The Scope of Scope-3

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Abstract

We propose a novel network-based methodology in order to measure emissions along complex international supply chains (SC). Using international data for about 50,000 firms, we characterize SC-level emissions across countries and industries. Our methodology enables us to run counterfactual experiments and formulate granular forecasts about high-scope emissions with respect to many different scenarios such as maritime disruption, military conflicts, trade wars, revised carbon taxes.

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1 Introduction

The increase in $CO2_e$ concentration in the atmosphere is a global phenomenon that requires thinking about emissions in a global framework. In this spirit, climate experts have defined different scopes of emissions which comprise direct emissions (Scope-1), emissions associated with the acquisition of inputs (Scope-2), and emissions created along the supply chain (Scope-3). While these concepts are well established (see Greenhouse Gas Protocol (2011)), both their measurement and management require additional effort (in this spirit, see, among others, Reichelstein 2025).

In this paper, we propose a transparent, verifiable, and general equilibrium–based methodology to both (i) measure current Scope-3 emissions across different levels of granularity, and (ii) conduct scenario analysis in order to forecast Scope-3 emissions when supply chains adapt to a wide range of shocks.

The first task, that is, measuring current Scope-3 emissions is important for several reasons. First, different data providers offer substantially different measures of high-scope emissions. These discrepancies arise from different assumptions on the input-output matrix across firms, as well as the heterogeneous firm coverage. We propose a methodology which requires only direct emissions and can therefore be independently replicated and verified. Direct emissions tend to be measured with less variability both across data providers, and over time as firms revise their sustainability reports (Cohen et al. 2026).

Second, the accounting of emissions has not fully matured yet. Our methodology is an important new tool to measure high-scope emissions and it can help corporations to better assess their global climate risk exposures, as well better benchmark against other firms operating in their industry and/or country. Importantly, since many companies are not required to disclose their sustainability reports, our methodology increases coverage across thousands of firms. Furthermore, our setting enables us to compute embodied emissions (Hertwich and Wood 2018), that is, a measure that accounts for all emission exchanges along the entire supply chain.

Third, our methodology explicitly accounts for the emissions induced by the international shipping of goods along different roads and maritime routes. By doing so, we increase awareness about high-scope emissions imported from remote, low-cost providers, and enable counterfactual analysis about shocks that alter international trade routes. A key advantage of our methodology is that it highlights firms embedded in local networks with lower transport emissions. In addition, our equations enables us to look at the contribution to the embodied emissions of a focal firm across upstream suppliers, and over different tiers of connections. By doing so, we provide direct guidance on the origins of embodied emissions.

Our second task is to use our general equilibrium approach to run scenario analysis and forecast how emissions across different supply chains respond to relevant shocks. This exercise is relevant for (i) managers who want to make their supply chains more emission-resilient, (ii) investors aiming to build low-carbon portfolios, and (iii) policymakers interested in the link between global emissions and economic and geopolitical shocks.

For the purposes of this manuscript, we focus on the following illustrative questions. First, what would happen to emissions under geopolitical stress causing major maritime route disruptions? Second, what would happen if an entire emerging economy were removed from a supply chain? These experiments illustrate the insights that our measurement of high-scope emissions can deliver. To keep the analysis focused, we select Heidelberg Materials as the focal firm and study its supply chain, a benchmark example in the literature (Reichelstein 2024).

Our methodology is flexible enough to accommodate many additional scenarios. Future research should also address first-order questions such as: what should we expect for high-scope emissions in the aftermath of the EU CBAM? More broadly, how would high-scope emissions change when a large economy imposes highly heterogeneous tariffs across countries?

Methodology and data. We think of a supply chain as a network of firms identified around a focal firm. Using the classic model of Long and Plosser (1983) requires us to

identify: (1) N firms; (2) $N \times N$ production function intensity coefficients; (3) N productivity levels; and (4) the total size of a common factor that in our model is capital. After choosing the focal firm, we use FactSet to identify links to customer and supplier firms. This step determines N. Usually, these firms operate in very different countries and sectors. We use the OECD input-output matrix to infer their production function intensity coefficients. From FactSet, we obtain standardized productivity measures for each firm in the network. After matching revenues reported in FactSet, and targeting a cost of capital set to a standard value of 10%, we rescale all productivity measures and recover total capital in the network. In sum, this procedure enables us to uniquely retrieve quantities produced in the network starting from observed data.

Once quantities are obtained, we augment our network setting with an emission matrix that accounts for both direct emissions due to production and additional emissions due to transport. Direct emissions are obtained from Trucost. Granular transport data are not available. As a result, we proceed with a novel AI-powered empirical effort. First of all, we need to identify firms that require physical delivery of products. We apply an LLM to both the FactSet description of each firm and its SIC code to determine which transport the company likely uses, if any. We use (i) Google Maps and SeaRoute (https://eurostat.github.io/searoute/) to identify shipping routes across firms, and (ii) emission data from International Maritime Organization (2024) to convert routes in tons of CO_2e.

When we simulate a disruption in maritime routes, we keep the original network unchanged and hence the equilibrium quantities remain unchanged as well. The only object that needs to be recomputed is the emission matrix. When instead we simulate a ban on an entire country, we use remove all firms located in that country from the network and replace them with comparable firms located nearby. To identify potential replacement we use both FactSet 'known competitors', and an additional list obtained via advanced text analysis. Specifically, we apply cosine similarity to firm description in FactSet and complement this approach with an LLM that determines whether firms are competitors (binary outcome) and

the confidence level of such answer. After the network is reformed, the equilibrium model is recalibrated and solved. Equilibrium quantities and emissions are reassessed.

Literature. This paper contributes to a fast-growing literature on the economics of climate and sustainability. For a recent and comprehensive review of the carbon accounting literature, see Stechemesser and Guenther (2012), He et al. (2022), and Stachelscheid and Dutzi (2025). For a seminal review on climate finance and economics, we refer to Giglio et al. (2021), and Hassler et al. (2021) and Heal (2009), respectively.

Our work is related to Hertwich and Peters (2009), who measure carbon footprint across 73 nations and 8 industry aggregates. We differ in our focus on supply-chains, our network equilibrium approach, and the novel AI-powered tools that we employ in order to merge and interpret our large datasets.

Pástor et al. (2021) estimate the present value of future emission-related damages. Greenstone et al. (2023) estimate the monetary value of current damages. Both papers focus on Scope-1 emissions. We do not price damages, instead we promote a new methodology to assess emissions at different scope levels. In addition, we compute firm-level embodied emissions, i.e., a broader measure of emissions (Hertwich and Wood 2018) that can better help in identify 'brown' and 'green' firms.

Pankratz and Schiller (2024) investigates whether in the data companies change their supply chains in response to climate news shocks. We run scenario analysis and find potential replacements via AI-powered algorithms.

2 Data

Merging. We start by merging data from FactSet and Trucost. These two datasets have very different sizes and scope, as shown in the top portion of Table 1. Most importantly, these two datasets do not have a common identifier for their firms, implying that a matching algorithm is required. We describe our merging procedure in detail in Appendix A. Here,

Table 1: Comparison of Full FactSet and Trucost Datasets

Panel A: Comparison of source datasets

	FactSet	FactSet Financials	Trucost
Total Number of Unique Companies	275,631	54,912	3,629,434
Total Number of Unique Countries	219	124	203
Percentage of Private Companies	51.5%	22.2%	99.0%
Percentage of Public Companies	14.3%	66.6%	0.5%
Percentage of Other Companies	34.2%	11.2%	0.5%

Panel B: merged dataset

Total Companies	43,117
Perfect Matches (Identifier)	6,259
Average Match Score	96.71
Median Match Score	100.00
Total Countries	109

Panel C: entity type in merged sample

Public Companies (PUB)	26,403	61.2%
Private Companies (PVT)	11,765	27.3%
Other Types	4,949	11.5%

Notes: The top panel of this table compares the full FactSet and Trucost datasets. FactSet provides standardized global financial data and supply chain information. Trucost provides standardized global emissions information, enabling the assessment of corporate environmental impacts across direct operations and value chains. Factset captures 275,631 companies in 219 countries, but only 54,912 companies in 124 countries have the full financial information required by our model. Trucost has 3,629,434 companies in 203 countries over an annual sample starting in 2003 and ending in 2023. In panel B and C, we provide the summary statistics of our matched companies, with full financial information and emission information. In panel C, 'Other types' includes Government entities, Not-for-profit organizations, Subsidiaries, Holding companies, Joint ventures, Limited partnerships, Limited liability companies, Corporations (not specifically public/private), Cooperatives, Trusts, Investment funds, Insurance companies, Utilities, Real Estate Investment Trusts.

we point out that, unlike off-the-shelf entity resolution packages, our solution is specifically designed to handle the hierarchical corporate structures present in financial data, where companies can have complex parent-child relationships across different supply chains.

The system performs multi-pass matching across different organizational levels, combining exact identifier matching, fuzzy string similarity, and AI-based validation to achieve high-quality matches. This approach is particularly valuable for financial analysis, where understanding corporate hierarchies and subsidiary relationships is crucial for accurate emissions accounting and risk assessment.

As detailed in the Appendix, for many public companies the match is perfect because it is based on universal identifiers (CUSIP). Other companies may not have such identifiers, but they may be sufficiently well known that their name and country location coincide across

FactSet and Trucost. These matches feature a match score of 100%, reflecting maximum confidence in the entity resolution.

As shown in Panel A of Table 1, our final FactSet sample comprises 54,912 companies with complete financial and geolocation data. To maximize matching coverage while maintaining data quality, we employ a two-pass fuzzy matching procedure augmented with AI validation for ambiguous cases. The first pass applies a 95% similarity threshold, while the second pass uses an 85% threshold with AI review for borderline matches. As reported in Panel B, this approach yields 43,117 successfully matched firms (78.5% of our financial sample) distributed across 109 countries. The matched universe exhibits strong data quality, with an average match score of 96.7 and a median score of 100.0. Match types include 6,259 perfect identifier matches, 30,312 exact name-country matches, and 11,350 high-confidence fuzzy matches. AI validation confirmed an additional 1,868 matches that would have been rejected under purely algorithmic criteria. The resulting merged dataset features a distribution tilted towards public companies, which provides a higher proportion of complete financial and emission records compared to non-public companies.

Geographical distribution. Figure 1 shows both the geographical distribution of our sample and the total number of companies in each country. Our geocoding procedure employs a two-step approach to maximize coverage while maintaining accuracy. First, we geocode companies using structured address data (street address, city, postal code) from FactSet, querying Google's Geocoding API with complete location information. For companies lacking complete address data, we employ a second geocoding pass using only the company name and country, leveraging Google's ability to locate well-known establishments. This strategy yields geocoding coverage of 100%, providing coordinates for our 54,912 companies with financials. The geocoded sample spans all inhabited continents, with twenty-four countries containing more than 500 companies, ensuring that our results are not driven solely by a small cross-section of major locations. We report summary statistics for the top-15 countries

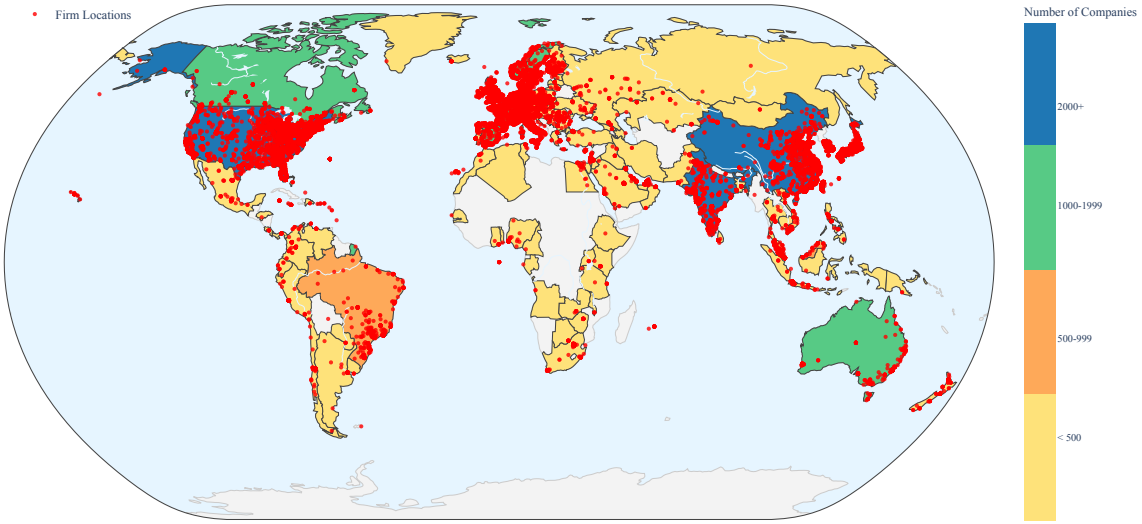


Fig. 1: Global Distribution of Establishments

Notes: This figure shows the geographical distribution of the firms in our dataset denoted as 'Financial FactSet' in table 1. Each dot corresponds to a company location. The color used for each country (right scale) refers to the total mass of firms located in that country.

sorted by number of companies in Table B.1 in the Appendix.

