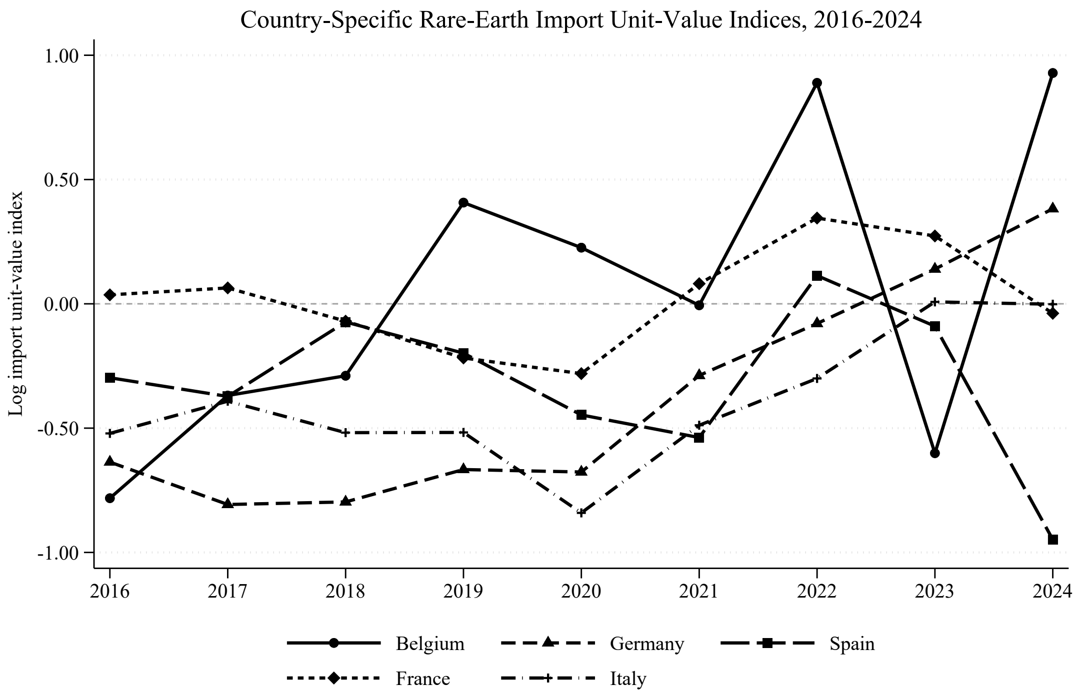

Figure 1: Country-Specific Rare-Earth Import Unit-Value Indices, 2016–2024
Notes: The figure plots the country-specific log rare-earth import unit-value indices used in the empirical analysis. The indices are constructed from fixed-weight combinations of HS 280530, HS 284610, and HS 284690 and are normalized relative to country-product-specific 2013–2015 baselines. The figure is descriptive and illustrates the limited number of national unit-value paths underlying the identifying variation.

4.3 Industry exposure and controls

The exposure measure follows the total-requirement logic of Alfaro et al. (2026). Detailed rare-earth activities are embedded in a 2017 U.S. supply-use system, and the Leontief inverse is used to capture both direct rare-earth use and rare-earth content embodied in upstream inputs. The resulting SUT requirements are mapped through NAICS and ISIC concordances into NACE4 industries. The baseline exposure is the mean across six combinations of two underlying rare-earth allocation assumptions and three aggregation rules; the median and maximum are used as robustness measures. The exposure is fixed at NACE4 and multiplied by 1,000 for readability. Full construction details and formulas are moved to Appendix A.

Across the 134 NACE4 industries in the final sample, the exposure measure has a median of 0.203 and a 90th percentile of 1.342 after the $\times 1000$ scaling. Table 5 summarizes the industry-equal distribution.

Table 5: Distribution of NACE4 Rare-Earth Exposure

Statistic	Exposure $\times 1,000$
Mean	0.4640
Standard deviation	0.5518
25th percentile	0.0978
Median	0.2028
75th percentile	0.6339
90th percentile	1.3419
Maximum	2.5602
Number of NACE4 industries	134

Highly exposed industries include engines and turbines, electric motors and generators, electricity distribution apparatus, bearings and gears, and other electrical equipment. These examples make clear that the mapped measure primarily captures production-network dependence in machinery and electrical manufacturing rather than direct purchases of raw rare-earth materials.