Supply chain features. We report basic network statistics in Table 2. In this table, we focus on 2023 data because (i) it is the most recent year in our sample, and (ii) coverage is higher in the second half of our sample. We report the time series of our data in Tables B.2-B.3 in the Appendix. The main takeaway from Table 2 is that, although our merged sample features a smaller cross section of firms, it preserves the main network characteristics reported in the FactSet universe. Notably, our merged sample exhibits higher network connectivity, i.e., on average our firms feature nearly twice as many suppliers (5.90 vs. 2.99) as in the full sample, while having a similar average of customer relationships. Hence our sample captures established and interconnected firms.

Emissions. In table 3, we report standard statistics for the emissions provided by Trucost. The same statistics for the entire Trucost universe are reported in table B.4, in the Appendix. We note three relevant points. First, both in our merged dataset and in Trucost, emission

Table 2: Supply Chain Network Analysis Comparison

Metric	All Companies	Matched Universe
Analysis Year	2023	2023
Total Firms Analyzed	329,151	54,912
Firms with Suppliers	92,412	29,006
Firms with Customers	33,188	30,806
Firms with Both	17,809	17,338
Firms with Neither	221,360	24,064
Avg Suppliers per Firm	2.99	5.90
Median Suppliers per Firm	1.00	2.00
Avg Customers per Firm	8.33	8.66
Median Customers per Firm	4.00	4.00
Max Suppliers per Firm	1,328	1,083
Max Customers per Firm	370	370
Total Supplier Relationships	276,435	171,073
Total Customer Relationships	276,435	266,989

Notes: This tables compares the network relationships between the entire Factset universe and our matched companies, for a selected year 2023.

intensity has been declining in the last twenty years. Second, Trucost has a limited coverage of Scope-3 emissions since it typically does not report downstream emissions. This is one of the dimensions in which our methodology is new and relevant. Third, in figure 2 we plot the distribution of emissions across firms in both Trucost and our our merged dataset. In 2010, the distribution of emissions in our merge dataset is essentially identical to that in the Trucost universe. In recent years, Trucost coverage has changed dramatically, and it has started to include many small private firms with modest reported emissions. As a result, the emission distribution has shifted to the left. In our merged dataset, this effect is mitigated and hence we have a more stable distribution over time.

International I-O data. In the next section, we present our network-based model to compute high-scope measures. This model can be calibrated only after knowing the shares of sales across all firms belonging to the network. Unfortunately, there is no dataset that provides these data at the firm-pair level. That is, we cannot find the full decomposition of sales (purchases) of a specific firm across customers (suppliers). For the sake of this project,

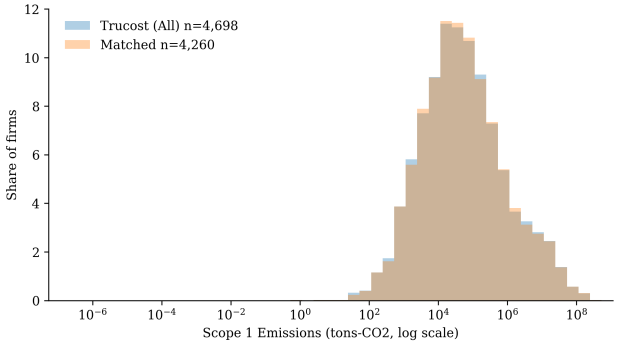
Table 3: Selected GHG Emission Measures in our Dataset

Year	Emission Intensity (Median)			Total Emissions		
	S1	S3 Up	S3 Down	S1	S3 Up	S3 Down
2002	34.96	289.18	0.00	4,186	3,742	0
2003	32.32	252.07	0.00	5,109	3,935	0
2004	30.79	217.27	0.00	6,470	5,074	0
2005	29.47	182.39	0.00	7,384	5,256	0
2006	28.43	169.58	0.00	8,014	5,414	0
2007	27.08	157.65	0.00	8,622	5,872	0
2008	25.78	141.62	0.00	8,960	5,517	0
2009	25.36	153.64	0.00	8,759	5,925	0
2010	26.02	146.20	0.00	9,518	6,207	0
2011	23.98	137.33	0.00	10,489	7,016	0
2012	22.78	129.07	0.00	10,357	7,174	0
2013	22.09	119.31	0.00	11,095	7,380	0
2014	20.67	112.34	0.00	11,089	7,173	0
2015	20.82	112.48	0.00	10,904	6,445	0
2016	18.93	123.01	0.00	12,271	8,113	0
2017	18.29	125.86	0.00	13,633	9,376	0
2018	18.89	116.92	0.00	19,416	11,193	0
2019	18.71	105.53	68.98	19,310	10,267	47,448
2020	18.84	97.77	0.00	19,431	11,595	49,263
2021	17.49	100.13	0.00	22,517	14,583	60,664
2022	16.10	76.99	0.00	20,691	11,704	69,722
2023	15.28	76.99	37.33	18,139	9,267	70,210

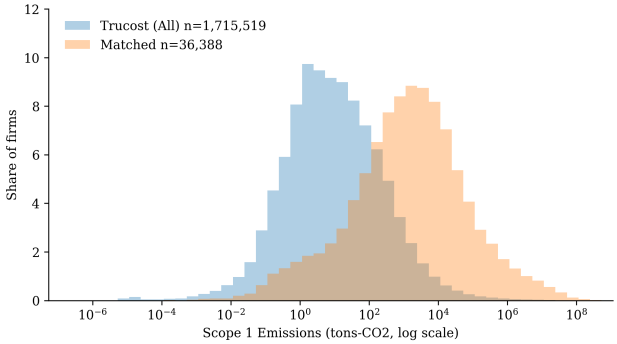
Notes: This table reports medians for emission intensity variables and sums for absolute emission variables from our matched database. Figures are aggregated by fiscal year over an annual sample starting in 2002 and ending in 2023. S1 refers to Scope-1 emissions. S3 Up (Down) refers to upstream (downstream) Scope-3 emissions. 'Emission Intensity' is measured as tons of emissions divided by sales in USD millions. 'Absolute Emissions' is measured in millions of tons.

the problem is even more pronounced relative to prior studies because of our international environment.

We address this issue by using the regular Inter-Country Input-Output (ICIO) tables produced by the OECD for their 2023 release (Yamano 2023; https://www.oecd.org/en/data/datasets/inter-country-input-output-tables.html). This matrix is quite granular as it provides data at the sector-country level (45 sectors for 76 individual countries) and hence features a total of 3420×3420 entries. In what follows, we map the ICIO sectors to FactSet sectors, reducing dimensionality to 15 sectors for 76 economies, i.e. 1140×1140



(a) 2010



(b) 2022

Fig. 2: Emissions Distribution

Notes: This figure shows the distribution of emissions across firms in both the Trucost universe and our merged dataset in 2010 and 2022.

entries.

Shipping. In order to properly compute high-scope emissions, we must account for shipping-related emissions. First, we identify 3,804 main ports across the globe from the World Port Index (WPI 2019, https://msi.nga.mil/Publications/WPI). We compute maritime routes between these ports using SeaRoute (https://github.com/eurostat/searoute), which determines the length of all possible routes connecting the ports through different straits and passages. From the OECD's maritime transport CO_2 emissions database (Clarke 2023), we obtain the average emission factors (kg CO_2 per nautical mile by vessel type). From the International Maritime Organization (International Maritime Organization 2024), we obtain the average cost intensity of a fleet, measured in USD per tonne-mile. This metric

is defined as the annual total cost of a representative fleet, including annualized capital, operational, and fuel expenditures, as well as regulatory revenues and expenses imposed by the policy measures, divided by the total transport work (based on cargo carried). Combining these averages allows us to estimate shipping-related emissions normalized by monetary transport work (USD per nautical-mile). We extend this methodology to road-related shipments by calculating the geodesic distance (conservative approach), and applying terrestrial emission factors (kg CO_2 per-km) from the Intergovernmental Panel on Climate Change guidelines (The Intergovernmental Panel on Climate Change 2023, https://www.ipcc.ch/).

Thanks to our geolocalization effort, we know exactly the routes that can be used to ship goods (we exclude services from these computations) across firm-pairs. A firm-pair comprises a producer (supplier) and user firm (customer). In our benchmark analysis, we select the shortest route to have a conservative estimate. As a result, we account for emissions induced by shipping goods (i) from the supplier firm location to its nearest port; (ii) from the departing to the arrival port using the shortest maritime route; and (iii) from the arrival port to the location of the customer firm. For the final consumers, we use an 'average' destination, namely the center of the country in which they reside. We note that our code is flexible and it enables us to consider many alternative shipping routes. This flexibility allows us to reassess high-scope emissions in counterfactual scenarios.

Figure 3 illustrates an example of alternative shipping routes from Shanghai to Rotterdam, including multi-leg connections through Los Angeles and Cape Town. The map shows Route 1 (Shanghai–Los Angeles), Route 2 (Los Angeles–Cape Town), and Route 3 (Cape Town–Rotterdam), as well as two alternative scenarios: the shortest possible direct route and the option avoiding both the Suez and Panama Canals. Different route lengths translate into different emissions estimates, which are incorporated in our framework.

Financial constraints. In the data, we have information about sales, but emissions are related to quantities produced, that is, sales divided by prices. In the next section, we show

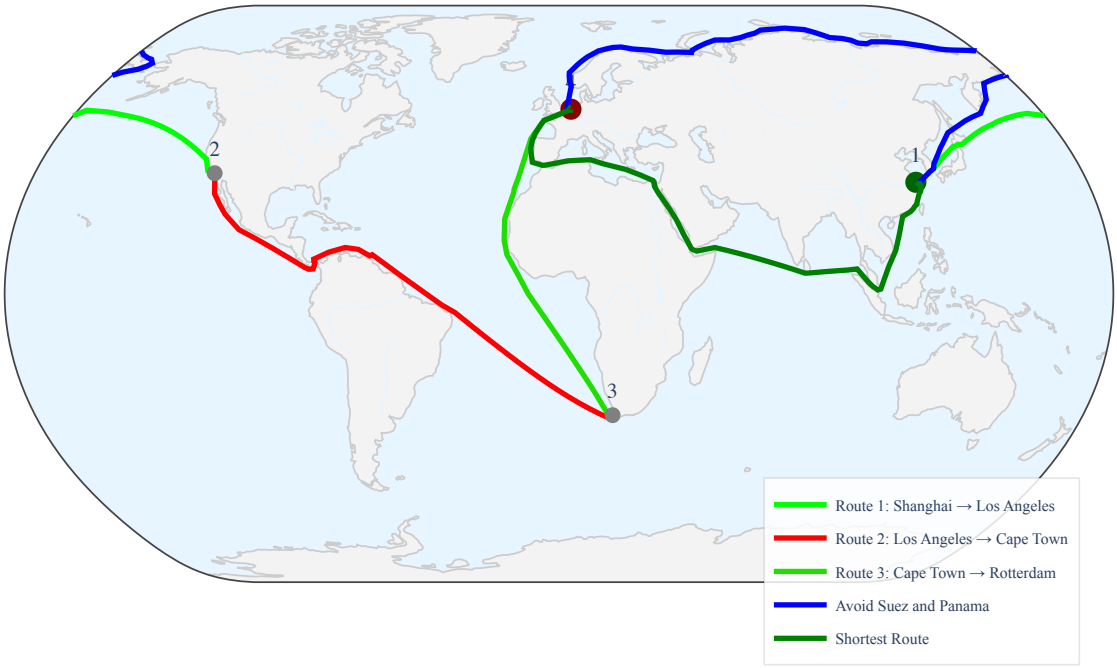


FIG. 3: Multi-leg maritime routes between Shanghai and Rotterdam

Notes: This figure shows the multi-leg maritime route from Shanghai to Rotterdam via Los Angeles and Cape Town. The map illustrates alternative paths between major ports: Route 1 (Shanghai–Los Angeles), Route 2 (Los Angeles–Cape Town), and Route 3 (Cape Town–Rotterdam). Alternative scenarios include the shortest possible route and a diversion avoiding both the Suez and Panama Canals. For a shipment of 50,000 tons of cargo, the benchmark route covers 39,800 km with estimated emissions of 15,920 tCO_2, while the shortest and canal-avoiding alternatives are associated with 6,154.4 tCO_2.

a general equilibrium network model that is used to recover quantities from observed sales. In contrast to the standard Long and Plosser (1983) approach, we account for financial constraints because they can substantially alter prices across firms. To capture firm-level financial constraints in our sample, we calculate the Altman Z-Score (Altman 1983), a widely used bankruptcy prediction model based on accounting ratios. We employ different formulations for public and private firms to account for differences in data availability and capital structure. For public companies, we use the original five-factor model:

$$Z = 1.2\frac{WC}{TA} + 1.4\frac{RE}{TA} + 3.3\frac{EBIT}{TA} + 0.6\frac{MVE}{TL} + 1.0\frac{S}{TA}, \tag{1}$$

where WC denotes working capital, TA total assets, RE retained earnings, $EBIT$ earnings before interest and taxes, MVE market value of equity, TL total liabilities, and S sales. For public firms, the distress zone is defined as $Z < 1.81$, the gray zone as $1.81 \leq Z < 2.99$, and the safe zone as $Z \geq 2.99$. For private firms, where market value of equity is unavailable, we employ book value of equity (BVE):

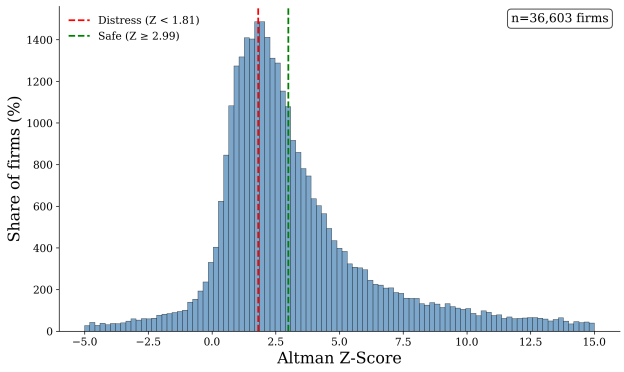
$$Z' = 0.717\frac{WC}{TA} + 0.847\frac{RE}{TA} + 3.107\frac{EBIT}{TA} + 0.420\frac{BVE}{TL} + 0.998\frac{S}{TA}, \tag{2}$$

with corresponding thresholds of $Z' < 1.23$ for distress, $1.23 \leq Z' < 2.90$ for the gray zone, and $Z' \geq 2.90$ for the safe zone. Lower Z-Scores indicate a higher likelihood of financial distress and, by extension, tighter financial constraints. Figure 4 presents the distribution of Z-Scores for both public and private firms in our sample, revealing substantial variation in financial health across entities. This measure allows us to systematically rank firms' financial health and incorporate financial frictions into our analysis of supply chain exposures.

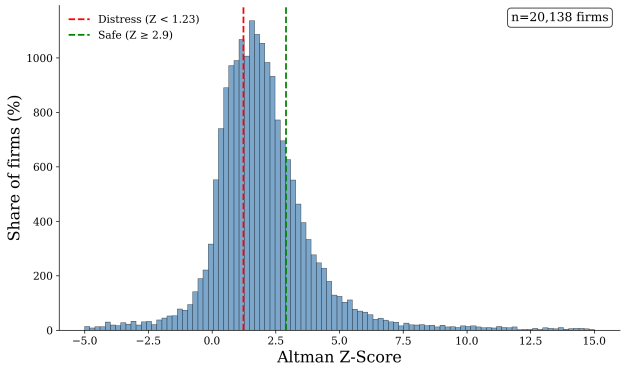
In figure 5, we show the average distress level across country-sector combinations in our sample. The heatmap reveals heterogeneity in financial health across industries and geographies. Some sectors, such as industrial services, transportation and utilities, exhibit higher average distress levels. Gray cells indicate country-sector combinations with insufficient data. This geographic and sectoral variation in financial constraints motivates our granular approach to modeling firm-level production decisions and their implications for emissions allocation.

3 The model

In what follows, we introduce our general equilibrium model that enables us to conduct counterfactual analyses. In a second step, we introduce equations essential for emissions accounting.



(a) Public



(b) Private

FIG. 4: Altman Z-Score Distribution

Notes: This figure shows the distribution of Altman Z-Scores for public and private firms. Vertical dashed lines indicate distress and safe zone thresholds for each firm type. Histograms exclude the top and bottom 3% of observations.

3.1 The Decentralized Economy

Consider a network of n companies defined through an input-output matrix, $\mathbf{A} = (\alpha_{m,u})_{u,m}$. Each firm has a Cobb-Douglas production function for good j,

$$y_j = f(k_j, \mathbf{x}_j) = z_j k_j^{\alpha_{0,j}} \prod_{m=1}^{n} x_{m,j}^{\alpha_{m,j}}, \tag{3}$$

where k_j is capital, traded in a common market, and $\mathbf{X} = (x_{m,u})_{m,u=1}^{n}$ comprises all inputs produced by company m (manufacturer) and purchased by company u (user). The

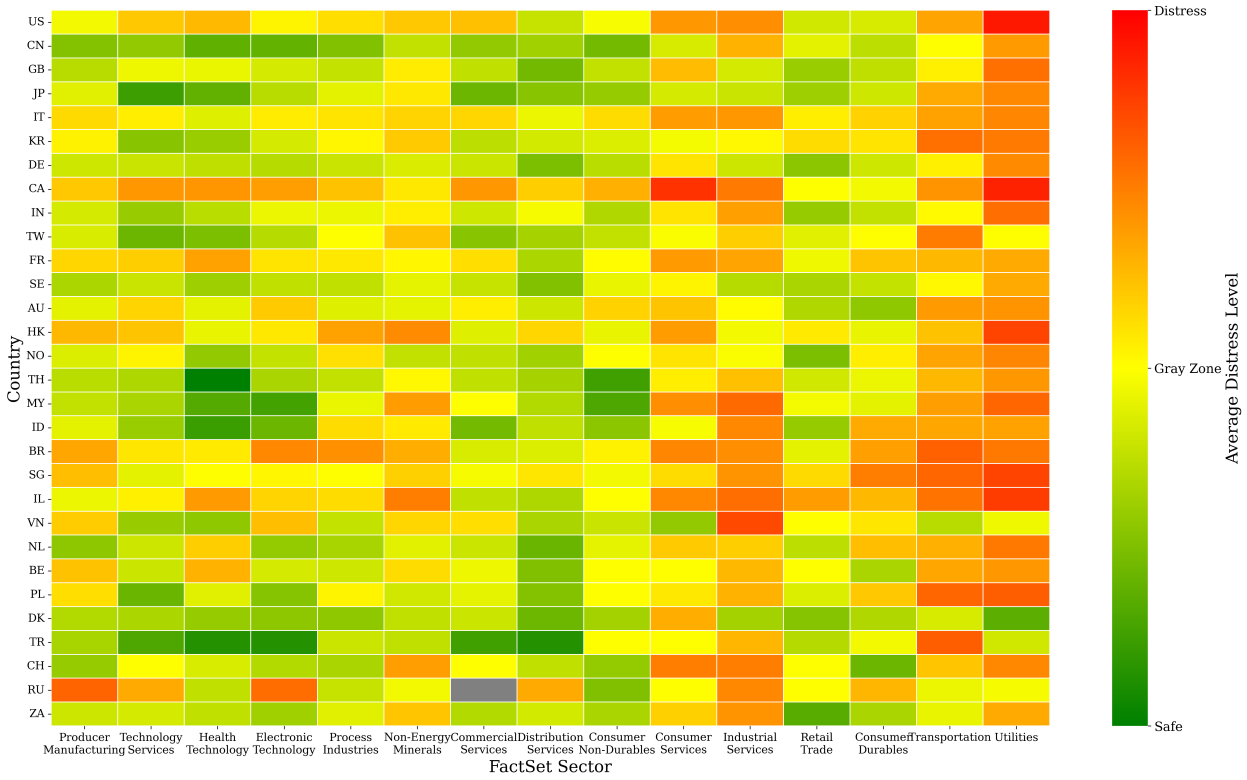


FIG. 5: Average Financial Distress for Selected Country-Sectors

Notes: This figure shows the average distress level calculated from the Altman Z-Score measure among firms in the 30 countries and 15 sectors with the highest observation density in our sample. The color scale ranges from green (safe zone, distress=0) through yellow (gray zone, distress=1) to red (distress zone, distress=2). Gray cells indicate country-sector combinations with no firms in our sample.

household's consumption bundle is standard:

$$\mathrm{C}(\boldsymbol{\chi}) = \prod_{j=1}^{n} \chi_j^{\omega_j}.$$

In order to properly disentangle quantities from prices, we need a model that captures key frictions in the data. We consider a decentralized economy in which (i) emissions are not priced and are taken as given by the household, and (ii) firms access the capital market individually and are subject to individual borrowing constraints. Specifically, firm j solves

the following problem:

$$\begin{aligned}
&\max_{y_j,\mathbf{x}_j,k_j} \pi_j\left(k_j,\mathbf{x}_j\right) := p_j y_j - \mathbf{p}^{\mathrm{T}}\mathbf{x}_j - r^D g\left(k_j,\mathbf{x}_j\right) - c_B\left(k_j,\mathbf{x}_j\right)\\
&\quad s.t. \quad g\left(k_j,\mathbf{x}_j\right) = k_j + \delta \underbrace{\mathbf{p}^{\mathrm{T}}\mathbf{x}_j}_{\text{working capital}}, \quad \delta \in [0,1]\\
&\qquad c_B\left(k_j,\mathbf{x}_j\right) = \phi_1 \cdot \exp(\phi_2 \cdot (g_j - \bar{d}_j)), \quad \phi_1 \approx 0^+, \quad \phi_2 >> 0,
\end{aligned}$$

where g_j represents the total amount that firm j must borrow and it includes working capital if $\delta > 0$ (Bigio and La'O 2016); the convex function c_B convexifies/mimics the hard borrowing constraint $g_j < \bar{d}_j$; and $\bar{d}_j$ is a firm-specific borrowing limit that each firm takes as given. Using the convex distress cost c_B enables us to find the network equilibrium by 'staying in the interior', i.e., by solving a system of first-order conditions without needing to keep track of occasionally binding constraints across firms. As in the model with hard borrowing constraints, the effective cost of capital is firm-specific and depends on the tightness of the constraint:

$$R_j := r^D + \phi_2 c_B\left(k_j,\mathbf{x}_j\right).$$

In practice, when $g_j = \bar{d}_j$, the size of firm j cannot adjust upward, so this financial friction acts as a strong upward adjustment cost. The supply curve of good j becomes nearly rigid, and the entire network is affected as a result.

The household solves the following problem:

$$\begin{aligned}
&\max_{\boldsymbol{\chi}} \quad C\left(\boldsymbol{\chi}\right),\\
&s.t. \quad \sum_{j=1}^{n} \left(\underbrace{r^D g_j\left(k_j^*,\mathbf{x}_j^*;\theta\right) + c_B\left(k_j^*,\mathbf{x}_j^*;\theta,\phi\right)}_{\text{tot. capital income}} + \pi_j\left(k_j^*,\mathbf{x}_j^*;\theta\right) \right) = \mathbf{p}^{\mathrm{T}}\boldsymbol{\chi},
\end{aligned}$$

and all markets clear:

$$y_j = \chi_j + \sum_{u=1}^{n} x^*_{j,u}, \quad j = 1, \ldots, n$$
$$K \geq \sum_j k_j.$$

At the equilibrium, we have the following conditions:

$$k_j = \alpha_{0,j} \frac{p_j y_j}{R_j} \tag{4}$$
$$x_{m,u} = \alpha_{m,u} \frac{p_u y_u}{p_m} \frac{1}{1 + \delta R_u} \tag{5}$$
$$\chi_j = \omega_j \frac{C(\boldsymbol{\chi})}{p_j}. \tag{6}$$

Equation (4) differs from what we would get in a standard Long and Plosser (1983) economy because of the firm-specific cost of capital, R_j. Equation (5) captures the role of working capital borrowing costs through the wedge $(1 + \delta R_u)^{-1}$, which disappears when $\delta = 0$. Equation (6) is standard. Importantly, the capital allocation is distorted when different firms face different effective borrowing costs, and this channel has a general equilibrium effect on quantities and prices.

3.2 Emission networks

Network emissions. Each company m is characterized by a company-specific emission intensity coefficient θ_m. The emissions associated with supplying one unit of good m to user u are $\theta_m \xi_{m,u}$. This term accounts for the fact that the same product can have different emissions when delivered across industries that differ, for example, in their location. When the same good is delivered to the final consumer, direct emissions are $\theta_m \xi^c_m$. Hence total

network emissions are:

$$E^{tot} = \sum_{m=1}^{n} \theta_m \xi_m^c \boldsymbol{\chi}_m + \sum_{u=1}^{n} \sum_{m=1}^{n} \theta_m \xi_{m,u} x_{m,u} = \boldsymbol{\theta}^{\mathrm{T}} (\boldsymbol{\xi^c} \circ \boldsymbol{\chi}) + \boldsymbol{\theta}^{\mathrm{T}} (\mathbf{E} \circ \mathbf{X}) \, \mathbf{1}, \tag{7}$$

in which $\mathbf{E} = (\xi_{m,u})_{m,u=1}^{n}$ is a matrix that comprises all business-to-business (i.e., pair-specific) emissions, $\boldsymbol{\xi^c} = (\xi_m^c)_{m=1}^{n}$ is a vector comprising business-to-consumer (i.e., product-specific) emissions, and the vector $\boldsymbol{\theta} = (\theta_m)_{m=1}^{n}$ reports company-specific emission intensities. Note that this setting can account for offsets, since both $\theta_m \xi_{m,u}$ and $\theta_m \xi_m^c$ are allowed to be negative. Hence, this variable represents the actual *net* level of emissions, i.e., the net amount of molecules of CO_2 (or other greenhouse gas) emitted.