The PPI control is a country–NACE2–year domestic producer-price index and should be interpreted as a broad price proxy rather than a pure input-price measure. Labor intensity is employee costs divided by employee plus material costs, while capital intensity is log tangible fixed assets per employee. Each is collapsed to the NACE4 median using 2016–2017 firm data and then held fixed.

Table 6: Sequential Construction of the Estimation Sample

Restriction	Observations	Firms
Initial Orbis panel	4,933,503	548,167
Positive material costs and operating revenue	1,917,186	299,452
Fixed-effects sample requirements	1,887,895	270,161
Matched non-missing NACE4 exposure	1,044,968	146,179
Valid price, PPI, and controls	1,044,805	146,171

Notes: Restrictions are sequential. The largest loss after accounting-variable restrictions comes from the exposure crosswalk.

The results therefore apply to the subset of European manufacturing industries that can be connected to the rare-earth-augmented U.S. supply-use system through the concordance chain.

5 Empirical Strategy

5.1 Sequential specifications

I estimate four nested specifications. M1 contains Z_{sct} and firm, country-year, and NACE4-year fixed effects. M2 adds the industry PPI; M3 adds country-year-specific labor-intensity slopes; and M4 adds country-year-specific capital-intensity slopes. M4 is treated as the preferred empirical specification because it most closely incorporates the controls motivated by the non-REE cost channels in the conceptual framework. These controls are imperfect proxies, so M4 is an empirical approximation rather than a structural implementation. Variation across M1–M4 is therefore also informative about specification sensitivity.

5.2 Identification

Identification comes from the interaction of fixed cross-industry differences in measured rare-earth dependence with country-year variation in rare-earth import unit values, after conditioning on firm, country-year, and NACE4-year fixed effects and the included controls. The coefficient is identified from whether industries with different fixed exposure exhibit different material-cost-share responses across countries experiencing different unit-value movements.

The identifying assumption is that the remaining country-specific variation in unit values is not systematically correlated with unobserved country-industry-year shocks that differentially affect industries according to fixed rare-earth exposure. This condition may fail if, for example, a country-specific demand or production shock to rare-earth-intensive industries simultaneously affects firms' material-cost shares and the quantity, sourcing, quality, purity, or product composition of rare-earth imports. Because the empirical measure is an import unit value rather than a transaction price for a homogeneous good, such changes may correlate the exposure–unit-value interaction with the regression residual.

The fixed exposure measure limits contemporaneous feedback from firm outcomes into measured industry dependence. The PPI and factor-intensity slopes are intended to absorb observable channels through which broader price and factor-cost conditions may load differently across industries, but they do not rule out all unobserved country-industry-year shocks. The estimates are therefore interpreted as exposure-based reduced-form associations rather than as causal effects of exogenous rare-earth transaction-price changes, because the observed shifter is an import unit value rather than a homogeneous transaction price.

5.3 Inference

Baseline standard errors are clustered by country–NACE4. Because the treatment shifter ultimately comes from only five national unit-value paths, I also report NACE4-only clustering and a country-sequence permutation diagnostic over all $5! = 120$ assignments. The permutation exercise is a finite reallocation diagnostic, not design-based randomization inference, because the observed national paths are not assumed exchangeable.

6 Results

6.1 Main estimates and economic magnitude

Table 7: Rare-Earth Unit Values and the Log Material-Cost Share

	(1)	(2)	(3)	(4)
REE exposure × log REE unit value	0.00561	0.00448	0.00606	0.00888**
	(0.00413)	(0.00416)	(0.00416)	(0.00424)
Firm FE	Yes	Yes	Yes	Yes
Country-year FE	Yes	Yes	Yes	Yes
NACE4-year FE	Yes	Yes	Yes	Yes
Industry PPI	No	Yes	Yes	Yes
Labor-intensity slopes	No	No	Yes	Yes
Capital-intensity slopes	No	No	No	Yes
Observations	1,044,805	1,044,805	1,044,805	1,044,805
Firms	146,171	146,171	146,171	146,171
Clusters	654	654	654	654

Notes: Dependent variable is log(MaterialCosts/OperatingRevenue). Exposure is multiplied by 1,000. Standard errors clustered by country–NACE4 in parentheses. ** denotes 5 percent significance.

The point estimate is positive in each specification and rises to 0.00888 in M4. The sequential pattern should not be read as evidence that the additional controls are structurally correct; it shows how the coefficient changes as theory-motivated proxies are introduced.