In what follows, we adopt the following normalizations:

$$\xi_m^c \;\; := \;\; 1 + t_m^c, \qquad \xi_{m,u} := 1 + t_{m,u}, \tag{8}$$

that is, we disentangle the emissions from the direct transformation of the inputs from the additional emissions related to shipping, transportation, and potential sequestration. Importantly, in the rest of this study we include in t_m^c only transportation-related emissions. We abstract away from additional emissions stemming from the consumer's use of these goods since we do not have reliable estimates of such emissions. Trucost provides granular data about companies, not about households.

Emissions scopes. Scope-1 is defined as all direct emissions from owned/controlled sources. This definition excludes transportation and shipping. Thus in our model Scope-1 of firm j is defined as follows:

$$E^1(j) := \theta_j \cdot \left(\underbrace{\chi_j}_{\text{b2c}} + \underbrace{\sum_{u=1}^{N} x_{j,u}}_{\text{b2b}} \right), \tag{9}$$

where 'b2c' ('b2b') refers to the quantities sold to the household (to other businesses).

Scope-3 refers to indirect emissions from the firm's supply chain and it is distinguished between 'upstream' and 'downstream'. Both definitions include several categories, but in our model we can keep track of only a subset of them. Upstream Scope-3 comprises both emissions related to inputs purchased from suppliers and emissions from transportation of inputs. Downstream Scope-3 refers to downstream transport and distribution, as well as processing of sold products. As a result, in our model we can define the following measures:

$$E^3_{up}(j) := \underbrace{\sum_{\substack{m=1,\\ m\neq j}}^{N} \theta_m x_{m,j}}_{\text{Purchased Goods}} + \underbrace{\sum_{\substack{m=1,\\ m\neq j}}^{N} \theta_m t_{m,j} x_{m,j}}_{\text{Inbound Transport}} = \sum_{\substack{m=1,\\ m\neq j}}^{N} \theta_m \xi_{m,j} x_{m,j}, \tag{10}$$

$$E^3_{down}(j) := \underbrace{\sum_{\substack{u=1,\\ u\neq j}}^{N} \theta_u y_u \times \frac{p_j x_{j,u}}{\sum_{m=1}^{N} x_{m,u} p_m}}_{\text{Sold goods}} + \underbrace{\sum_{\substack{u=1,\\ u\neq j}}^{N} \theta_j t_{j,u} x_{j,u}}_{\text{Outbound Transport}}, \tag{11}$$

and

$$E^{tot}_j := E^1(j) + E^3_{up}(j) + E^3_{down}(j). \tag{12}$$

Our definition of downstream Scope-3 deserves further discussion. First, we note that in the data we do not have a decomposition of the emissions produced by firm u while using the inputs acquired from firm j. Perhaps for this reason, downstream Scope-3 is not provided by Trucost. We bridge this gap by assigning to firm j a share of the direct emissions of each customer, i.e, firm $u = 1, ...$ The share of direct emissions of firm u assigned to firm j depends on how much firm u spends on the input purchased from firm j ($p_j x_{j,u}$) relative to its total expenditure ($\sum_{m=1}^{N} x_{m,u} p_m$).

Both Scope-3 downstream and Scope-3 upstream use information only from the first layer of suppliers or customers of firm j. Equivalently, these definitions do not account for the full set of emissions along the entire supply chain, and hence $E^{tot}(j)$ is potentially a misleading indicator. In order to overcome this limitation, in what follows we define *rescaled emissions*

and use them to recursively compute *embodied emissions* at the firm level (Hertwich and Wood 2018). In contrast to scope-3 measures, embodied emissions account for all possible higher layers of network links.

Rescaled emissions and Scope-3. Let s_j represent the emissions associated with the production and deliver of one unit of good j. Equivalently, s_j must satisfy the following equation:

$$s_j y_j = \xi_j^{\chi} \theta_j \chi_j + \theta_j \sum_{u=1}^{n} \xi_{m,u} x_{m,u}.$$

If we sum across all goods, we get

$$\mathbf{s}^{\mathrm{T}} \mathbf{y} = \sum_{m=1}^{n} \xi_m^{\chi} \theta_m \chi_m + \sum_{m=1}^{n} \theta_m \sum_{u=1}^{n} \xi_{m,u} x_{m,u} = E^{tot}, \tag{13}$$

implying that rescaled emissions enable us to go back to the total emissions $\mathbf{s}^{\mathrm{T}}\mathbf{y}$ produced by the considered supply chain.

In the remainder of this section, we use rescaled emissions, s_j, to obtain embodied emissions, ψ_j. To better understand the meaning of rescaled emissions, it is convenient to define

$$\widehat{\mathbf{X}}^{\mathrm{T}} := \mathrm{diag}\,(\mathbf{y})^{-1}\, \mathbf{X}^{\mathrm{T}},$$

which is the matrix of input allocations per unit of output, i.e., whose components are $\hat{x}_{m,u} = \frac{x_{m,u}}{y_u}$.

When $\xi_{m,u} = 1$ for all m, u and $\xi_m^c = 1$ (no heterogeneous transport factors), the accounting identity $y_m = \chi_m + \sum_u x_{m,u}$ implies

$$s_m = \theta_m$$

for all m (with $y_m > 0$). That is, rescaled emissions are equal to the vector comprising emission intensity, θ_m, across firms.

If we additionally assume that there are no self-loops, $x_{j,j} = 0$, we obtain

$$E^3_{up} = \widehat{\mathbf{X}}^{\mathrm{T}}\mathbf{s}. \tag{14}$$

i.e., rescaled emissions and output shares are enough to determine the Scope-3 emissions across our n firms.

In the most general case, one can prove that

$$E^3_{up} = (\widehat{\mathbf{X}}^{\mathrm{T}} - D)\mathbf{s} + \mathbf{tc}, \tag{15}$$

where $D := \mathrm{diag}(\hat{x}_{1,1}, \ldots, \hat{x}_{n,n})$ collects the self-loop coefficients, and $\mathbf{tc}$ is a vector of transport-related correction terms defined as follows:

$$tc_j = \sum_{m \neq j} \theta_m (\xi_{m,j} - \bar{\xi}_m)\, \hat{x}_{m,j}, \tag{16}$$

where

$$\bar{\xi}_m := \frac{\xi^c_m\, \chi_m + \sum_u \xi_{m,u}\, x_{m,u}}{y_m}. \tag{17}$$

In short, equation (15) (i) removes emissions comprised in Scope-1 from Scope-3 via the D matrix, and (ii) accounts for the dependence of Scope-3 on direct (i.e., layer-1) transport adjustment, whereas rescaled emissions use average transport coefficients, $\bar{\xi}_m$.

Embodied emissions. Embodied emissions account for emissions "embedded" within a unit of input, thus capturing its entire production process. Let us denote by ψ_j the embodied emissions share associated with good j, implying that $\psi_j y_j$ represents total embodied emissions of good j.

Embodied emissions are defined through the following recursive system of equations:

$$\psi_j y_j = s_j y_j + \sum_{m=1}^{n} \psi_m x_{m,j}, \tag{18}$$

which we can also write as,

$$\operatorname{diag}(\mathbf{y})\,\boldsymbol{\psi} = \operatorname{diag}(\mathbf{y})\,\mathbf{s} + \mathbf{X}^{\mathrm{T}}\boldsymbol{\psi}. \tag{19}$$

Given this definition, we get a closed-form solution for embodied emissions in terms of rescaled emissions $\mathbf{s}$.

$$\boldsymbol{\psi} = \left(\mathbf{I} - \widehat{\mathbf{X}}^{\mathrm{T}}\right)^{-1}\mathbf{s}. \tag{20}$$

Notice that this definition coincides with the authority-based Katz centrality (Sargent and Stachurski, 2022) of the weighted digraph defined by the input-output matrix, $\hat{\mathbf{X}}$. An equivalent interpretation is by means of "downstreamness", i.e., we look at a good j through the lens of all possible emissions that are involved in the production process through the intervention of multiple suppliers. Given these considerations, we are ready to state our main proposition.

Proposition 1. *If the resource constraint is satisfied, total emissions* $E^{tot} = \mathbf{s} \circ \mathbf{y}$ *equal the embodied emissions of final consumption goods plus an adjustment coming from the individual* ***net*** *flows of inputs' embodied emissions:*

$$\mathbf{s} \circ \mathbf{y} = \boldsymbol{\psi} \circ \boldsymbol{\chi} + \boldsymbol{\psi} \circ \left[\left(\boldsymbol{X} - \boldsymbol{X}^{T}\right)\mathbb{1}\right],$$

or, equivalently,

$$\mathbf{s}^{T}\boldsymbol{y} = \boldsymbol{\psi}^{T}\boldsymbol{\chi} + \boldsymbol{\psi}^{T}\left[\left(\boldsymbol{X} - \boldsymbol{X}^{T}\right)\mathbb{1}\right]. \tag{21}$$

In order to better understand these results, Figure 6 illustrates a simple supply chain example in which we can measure both direct and embodied emissions. Panel (a) shows the physical production network, where a Factory supplies inputs to two intermediate services: a Brown service that generates emissions and a Green service that does not. Each service then provides goods to a distributor, who delivers them to the final consumer. Panel (b) translates this network into the direct emissions vector and the corresponding input–output structure.

Using these inputs, we compute embodied emissions, which account for all possible upstream links in the network and thus reallocate emissions downstream toward the final users. By construction, embodied emissions double count direct emissions, so their total always exceeds direct emissions, similar to what happens with Scope-3 measures. The key point, however, is that embodied emissions allow us to allocate the share of emissions attributable to each member of the supply chain.

From this example, the Scope-3 emissions associated with Distributor 1 equal $0.1E_F + E_B - E_{d_1} = 50$, while those for Distributor 2 equal $0.9E_F + E_G - E_{d_2} = 70$. Hence, although the green service emits nothing directly, the supply chain passing through it is effectively ranked as more polluting because it embodies a larger share of upstream emissions.

Embodied emissions, Scope-3, and spectral decomposition. Equation (20) can be rewritten as follows:

$$\boldsymbol{\psi} = \mathbf{s} + \widehat{\mathbf{X}}^{\mathrm{T}}\mathbf{s} + \widehat{\mathbf{X}}^{\mathrm{T}} \cdot \left(\widehat{\mathbf{X}}^{\mathrm{T}}\mathbf{s} + (\widehat{\mathbf{X}}^{\mathrm{T}})^2\mathbf{s} + ... \right).$$

In the special case in which we abstract away from transport costs and self purchases, the expression above collapses to

$$\boldsymbol{\psi} = \underbrace{\mathbf{s}}_{\text{Scope-1}} + \underbrace{E^3_{up}}_{\text{(Scope-3, up)}} + \underbrace{\widehat{\mathbf{X}}^{\mathrm{T}}(I - \widehat{\mathbf{X}}^{\mathrm{T}})^{-1}E^3_{up}}_{\text{All layers}},$$

implying that embodied emissions add to Scope-1 plus Scope-3 emissions all possible additional layers of upstream emissions. In the remainder of this manuscript, however, we will use the following representation, as it is general and accounts also for transport emissions and self-purchases:

$$\boldsymbol{\psi} = \underbrace{\mathbf{s}}_{\text{tier-0}} + \underbrace{\widehat{\mathbf{X}}^{\mathrm{T}}\mathbf{s}}_{\text{tier-1}} + \underbrace{(\widehat{\mathbf{X}}^{\mathrm{T}})^2(I - \widehat{\mathbf{X}}^{\mathrm{T}})^{-1}\mathbf{s}}_{\text{hidden gap (tiers 2+)}}.$$

Let us define $G := (\widehat{\mathbf{X}}^{\mathrm{T}})^2(I - \widehat{\mathbf{X}}^{\mathrm{T}})^{-1}$, and notice that

$$\lim_{K\to\infty} \underbrace{\sum_{k=2}^{K} \left(\widehat{\mathbf{X}}^{\mathrm{T}}\right)^k}_{G^K} = G.$$

We can decompose the 'hidden gap' between embodied emissions and tier 0-1 of emissions across firms and tiers. Specifically, the contribution of firm i to firm-j's embodied emissions, ϕ_j, along paths network paths of length K is simply $G^K_{ji}\mathbf{s}_i$. In what follows, we focus on the following two concepts:

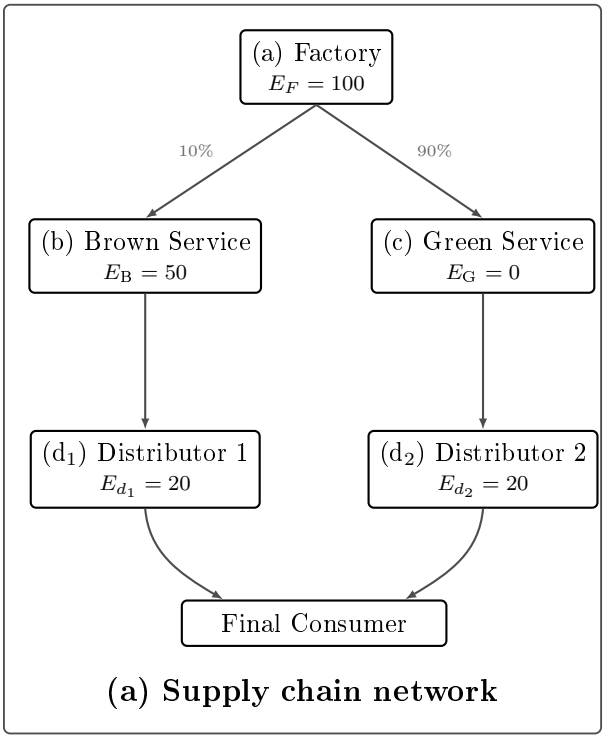
$$\rho^i_j := \frac{G_{ji}\mathbf{s}_i}{\sum_{i=1}^n G_{ji}\mathbf{s}_i}, \text{ and } \rho^K_j := \frac{\sum_{i=1}^n G^K_{ji}\mathbf{s}_i}{\sum_{i=1}^n G_{ji}\mathbf{s}_i}. \tag{22}$$

The variable ρ^i_j determines the relative contribution of firm i in the determination of ψ_i when use all possible network paths ($K \to \infty$). ρ^K_j determines contribution of all firms toward ψ_j, when we stop the path length of K.

In Appendix C, we discuss the limitations of a spectral decomposition approach in our setting. While hub and authority scores tend to be very informative in well-integrated networks, they add little value in our case. International supply chains have several local clusters that manifest as a multitude of sizeable eigenvalues. Absent a dominant eigenvalue, identifying dominates hubs and authorities becomes challenging. For this reason, instead of reducing dimensionality after the formation of a network, we cluster firms at the port-sector level when creating the network, if necessary.

4 Network Characterization

We use our unique combination of firm-level environmental, supply chain, and financial data, country-sector macroeconomic data, and country port data to calibrate a multi-sector economic model. Our methodology follows a two-stage approach. First, a data pipeline



(a) Supply chain network

Direct emissions vector:

$$\boldsymbol{S}^\top = \begin{bmatrix} 100 & 50 & 0 & 20 & 20 \end{bmatrix}$$

Input-Output matrix:

$$X^\top = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0.1 & 0 & 0 & 0 & 0 \\ 0.9 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix}$$

Embodied emissions:

$$\boldsymbol{\psi} = (I_5 - X^\top)^{-1}\boldsymbol{S}$$

$$= \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0.1 & 1 & 0 & 0 & 0 \\ 0.9 & 0 & 1 & 0 & 0 \\ 0.1 & 1 & 0 & 1 & 0 \\ 0.9 & 0 & 1 & 0 & 1 \end{bmatrix} \begin{bmatrix} 100 \\ 50 \\ 0 \\ 20 \\ 20 \end{bmatrix} = \begin{bmatrix} 100 \\ 60 \\ 90 \\ 80 \\ 110 \end{bmatrix}$$

(b) Input-output emissions accounting

Fig. 6. Supply chain network emissions mapping to model framework. Panel (a) shows a physical network, where a factory provides inputs to two intermediate manufacturers. The Brown manufacturer creates emissions as a result of its activities, while the Green one does not. The final consumer can purchase the final good from two different distributors that show a similar level of emissions as result of their operation; Panel (b) maps the information on the supply chain network to the key measures in our model.

processes and clusters firm-level data into a tractable macroeconomic structure. Second, a calibration process converts this structure into parameters for a competitive equilibrium model. In doing so, our approach addresses two critical challenges: (1) converting transport-based CO2 emissions into economically consistent parameters, and (2) implementing financial constraints to capture the heterogeneous borrowing capacity of firms across the supply chain.

4.1 Network, Transport and Firm Clustering

Network determination. The supply chain of a focal firm is built from FactSet relationship data. Level 1 consists of the firm's direct suppliers and customers, that is, the other firms with which Heidelberg reports a buyer-supplier or customer relationship. Level 2

comprises (i) the direct suppliers of level 1 suppliers, and (ii) the direct customers of level 1 customers. When running counterfactual exercises, we identify alternative firms by using both the “Known competitors" list provided by FactSet and additional AI tools to complement this list with other firms. We provide further details on this step in the next section.

Firm-level transport classification. When assessing transportation-related emissions, we consider only firms that actually require the transport of physical goods. Unfortunately, explicit data on transport logistics for each firm are missing. To overcome this fundamental limitation, we use a two-step text analysis process. First, we determine the company's core business. Second, we identify its most likely mode of transport, that is, either land, maritime, or air. More specifically, FactSet provides a narrative description of each company's business activity, its Standard Industrial Classification (SIC) code, and a list of customers. We employ an LLM that determines whether a company's core business requires the physical transport of goods at all. If so, a second prompt classifies the most likely transport mode based on the product type and the presence of international customers. When entity profiles are vague, we augment the information set by using SIC code descriptions. As a result, our two-step algorithm allows for a more robust and auditable classification of our entire firm universe. This is both a necessary foundation for our emissions calculations, and a major accomplishment in the literature.

Trade flow-based clustering. When a dimensionality reduction is required, we transform a vast network of individual firms into a set of representative clusters. We start by constructing a firm graph around a focal company's supply-chain. Each firm is tagged with its country, sector, and inferred transport mode. To each pair of firms in our network $\{i, j\}$, we assign a weight based on the corresponding dollar entry of the OECD ICIO table, i.e, an input-output matrix created at the country-sector level for a large cross section of economies. The weight computation is described in the next subsection, where we detail our calibration of the $\alpha_{i,j}$ coefficients. We apply the Louvain community detection algorithm (Blondel et al.

2008) to the weighted graph in order to obtain a manageable number of clusters. Each cluster comprises firms that are relatively more densely connected.[1] Finally, firm-level emissions and financial data are aggregated to the cluster level.

4.2 Calibration

Input-Output Matrix (A). The firm-level $\mathbf{A}$ matrix is constructed from the OECD ICIO tables. The OECD tables feature country-sector level data. Let Z_{ij} denote intermediate inputs from supplying country-sector i to using country–sector j. Letd x_j be the gross output of country-sector j. Thus, OECD country-sector input–output coefficients are $A_{ij}^{\text{OECD}} = Z_{ij}/x_j$.

Using Factset, we map each firm to a specific country-sector using. Unfortunately, this mapping is not trivial since the OECD tables use a slightly different sector nomenclature and, for some countries, a different country coding than Facset. We create FactSet-to-OECD sector mapping tables so that each firm inherits the correct row and column of $\mathbf{A}^{\text{OECD}}$. Each OECD country-sector combination is unique, but multiple firms in our dataset may share the same country-sector combination. If the network comprises multiple firms with the same country-sector combination, we allocate the input mass proportionally to their revenues. Stacking these allocations yields a square matrix $\mathbf{s}^{\text{prior}}$ of the same dimension as the desired $\mathbf{A}$, with nonnegative entries and unit column sums wherever the sector is represented in the OECD block.

In a specific supply chain, intermediate flows appear only where we observe supplier-customer links. We define $M_{ij} = 1$ if firm i is a recorded supplier of firm j in the relationship data or if $i = j$ (self-supply). In all other cases, when a link is missing, we set $M_{ij} = 0$. Then, we compute $\tilde{s}_{ij} = s_{ij}^{\text{prior}} M_{ij}$ and renormalise each column of $\tilde{\mathbf{s}}$ to sum to one. We then set

[1] Louvain is a fast community-detection heuristic that groups nodes into "communities" by maximizing *modularity*—a score that is high when edges are much denser within groups than across them, relative to a random graph with the same degree distribution. It greedily moves nodes to neighboring groups to raise modularity, then contracts each group to a super-node and repeats; the process quickly yields clusters that are tightly connected internally and sparsely connected externally.

$A_{ij} = (1 - \alpha_{0,j}^{\text{OECD}})\,\tilde{s}_{ij}$, where $\alpha_{0,j}^{\text{OECD}}$ is the OECD value-added share for j's country–sector. Column sums therefore reproduce the OECD intermediate intensity for each firm, restricted to the network.

For each firm in the network, we must make sure that intermediate sales are consistent with revenues (R_j), otherwise the resulting $\mathbf{A}$ matrix would be infeasible. To ensure a matrix that is consistent with revenues, we cap self-supply and introduce iterative proportional fitting (two-sided RAS). Specifically, for each column j, a fraction $\tau = 5\%$ of the column total is targeted on the main diagonal. This adjustment is required because self-supply is large at the sector-level, but not at the individual firm level. The remaining $(1 - \tau)$ mass is reallocated to the non-negative off-diagonal terms in proportion to their current values, holding the column sum fixed. Second, we form a matrix of intermediate purchase values $W_{ij} = A_{ij}R_j$, and apply a two-sided RAS on the support where W_{ij} may be positive. Equivalently, we seek nonnegative $\mathbf{W}$ with the same zero pattern such that (1) column sums match desired intermediate purchases, and (2) row sums match a proportional allocation of revenue across suppliers (Deming and Stephan, 1940; Bacharach, 1970). These results are obtained, by defining column targets as

$$c_j \;=\; \left(1 - \alpha_{0,j}^{\text{OECD}}\right) R_j,$$

and row targets as $r_i = \lambda R_i$ with

$$\lambda \;=\; \frac{\sum_j c_j}{\sum_j R_j},$$

so that total intermediate supply equals total intermediate demand.[2]

The coefficient matrix used in the model is then $A_{ij} = W_{ij}/R_j$, for $R_j > 0$. Row-column consistency implies that each firm's intermediate sales $\sum_j A_{ij}R_j$ are proportional to

[2]Starting from $\mathbf{W}$ after diagonal redistribution, the algorithm alternates column scaling (multiplying column j by $c_j/\sum_i W_{ij}$ where the denominator is positive) and row scaling to match the r_i, reapplying the mask after each sweep; columns with only the diagonal admissible are fixed to meet c_j exactly. Under standard positivity conditions on the restricted support, the iteration converges to the unique biproportional adjustment of the initial $\mathbf{W}$ with those margins (Bacharach, 1970).

its revenue at the common factor λ, so that revenue net of intermediate sales is nonnegative and aligns with a single economy-wide intermediate-sales-to-revenue ratio. The resulting $\mathbf{A}$ matrix is a sparse firm-by-firm system of value shares, built from OECD ICIO tables and calibrated to match firm revenues and active network linkages.

Productivity (z). Firm-level productivity, z_j, is constructed from FactSet financials as sales-per-employee. For some private firms, number of employees is missing from the financial data. In this case, we use return on assets as an alternative measure of productivity. We note that we use return on assets only for 11.1% of our firms. Because these measures are not directly comparable, we normalize each productivity measure to range from 0 to 100. This scaling convention enables us to retain cross sectional heterogeneity without loss of generality. In our log-linear environment, we can rescale all productivity levels by a common factor in order to match the size of sales. We detail this step in what follows.

Revenue ($\mathbf{R}$), preferences (ω), and the deposit rate (r^D). Revenues are obtained from Factset financials and included in the vector $\mathbf{R}$. According to the model, the implied income vector can be computed using the $\mathbf{A}$ matrix: $(I - \mathbf{A})\,\mathbf{R}$. Since the consumption bundle weights (ω) represent consumption expenditure shares, we can recover them from the data using the following formula:

$$\omega_j = \frac{(I - \mathbf{A})\,\mathbf{R}_j}{\sum_j (I - \mathbf{A})\,\mathbf{R}_j}.$$

In this case, the composition of final expenditure in the model is aligned with the composition of value added in the data.

In the frictionless Cobb-Douglas benchmark ($\delta = 0$ and no financial constraints), there exists a positive scalar $\kappa > 0$ so that $(I - \mathbf{A})\mathbf{R} = \kappa\,\boldsymbol{\omega}$. As a result,

$$\mathbf{R} \;=\; \kappa\,(I - \mathbf{A})^{-1}\boldsymbol{\omega},$$

and the cross-sectional distribution of revenues is determined by $(\mathbf{A}, \boldsymbol{\omega})$ alone. A uniform rescaling of all productivities changes all prices proportionally and it alters κ, meaning that we can renormalize the productivity vector to match the total scale of revenues in the network.

After normalizing the price of the consumption bundle to one, we set the benchmark deposit rate, r^D, to a target value of 10%. In a frictionless setting, a target deposit rate r^D uniquely determines a common scaling factor applied to the measured productivity vector $\mathbf{z}^0$. In the presence of occasionally non binding constraints, r_j^D becomes endogenous and may differ from the target when some firms are financially constrained ($\zeta_j > 0$ in equation (4)).

Aggregate capital (K), and firm-level capital (k_j). We set the total network capital as follows: $K \approx \frac{\bar{\alpha}_0}{r^D} \sum_j R_j$. Thus K is tied to the data via $\mathbf{A}$ and the targeted r^D.