Economic magnitudes are modest for the typical industry. Using the industry-equal exposure distribution, a 50 percent increase in the rare-earth unit-value index implies an approximate increase in log material-cost share of 0.073 percent at the median exposure and 0.483 percent at the 90th percentile.

6.2 Timing and inference

The labor and capital intensities are constructed from 2016–2017 firm data, so I re-estimate M4 using only 2018–2024 outcomes while leaving those intensities unchanged. Table 8 shows that the coefficient is 0.00965 with a standard error of 0.00429 ($p = 0.025$), based on 826,899 observations and 653 clusters. The result is therefore not driven by overlap between the years used to construct the intensity proxies and the outcome estimation period. This check addresses timing only; it does not establish that the proxies are exogenous.

Table 8: Pre-Period Intensity Robustness

Period	Coefficient	SE	p-value	Observations	Firms
2016–2024	0.008877	0.004236	0.037	1,044,805	146,171
2018–2024	0.009648	0.004291	0.025	826,899	139,872

Inference is more conservative when dependence in the national shifters is treated differently. Table 9 compares the alternatives.

Table 9: Inference for the M4 Estimate

Inference method	Coefficient	Standard error	p-value	Clusters/assignments
Country–NACE4 clustering	0.008877	0.004236	0.037	654
NACE4-only clustering	0.008877	0.005375	0.101	134
Country-sequence permutation	0.008877	–	0.133	120

The point estimate is therefore positive under the baseline specification, but the strength of statistical evidence is not invariant to inference choices.

6.3 Measurement and weighting sensitivity

Table 10 summarizes the main sensitivity results retained in the text; fuller tables are reported in Appendix B.

Alternative exposure summaries based on the median and maximum across the six underlying exposure variants also yield positive estimates, although the coefficient magnitudes are not directly comparable because the exposure measures have different scales and distributions (Appendix Table 14).

Table 10: Selected Sensitivity Exercises

Specification	Coefficient	Standard error	p-value
Baseline M4	0.008877	0.004236	0.037
Price composition			
Drop HS 280530	0.007696	0.003651	0.035
Drop HS 284610	0.006043	0.003280	0.066
Drop HS 284690	0.000955	0.003344	0.775
HS 284690 only	0.004107	0.002370	0.084
Weighting			
Country-equal firm weights	0.003280	0.006691	0.624
Unweighted country–NACE4–year cells	-0.000673	0.020261	0.974
Firm-count-weighted cells	0.015451	0.006803	0.023
Outcome/denominator			
Winsorize upper 0.1%	0.006789	0.004060	0.095
Exclude revenue <1% of firm median	0.006283	0.003887	0.107
Exclude revenue <10% of firm median	0.006063	0.003640	0.096

Notes: All rows use the M4 control structure unless the row itself defines a different aggregation or weighting estimand. Missing single-HS unit values are not replaced with zero or interpolated. Coefficient magnitudes are not directly comparable across single-product indices because the normalized unit-value series have different variances.

The price exercises narrow the substantive interpretation. Removing HS 284690 reduces the aggregate coefficient to approximately zero. This is not dependence on a quantitatively minor product: HS 284690 carries 63.71 percent of the baseline basket in Germany, 78.35 percent in Spain, 94.23 percent in France, and 77.99 percent in Italy. Single-product regressions likewise show a positive HS 284690 estimate of about 0.004, while HS 280530 is negative and HS 284610 is small and imprecise. On a common three-HS sample the same ordering remains, and the baseline basket coefficient is nearly unchanged. The aggregate association is therefore concentrated in the dominant HS 284690 category. Because that category is broad, however, the concentration may reflect both economic relevance and composition-related unit-value movements.

Weighting changes the estimand substantially. Giving each country equal total weight weakens the coefficient, and an unweighted country–NACE4–year cell regression is essentially zero; weighting cells by their number of firms restores a positive estimate. The baseline should therefore be interpreted as a firm-weighted relationship concentrated in larger country-industry cells rather than as an equally weighted European effect.

Outcome-tail treatment gives a similar qualification. The raw material-cost share has a long upper tail, and trimming or winsorization attenuates the estimate. Many extreme ratios coincide with sharp within-firm revenue collapses. Excluding observations with revenue below 1 percent of the firm's own median leaves about 71 percent of the baseline coefficient but weakens conventional significance. The positive sign is therefore not generated solely by a handful of extreme ratios, while its magnitude and precision remain tail-sensitive.