By contrast, how K is distributed across firms is an equilibrium outcome. Each firm's capital k_j satisfies equation (4). As a result, a firm with higher revenue $p_j y_j$ or larger capital share $\alpha_{0,j}$ demands more capital. A tighter borrowing limit raises its effective borrowing cost, R_j, and it reduces the capital it can employ. An unconstrained firm simply sets $k_j = \alpha_{0,j} p_j y_j / r^D$. In equilibrium, individual capital demands must exhaust the aggregate supply,

$$\sum_j k_j \;=\; \min\left\{ K,\; \sum_j \bar{d}_j \right\}.$$

Financial Constraints ($\mathbf{Z_c}$). Financial distress is tied to firm-level Altman Z-Scores constructed from FactSet balance-sheet and market data. Accounting ratios are winsorized in the tails, after which the appropriate public or private Altman mapping is applied and firms are classified into distress zones using the standard cutoffs. We harmonize firm-level Z-Scores across formulas and standardize within country-sector-year cells.

When working with clusters, each cluster's financial position is the asset-weighted aggregation of firm scores within the cluster:

$$Z_c = \frac{\sum_{f \in c} \text{Assets}_f \, Z_f}{\sum_{f \in c} \text{Assets}_f}.$$

The cluster score is then mapped to a borrowing-capacity multiplier $\lambda_c \in [\lambda_{\min}, \lambda_{\max}]$ using either a piecewise rule tied to the canonical Altman thresholds or a smooth logistic function. The borrowing limits are set as:

$$\bar{d}_c = \lambda_c K_c, \qquad K_c = \sum_{f \in c} K_f,$$

with the understanding that if clustering is not required, this equation is applied at the firm-level.

Transport emissions matrix (E). The **E** matrix augments emissions by accounting for the transport between origin–destination pairs required for the shipping of intermediate goods. For each firm in our dataset, we use Facset to find its address and extract latitude and longitude via Google maps. This step allows us to assign them to a primary seaport, and obtain inland distance from plant to port.

For distinct firms i and j, the route length d_{ij} (kilometres) is the sum of three legs: overland from i to its port, maritime distance between i's port and j's port, and overland from j's port to j. The middle leg is computed with SeaRoute (https://eurostat.github.io/searoute/), which takes port coordinates and returns the shortest feasible sea path length in kilometres, optionally restricting routes that pass through certain canals and straits. When transport is absent, like, for example, for service companies, we have $E_{ij} = 1$ for all $i \neq j$. Additionally, we assume that $E_{ii} = 1$ for each company.

According to equation (8), we must map distances into emission intensities. For each ordered pair with $i \neq j$ and $A_{ij} > 0$, we set

$$t_{ij} \;=\; \kappa \, d_{ij} \,, \tag{23}$$

where $\kappa = 2 \times 10^{-5}$ represents the well-to-wake CO_2 intensity of international maritime shipping (tonnes CO_2 per tonne–kilometre) calibrated from International Maritime Organization (2024). We combine physical emission factors with a single representative valuation of shipped goods per tonne–kilometre so that route length in kilometres maps into a dimensionless augmentation of input-side emissions. All other entries remain at one if $A_{ij} = 0$.

For illustration, suppose firms i and j trade ($A_{ij} > 0$) and their combined routing yields $d_{ij} = 10{,}000\,\text{km}$. Then $\kappa\, d_{ij} = 0.2$ and $E_{ij} = 1.2$: relative to a benchmark link with no associated distance, the emissions intensity attributed to inputs shipped from i to j is multiplied by 1.2 in the direct-emissions formula.

Summary. Summarizing, our calibration approach uses observables to fix the input-output matrix $\mathbf{A}$, the capital shares $\boldsymbol{\alpha}_0$), firm-level productivity $\mathbf{z}$, preference weights $\boldsymbol{\omega}$, aggregate capital K, borrowing ceilings $\bar{d}_j$, emission intensities $\boldsymbol{\theta}$, and the transport matrix $\mathbf{E}$. Given these parameters, the model solves for equilibrium prices $\mathbf{p}$, quantities $\mathbf{y}$, firm-level capital $\mathbf{k}$, intermediate flows $\mathbf{X}$, final demand $\boldsymbol{\chi}$, and the cost of capital r_j^D.

5 Results

Heidelberg Materials. We illustrate our methodology focusing on a specific company. By doing so, we keep the dimension of the network limited and solve the model without clustering. The advantage of this strategy is twofold. First, we can clearly identify each node in our network as one of the companies in our sample. Second, we can directly compare our results and interpret our counterfactuals. As a case study, we choose Heidelberg Materials. This company is (i) a global leader in building materials (cement, aggregates, and ready-mixed concrete); (ii) the only construction company listed in the German benchmark index DAX; (iii) a regular reporter of emissions, and (iv) a well-known benchmark in the accounting literature (Reichelstein 2024). Heidelberg Materials employs roughly 60,000 people across approximately 3,000 locations in 60 countries, and is widely recognized for its efforts to

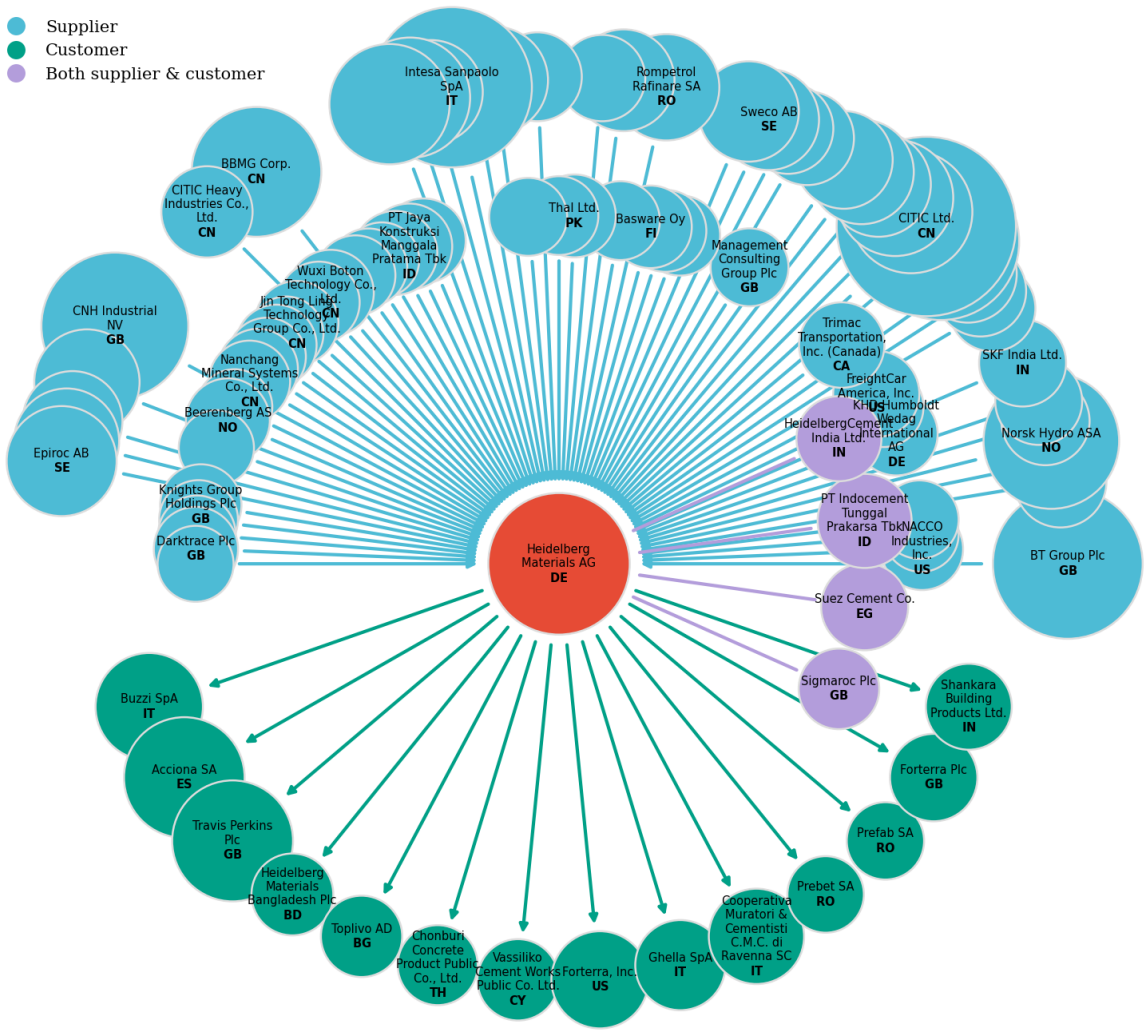


FIG. 7: Heidelberg Materials, Direct suppliers and customers by revenue

Notes: The figure shows Heidelberg Materials AG (center), its first-level suppliers (arrows into the center) and customers (arrows out). A number of entities appear as both supplier and customer. Node size reflects transformed revenue (transformed for visualization purposes), select nodes provide the name and country codes of the counterparties.

decarbonize cement production and to advance carbon capture (CCUS) and circular-economy solutions.[3] In what follows, we treat all companies as financially unconstrained.

Figure 7 depicts the level 1 network with a total of 88 firms. We have 68 suppliers, 15 customers, and 5 firms that are both suppliers and customers. When focusing on level 2, we have a total of 534 firms, i.e., too many to visualize in a figure, but still few enough to solve our model without clustering.

[3]We thank the employees at Entsorga for their insights (https://www.entsorga.it/).

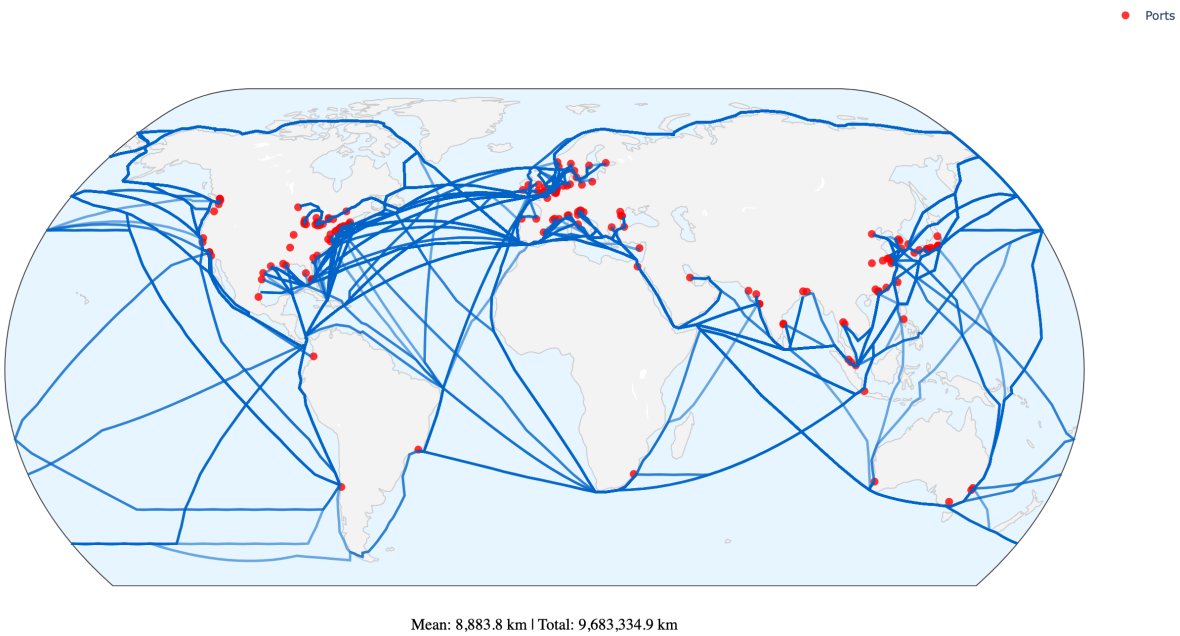


FIG. 8: Heidelberg Materials, Maritime routes on the extended network

Notes: The map shows the routes used to ship or transport goods between Heidelberg Materials (and its direct and second-level counterparties) and their trading partners. Firms are mapped to their nearest port, which is marked as a dot. Segments reflect the shortest maritime route between the ports, using Dijkstra's algorithm as provided by SeaRoute. This maritime network is based on the Oak Ridge National Labs CTA Transportation Network Group, Global Shipping Lane Network, World, 2000, enriched with lines around European coast based on AIS data.

In the top portion of Table 4, we compare Trucost emission figures with hand-collected Scope-1, Scope-2, and Scope-3 figures from Heidelberg Materials' annual sustainability reports. Scope-2 and Scope-3 are reported only since 2019. Scope-1 is very similar across the reports and the Trucost dataset. In contrast, Scope-3 exhibits larger percentage gaps and hence it is an interesting object to independently assess with our equilibrium-based approach. In Panel B, we report selected equilibrium objects from the baseline calibration obtained by considering both level 1 and level 2 connections. The rightmost column reports the average values across all firms. These quantities are used to recover our emission values.

To attribute emissions to the transport of goods along the supply chain, we compute shipping and road routes on the extended Heidelberg network using firm locations and port data, to obtain distances. The mapping comprises 44 countries. Figure 8 illustrates the resulting maritime and overland routes between Heidelberg Materials and its counterparties.

Table 5 reports Heidelberg Materials' emissions as well as a summary average across

Table 4: Heidelberg Materials

Panel A: Emission Scopes from the data

	Scope 1			Scope 2			Scope 3		
Year	Trucost	Report	Δ%	Trucost	Report	Δ%	Trucost	Report	Δ%
2018	77.52	75.40	2.8%	6.12	—	—	14.88	—	—
2019	73.43	72.60	1.1%	5.59	5.40	3.5%	20.14	22.70	−11.3%
2020	68.71	67.90	1.2%	4.96	4.90	1.2%	18.10	21.30	−15.0%
2021	69.38	69.00	0.5%	5.24	4.80	9.1%	21.86	23.90	−8.5%
2022	66.22	65.40	1.3%	4.82	4.50	7.1%	17.87	20.70	−13.7%
2023	62.08	61.20	1.4%	4.75	4.40	8.0%	24.97	15.10	65.3%

Panel B: Endogenous Variables

Metric	**Heidelberg**	**Average**
Revenue ($p_j y_j$)	21.10	44.89
Output (y_j)	4,592.25	15,745.95
Price (p_j)	0.004595	0.005241
Consumption (χ_j)	3,325.30	11,184.33
Capital (k_j)	157.91	325.57
Capital share ($\alpha_{0,j}$)	0.7484	0.7222
Preference weight (ω_j)	0.000879	0.001873
Value added ($(I-A)\cdot p_j y_j$)	0.02	0.03
Firms (n)	1	534

Notes: In panel A, all emissions are in million tonnes CO_2e (Mt CO_2e). 'Trucost' refers to Trucost estimates. 'Report' refers to hand-collected information from Heidelberg Materials' Annual and Sustainability Reports. Scope 2 and Scope 3 are only self-reported since 2019. Δ% is the percentage difference between Trucost and the Sustainability Report. Scope 1 covers direct emissions, Scope 2 covers indirect emissions from purchased energy, and Scope 3 covers other indirect emissions (both upstream and downstream). Panel B provides equilibrium values for both Heidelberg and the average value for all firms in the extended network. In this panel, y_j is total output; p_j refers to price per unit; $p_j y_j$ is gross revenue (billion USD); χ_j refers to final consumption (household demand for firm j's good); k_j is capital employed; $\alpha_{0,j} = 1 - \sum_m \alpha_{m,j}$ is the capital share (residual from Cobb–Douglas); $\omega_j = C_j / \sum_{j'} C_{j'}$ is weight in the consumption bundle; and $(I-A)\cdot \mathbf{p} \circ \mathbf{y}$ is the value added in billion of USD. Aggregate capital is set to match a borrowing rate of 10%.

firms. In the appendix, we report also a detailed decomposition that separates purchased-goods emissions from transport-related components (see Table B.5). The model calibration is designed to replicate the Trucost Scope-1 measurement, so it should not be surprising that the model matches the figure from Trucost. Importantly, the model delivers a Scope-3 assessment not too far from the number reported by Heidelberg Materials. In the bottom part of the table, we also report summary statistics for the emission intensity coefficients that we estimate. These objects are important for our counterfactual analysis.

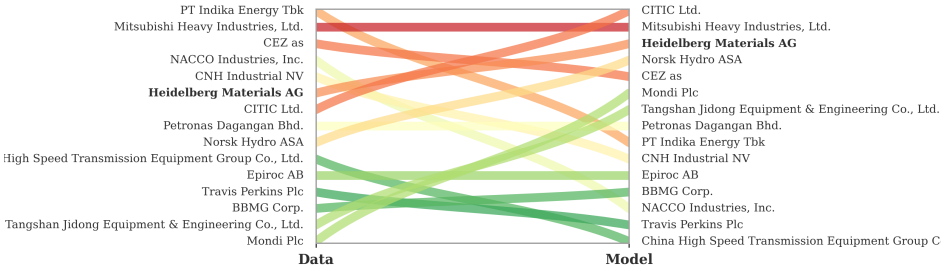
Table 5: Heidelberg Materials, Emissions and economic indicators

	Trucost	Report	Model
Scope 1 ($\theta_j y_j$)	69.04	61.20	69.04
Scope 3 Upstream (E^3_{up})	13.24	—	2.19
Scope 3 Downstream (E^3_{down})	5.62	—	7.86
Total Scope 3 ($E^3_{\text{up}} + E^3_{\text{down}}$)	18.87	15.10	10.05
Scope 1 + Total Scope 3	87.91	76.30	79.09
Emission intensity, Heidelberg (θ_j)	—	—	15,035
Emission intensity, network avg. ($\bar{\theta}$)	—	—	2,230
Network Emissions (E^{tot})	—	—	5,264.34

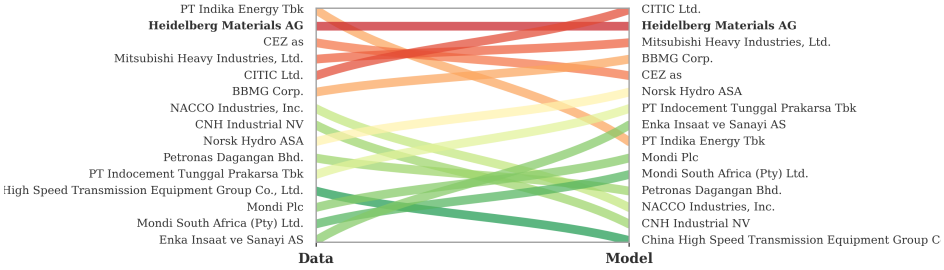
Notes: The table shows emissions for Heidelberg Materials from both Trucost and Heidelberg's sustainability reports. The last column shows the predictions of our model. Scope-3 emissions and firm-level total emissions are defined in equations (**??**)-(12). Supply-chain total emissions are computed as in equation (7) and aggregate emissions across all 534 firms in our network. All emission values are in million tonnes CO_2e (Mt CO_2e). Emission intensity coefficients, $\theta_j := \text{Scope}\,1_j/y_j$, are recovered from our model and are expressed in tonnes of CO_2e per unit of output.

Firms in the Heidelberg network can be ranked by their Scope-1 emissions, Scope-3 emissions, the sum of both scopes, and their embodied emissions, respectively. Our model imputes emissions along the supply chain and thus yields a complete ranking across all scopes. In contrast, for this network, Trucost provides data on Scope-3 only for 49 firms. In addition, the data are partial, meaning that often they refer to either upstream or downstream Scope-3, not both. As a result, the relative classification of brown and green firms can change dramatically.

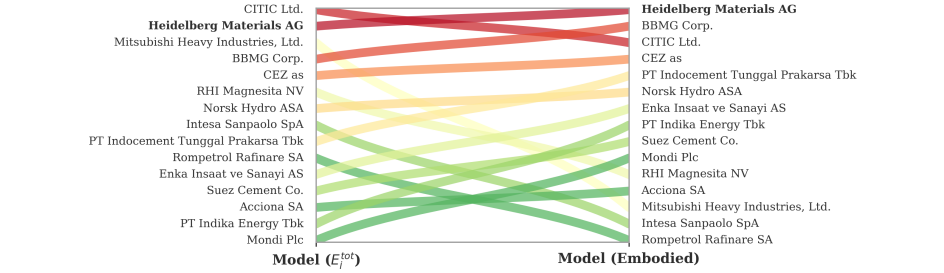
We visualize our results in Figure 9 across different emission scopes from the Trucost dataset and our model. We build these figures by focusing on the top-15 firms in the direct Heidelberg network. We note four important results. First, according to our model, Heidelberg Materials ranks in the top three in terms of Scope-3 emissions (panel a). In Trucost, this company scores sixth. Second, focusing on total emissions at the firm level (Scope-1 plus total Scope-3), we see an even more substantial disagreement between our model predictions and Trucost (panel b). Most importantly, ranking firms according to embodied emissions is significantly different from looking at total emissions (panel c and d). Once we account for all possible emission paths in the supply chain, Heidelberg Materials is



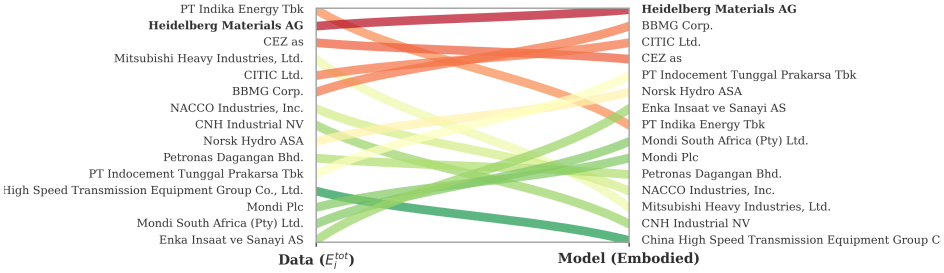
(a) Scope-3: data vs. model



(b) E_j^{tot}: data vs. model



(c) Model: E_j^{tot} vs Embodied



(d) E_j^{tot} data vs Embodied model

Fig. 9: Ranking comparisons for top-15 firms by emissions.

Notes: The figure shows the comparison of different rankings of emissions for the top-15 firms in the Hiedelberg Material's network. Scope-3 refers to the sum of upstream and downstream Scope 3 measures. $E^{tot}(j)$ is the sum of Scope 1 and Scope 3. Embodied emissions are computed as in equation (20). In each panel, the selected top-15 firms are reported at the left-hand side. We then show their alternative ranking on the right-hand side. As a result, the companies at the right-hand side of panel (c) and (d) are different.

ranked as a top emitter.

Table 6 reports rank-correlation and shift statistics for the direct network and for the top-15 emitters. In general, the data-based and model-based E_j^{tot} rankings are strongly aligned,

TABLE 6: Rank correlations and shift statistics

	Scope 3 Data vs Model		E_j^{tot} Data vs Model		Model E_j^{tot} vs Emb.		E_j^{tot} vs Emb. Data	E_j^{tot} vs Emb. Model
Metric	L-1	T-15	L-1	T-15	L-1	T-15	L-1	T-15
Spearman ρ	0.543	0.279	0.758	0.525	0.851	0.464	0.869	0.346
Kendall τ	0.399	0.162	0.597	0.352	0.718	0.371	0.722	0.200
Mean shift	18.21	4.13	13.38	3.60	9.90	3.73	9.39	4.27
Max shift	73	9	67	8	67	10	52	9

Notes: The table shows rank correlations and shift statistics for (i) the full level-1 network of firms (L-1), and (ii) the top-15 emitters (T-15). The focal firm is Hiedelberg Materials. 'Scope 3 Data vs Model' refers to the comparison of the ranking obtained by using total Scope 3 data (upstream and downstream) from Trucost and the model. 'E_j^{tot} Data vs Model' compares the sum of Trucost Scope 1 and Scope 3 (upstream and downstream) to the same objected predicted by our model. 'Model E_j^{tot} vs Embodied' the ranking implied by model-based embodied emissions ($\psi_j \times y_j$) and total emissions. 'E_j^{tot} Data vs Embodied Model' compares total emissions from the data and embodied emissions from the model. Both Spearman ρ (correlation of ranks) and Kendall τ (net proportion of pairwise agreements) measure rank-order similarity, where 1 is perfect agreement, and 0 is no association. Mean and max shift report the average and maximum absolute rank difference between the two orderings across firms.

with a Spearman $\rho = 0.81$, and a Kendall $\tau = 0.64$. These scores decline when we focus on the top-15 emitters, implying that our model results conform with the Trucost ranking mostly when focusing on mid- and small firms. Most importantly, ranking firms according to their embodied emissions produces a significantly different order relative to using total emissions. This result shows that accounting for the full path of emissions in the network matters when classifying brown and green companies.

Decomposition. In Figure 10, we depict the coefficients defined in equation (22). We learn three things. First, most of the embodied emissions are captured by the first five tiers in our supply chain. Second, most of the tier 2+ emissions attributed to the focal firm Heidelberg Materials are associated to only 12 firms. The most relevant is located in India and contributes to tier 2+ emissions by nearly 40%.