6.4 Country concentration of identifying variation

Leave-one-country-out and residual-variation diagnostics show that the pooled estimate is not a uniform five-country effect. Omitting Spain reduces the coefficient to about 0.0038, while omitting Italy produces a small negative estimate. Spain contributes roughly 51.8 percent of residualized treatment variation and Italy 23.7 percent; Belgium contributes about 15.3 percent despite its small observation share. These diagnostics reinforce the weighting results: the identifying variation is concentrated in a few national paths and large country-industry cells. Detailed country tables are left to Appendix B.

7 Measurement and Interpretation

Three limitations are central. First, identification relies on a small number of national unit-value paths. The alternative inference and weighting exercises show that the effective amount of independent variation is much smaller than the number of firm observations suggests. Second, the treatment uses import unit values. These can reflect composition, quality, purity, sourcing, and contract changes, and the product-level results show that the aggregate association is concentrated in HS 284690. Third, the mapped U.S.-based total-requirement measure is a proxy for European production dependence. Crosswalks, aggregation choices, and subsequent sourcing or substitution decisions create measurement error relative to firms' true effective rare-earth use.

These concerns constrain the economic interpretation. Within the benchmark identity, quantity cancels from the material-cost share, and a positive response is consistent with incomplete pass-through of rare-earth-related cost pressure. Outside that benchmark, accounting conventions, input substitution, sourcing, inventories, contracts, product composition, and markup adjustment can also affect the observed share. The data do not identify how much of the response operates through direct procurement, upstream intermediate prices, output-price adjustment, or markups. The appropriate conclusion is therefore qualitative: the sign is consistent with incomplete pass-through under the benchmark, but the coefficient is not a structural pass-through elasticity.

8 Conclusion

This paper studies whether measured production-network dependence on rare-earth inputs is associated with stronger firm-level material-cost-share responses to country-specific rare-earth import unit-value movements. Combining Orbis accounting data, Eurostat trade-based unit values, and a fixed NACE4 total-requirement measure, I estimate exposure-by-unit-value regressions with firm, country-year, and NACE4-year fixed effects. The preferred M4 specification yields a coefficient of 0.00888 with a country–NACE4 clustered standard error of 0.00424, and restricting the outcome period to 2018–2024 leaves the estimate essentially unchanged. The implied economic magnitude is modest for the typical industry.

The evidence is suggestive rather than definitive. Inference becomes more conservative under NACE4 clustering and country-path permutation; weighting exercises show that the baseline is a firm-weighted relationship rather than an equally weighted European effect; and the price result is concentrated in HS 284690, the dominant but broad customs category in most sample countries. Outcome-tail and denominator diagnostics further show that the positive sign persists under economically motivated data-quality filters, while the magnitude and conventional precision weaken.

Under the benchmark production framework, the positive sign is consistent with rare-earth-related unit costs changing by more than output prices. The analysis does not identify a structural pass-through elasticity, establish that country-specific import unit values are exogenous transaction prices, or show that the mapped exposure measure equals firms' true rare-earth use. Its contribution is instead to connect a production-network measure of rare-earth dependence to downstream firm accounting outcomes while making transparent how price measurement, weighting, inference, and accounting-data quality shape the resulting evidence.

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A Exposure Construction Details

Let z_{gj} denote intermediate input supplied by activity g to industry j, v_j value added, and $x_j = \sum_g z_{gj} + v_j$ gross output. The direct requirement matrix has elements $a_{gj} = z_{gj}/x_j$, and the Leontief inverse is

$$L = (I - A)^{-1}.$$

If E denotes rare-earth supplying activities, the total rare-earth requirement of source industry j is $TR_j^{\text{REE}} = \sum_{e \in E} L_{ej}$, capturing both direct and upstream requirements. Source industries are mapped through BEA SUT 2017 → NAICS 2017 → NAICS 2012 → ISIC Rev.4 → NACE Rev.2. For each of two element-share assumptions, I form equal-weighted, T018-weighted, and T019-weighted NACE4 aggregates. The baseline exposure is the mean across these six variants; their median and maximum are used in sensitivity checks. Repeated concordance paths from the same source to the same NACE4 are deduplicated before aggregation.