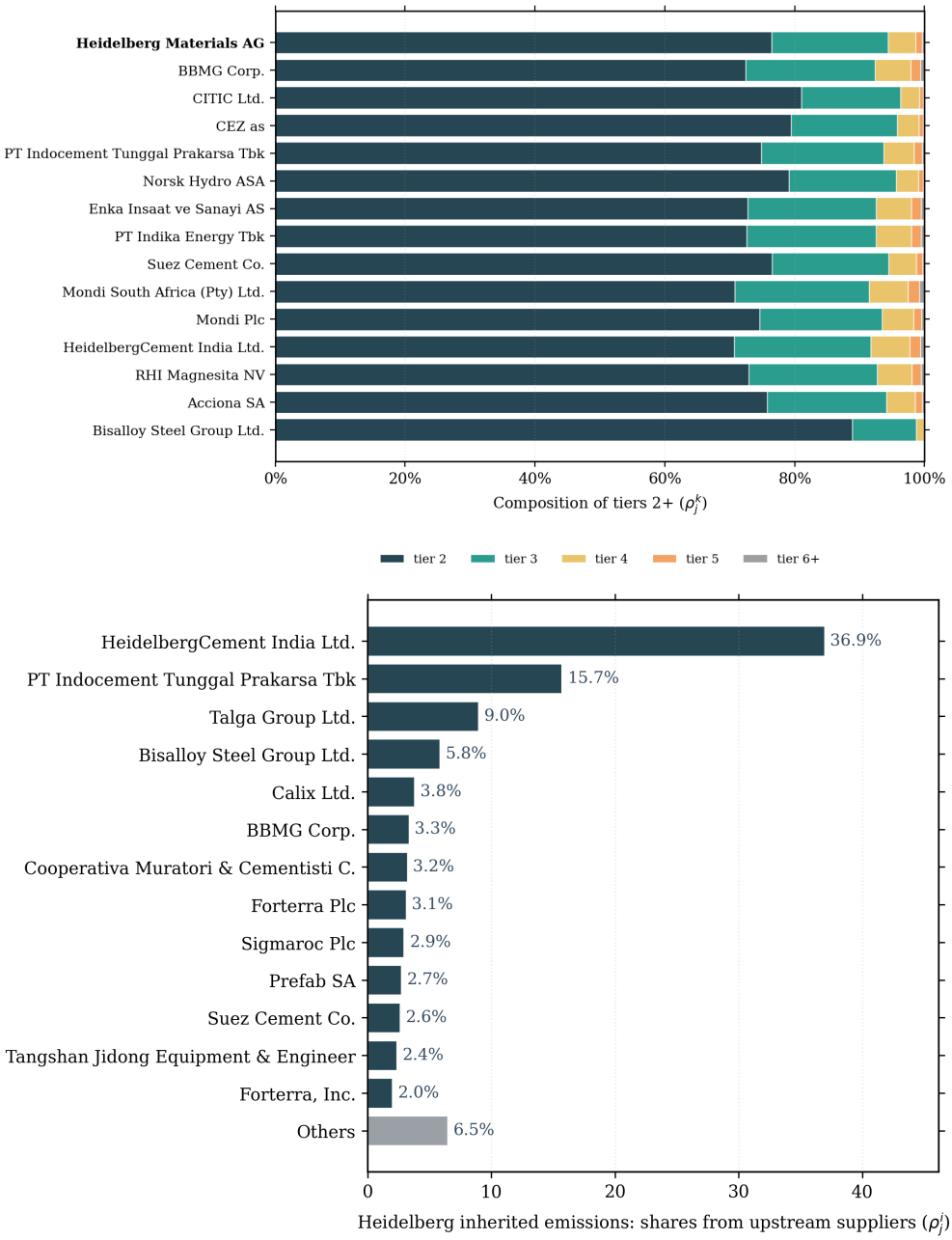


FIG. 10: Decomposing Tier 2+ Emissions

Notes: This figure shows the shares defined in equation (22). The top panel reports the shares of tier 2+ emissions obtained as we increase the length of the network paths. We compute the sum of Scope-1 and Scope-3 emissions and focus on the top-15 firms in the Hiedelberg Material's network. The bottom panel shows the contribution of different suppliers to the tier 2+ emissions of the focal firm, Hiedelberg Material.

6 Counterfactuals

One key positive aspect of our approach is the ability to run counterfactual analysis, or, equivalently, simulate scenarios. In what follows, we focus on two examples. In the first case, we assume a major disruption to major maritime routes. We think of it as the possible outcome of heightened global geopolitical tension. In this case, we keep the original Heidelberg network unchanged and we revise our $\mathbf{E}$ matrix, i.e., the shipping-related emissions. In the second case, we assume that Heidelberg cannot operate anymore with companies from China, Hong Kong, and Taiwan. We think of this as the result of a major trade war. In this case, we use AI to find likely replacements for these firms in nearby countries. Thus, we change the structure of the network and recompute both equilibrium quantities and routes.

Maritime routes disruption. Assume that the Panama Canal, the Suez Canal, the Strait of Malacca, the Sunda Strait, and the Northwest Passage are blocked. As a result, ships are forced to go over longer alternative routes and thus produce higher transport-related emissions per unit of trade. We assume that Heidelberg keeps the same network, but transport flows take different routes. Specifically, for every firm-pair link that involves sea transport, we recompute the shortest path subject to the above-mentioned route restrictions.

Figure 11 shows the new maritime routes for this scenario. Compared to Figure 8, many links between Asia, Europe, and the Americas are forced onto longer itineraries (e.g. via the Cape of Good Hope or the North Atlantic). The mean transport distance between firms increases from 8,884 km to 12,780 km, a 43.9% increase. Hence the transport-augmentation matrix $\mathbf{E}$ plays a more relevant role in the determination of both Scope-3 and embodied emissions. We note that in this case, both Scope-1 and the non-transport components of Scope-3 are unchanged. This is because both the network trade summarized in X and the emission intensity coefficients contained in θ are unchanged.

We report detailed results on the different subcomponents of emissions in Table B.6 in the Appendix. In the main text, we focus on a summary table comprising both economic

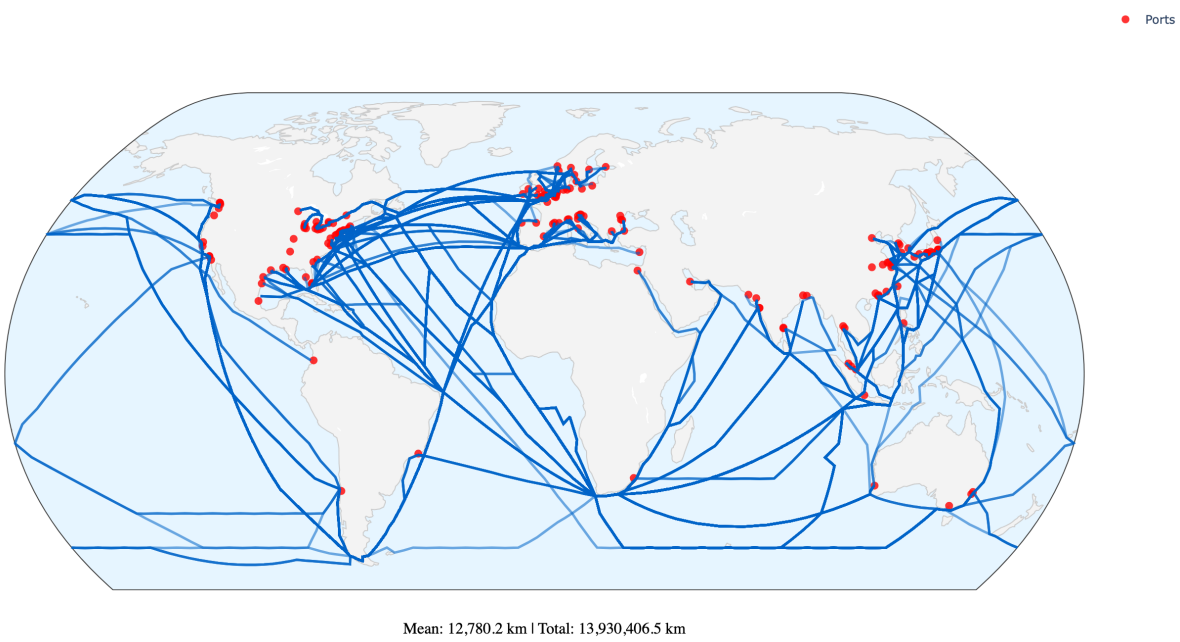


FIG. 11: Heidelberg Materials: Maritime routes disruption.

Notes: The map shows the maritime routes between firms in the Heidelberg supply chain (two-level network, 534 firms) when the Panama Canal, Suez Canal, Strait of Malacca, Sunda Strait, and Northwest Passage are restricted. Firms are mapped to their nearest port; segments are the shortest paths consistent with these restrictions (e.g. via the Cape of Good Hope or northern routes). These rerouted distances feed into the transport augmentation matrix E and thus into the counterfactual Scope-3 and embodied emissions. Route segments are the shortest maritime paths computed using SeaRoute.

and emissions data. See Table 7. According to our computations, this disruption could increase the emissions in the Heidelberg network by 7% per year. This is a substantial increase, especially if we take seriously Heidelberg's commitment to reduce emissions over time. In the next experiment, we consider a change in both network structure and economic performance.

Replacements. Assume that firms domiciled in China, Hong Kong, and Taiwan are removed from Heidelberg's supply chain and replaced by comparable non-blocked-country alternatives. The exercise captures a scenario in which geopolitical or regulatory constraints forcefully sever links to suppliers and customers, and the focal firm reconstitutes its network with substitute counterparties. We follow the procedure described below.

Replacement candidates are drawn from the universe of firms in our merged dataset and are restricted to countries with OECD input-output tables and valid sector mappings. Hence,

the new firms satisfy the same data requirements applied in the baseline calibration. We proceed in two stages. Breitung and Müller (2025) shows that a cosine similarity approach can successfully recover business networks (i.e., competitor, supplier, and customer links). In the first step, we compute cosine similarities between the business-description embedding of each blocked firm and those of all eligible candidates. The top 1% of candidates by cosine similarity (roughly 530 firms) form a pool of possible replacements.

In the second step, we enhance our algorithm by asking a large language model (ChatGPT-5) to evaluate each firm in this pool. The LLM determines whether it is a competitor of the blocked firm and reports both a binary answer, and a confidence score between 0 and 100. Firms classified as competitors are ranked by their confidence score, and the highest-confidence competitor is selected as the replacement. If no candidate receives a positive classification, the procedure falls back to the firm with the highest cosine similarity in the pool. This algorithm is applied to each supplier or customer to be removed from the network.

Further details on the replacement procedure are provided in Appendix C. When a FactSet-recorded competitor relationship exists and the competitor satisfies the eligibility criteria (present in the data universe, domiciled outside the blocked countries, and passing the data-completeness filters), it is chosen as the replacement.

In the Heidelberg network, 52 firms are domiciled in the blocked countries. Of these, 16 were replaced by a firm that was already in the network, 13 were replaced by a new firm, and 23 were replaced by firms with revenue near zero, making them infeasible replacements. After our replacements, the number of firms in the network declines by 39 units and becomes 495.

For a detailed analysis of the changes in the different scopes of emissions, see Table B.6. We compare emissions and economic outcomes for Heidelberg Materials across the baseline and counterfactual scenarios in Table 7 in the Appendix. For an example in which we reform the network by considering the replacement of a supplier in a single (multiple) supplier network, see Figure C.3 (C.4). According to our model, after such a shock, Heidelberg's

Table 7: Heidelberg Materials AG, Emissions and Economic Performance

	Baseline	Blockage (Δ%)	Repl. (Δ%)
Total Emissions, Heildelberg (E_j^{tot})	79.09	0	-1
Network Emissions (E^{tot})	5,264.34	7	-27
Network Revenues ($\sum_j R_j$)	23,972.90	0	-14
Network Added Value ($\sum_j p_j \chi_j$)	17,385.50	0	-10
Network Emissions-to-Added Value (%)	30.2	7	-19

Notes: The table provides emission and economic values under different counterfactual scenarios compared to the baseline. Added value and revenues are in Billions of USD. Emissions are measured in million of tonnes of CO_2e (Mt CO_2e). 'Blockage' assumes that major canals and straits (Panama, Suez, Malacca, Sunda, Northwest Passage) are simultaneously blocked. In this case, the network is unchanged, only transport emissions are recomputed. 'Repl.' refers to the case in which we assume a replacement of firms based in China, Taiwan, and Hong Kong.

total emissions would decline only by 1%. Recall, however, that total emissions are defined so that they comprise only one level of upstream and downstream emissions. If we look at the entire network, a reallocation of activity away from China could reduce network emissions by a staggering 27%. Unfortunately, only the network emissions-to-added value ratio improves only by about 19%, implying that the remaining gap is due to a reduction in network added value. Such a shock, could reduce the network added value by about 10%, i.e., there would be a significant contraction.

On the one hand, this scenario analysis rationalizes why this reallocation is not happening in real life: it would be very costly in terms of added value destruction. On the other hand, it is interesting to see that the impact on emissions abatement would be more substantial, as production would be redirected toward firms with better environmental performance.

7 Conclusion

We propose a novel network-based methodology to measure emissions along complex international supply chains (SC). Using international data for about 50,000 firms, we characterize SC-level emissions across countries and industries.

Our novel methodology enables us to run counterfactual experiments and formulate gran-

ular forecasts about high-scope emissions with respect to many different scenarios such as maritime disruption, military conflicts, trade wars, and changes in carbon taxes. Importantly, our methodology relies only on Scope-1 data to recover high emission scopes and has a broad coverage. In addition, it enables us to compute embodied emissions to better rank 'green' and 'brown' firms within a supply chain.

Future research should use our measurement technology to address ambitious questions related to policy interventions and their unintended consequences.

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