B Detailed Robustness Results

Table 11: Single-HS Rare-Earth Unit-Value Regressions

Price construction	Coefficient	Standard error	p-value	Observations
Panel A: Product-specific available samples				
Baseline three-product basket	0.008877	0.004236	0.037	1,044,805
HS 280530 only	-0.003133	0.002962	0.291	1,044,805
HS 284610 only	0.003770	0.003862	0.330	927,698
HS 284690 only	0.004107	0.002370	0.084	1,044,805
Panel B: Common three-HS sample				
Baseline three-product basket	0.008974	0.004297	0.037	927,698
HS 280530 only	-0.006517	0.004251	0.126	927,698
HS 284610 only	0.003770	0.003862	0.330	927,698
HS 284690 only	0.003987	0.002413	0.099	927,698

Notes: All specifications use M4 controls and country–NACE4 clustering. Panel B holds the sample fixed across products. Coefficient magnitudes are not directly comparable because the normalized unit-value series have different variances.

Table 12: Complete Material-Cost-Share Tail Sensitivity Path

Outcome treatment	Coefficient	Standard error	p-value	Observations
Preferred M4, untrimmed	0.008877	0.004236	0.037	1,044,805
Trim 0.5–99.5 percentiles	0.002583	0.002999	0.390	1,033,341
Trim 1–99 percentiles	0.002926	0.002544	0.250	1,022,172
Trim upper 0.1%	0.004326	0.003846	0.261	1,043,611
Trim upper 0.25%	0.003626	0.003809	0.341	1,041,871
Trim upper 0.5%	0.002365	0.003845	0.539	1,039,027
Trim upper 1%	0.002178	0.003839	0.571	1,033,407
Winsor upper 0.1%	0.006789	0.004060	0.095	1,044,805
Winsor upper 0.25%	0.005230	0.003884	0.179	1,044,805
Winsor upper 0.5%	0.004491	0.003812	0.239	1,044,805
Winsor upper 1%	0.004258	0.003778	0.260	1,044,805

Notes: All rows use M4 controls, fixed effects, and country–NACE4 clustering. The table reports a systematic sensitivity path and is not used to select a preferred cutoff.

Table 13: Country Concentration Diagnostics

Panel A: Leave-one-country-out estimates			
Omitted country	Coefficient	Standard error	p-value
None	0.008877	0.004236	0.037
Belgium	0.010333	0.004630	0.026
Germany	0.010097	0.004411	0.022
Spain	0.003797	0.007391	0.608
France	0.008974	0.004297	0.037
Italy	-0.003222	0.005226	0.538
Panel B: Residual identifying variation			
Country	Observation share (%)	Residual variation share (%)	
Belgium	1.56	15.30	
Germany	2.35	5.33	
Spain	33.83	51.75	
France	11.21	3.91	
Italy	51.04	23.71	

Notes: Panel A reports leave-one-country-out estimates using the M4 specification and country–NACE4 clustered standard errors. Panel B compares each country's share of firm-year observations with its share of residualized variation in the rare-earth exposure–unit-value interaction after applying the M4 fixed effects and controls.

Table 14: Alternative Rare-Earth Exposure Measures

Exposure measure	Coefficient	Standard error	p-value
Mean	0.008877	0.004236	0.037
Median	0.014274	0.006758	0.035
Maximum	0.003009	0.001141	0.009

Notes: Each row re-estimates the M4 specification using a different summary across the six underlying NACE4 exposure variants. Standard errors are clustered by country–NACE4. Coefficient magnitudes are not directly comparable across exposure measures because the measures have different scales and distributions.

Table 15: Alternative Weighting and Aggregation

Estimation level	Weighting	Coefficient	Std. error	p-value	Observations
Firm-year	Observation-equal	0.008877	0.004236	0.037	1,044,805
Firm-year	Country-equal	0.003280	0.006691	0.624	1,044,805
Country–NACE4–year cell	Equal cell weights	-0.000673	0.020261	0.974	5,837
Country–NACE4–year cell	Firm-count weights	0.015451	0.006803	0.023	5,837

Notes: The first two rows are estimated at the firm-year level. Observation-equal weighting gives each firm-year equal weight, while country-equal weighting gives each country equal total weight. The final two rows collapse the data to country–NACE4–year cells. Firm-count weighting assigns each cell a weight equal to its number of underlying firms.