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Beyond firm size: network position and shock transmission in firm-to-firm production networks across five economies*

Glenn Magerman
ECARES, ULB
CEPR, CESifo

Alberto Palazzolo
ECARES, ULB
National Bank of Belgium

Emmanuel Dhyne
National Bank of Belgium

Andras Borsos
Magyar Nemzeti Bank

Dmitry Kulikov
Eesti Pank

Andrea Linarello
Banca d'Italia

Alari Paulus
Eesti Pank

Giacomo Romanini
Banca d'Italia

Martin Saldias
Banco de Portugal

Abstract

How much a firm's shocks move the aggregate, and how they propagate to other firms, both depend on its position in the network of firm-to-firm trade. As firm-level networks are available for few economies, quantitative work typically relies on firm size and/or input–output tables as proxies. Using administrative VAT records and tax filings, we build harmonized production networks for five European economies (Belgium, Estonia, Hungary, Italy, and Portugal) and measure firms' positions directly. Five facts stand out. First, firm size and centrality summarize a firm's first-order aggregate impact, but not its vertical position along production chains, which is orthogonal to size and governs how shocks propagate across firms. Second, firm size is itself a function of the network: roughly half of within-industry size dispersion reflects the number of customers a firm has, rather than a primitive such as productivity. Third, granularity runs along several dimensions beyond firm size: network sales, transaction values, and the number of customers are heavy-tailed, spanning several orders of magnitude. Fourth, firm-to-firm networks differ structurally from IO tables: they are orders of magnitude sparser, "roundabout" production disappears, and input shares vary widely even within narrow sector pairs. These patterns are stable across all five economies and persist within narrowly defined industries, reflecting firm-level characteristics rather than sectoral composition or country-specific factors. Finally, these distinctions are economically relevant: firm-level responses to monetary policy vary systematically with vertical position, and cross-country differences in where firms sit along production chains generate heterogeneous aggregate responses to a common shock. We provide these moments as calibration targets and as a guide to when sector-level structure is an adequate approximation and when firm-level detail is first-order.

Keywords: Firm–to–firm production networks, input–output analysis, granularity, monetary policy transmission, firm heterogeneity
JEL Classification: C81, D57, E52, L14

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Non-technical Summary

Firms do not operate in isolation: they buy inputs from suppliers and sell to other firms, and these relationships shape how shocks travel through the economy. Yet comparable evidence on what these production networks across countries actually look like at the firm-to-firm level has been almost nonexistent, as the underlying data are collected separately by national administrations and are rarely analyzed in a harmonized way.

This paper provides the first systematic cross–country description of firm level production networks for five EU countries. Using e-invoicing and administrative value added tax (VAT) records, combined with firm level annual accounts and business registries, the authors construct harmonized networks of supplier and customer relationships for Belgium, Estonia, Hungary, Italy and Portugal, covering around 3 million firms and more than 100 million trading relationships for the year 2019.

The paper documents five key facts. First, production networks are extremely concentrated: the top 10% of firms account for 80% to 90% of network sales, and the top 1% of supplier and customer relationships for up to 80% of the value traded. Neither sector-level input-output (IO) tables nor standard firm-level datasets can capture this. Sector-level tables record only aggregate flows between industries, and firm-level datasets record how large a firm is and how much it buys, but not whom it trades with. As a result, the small set of relationships that contains most of the value, and through which shocks might disproportionately propagate, is invisible in both.

Second, firm level networks are not just a finer version of IO tables. While in IO tables almost every industry is connected to almost every other industry, firm-to-firm networks are extremely sparse and exposure runs along a small number of specific paths to specific firms. IO technical coefficients also hide substantial variation across firms: even firms buying from and selling to the same pair of sectors have very different input shares from one another, and the differences between individual firms are often bigger than the differences between sector pairs. In other words, a single sectoral coefficient describes almost no individual firm. Sector level policies targeting exposure or resilience therefore risk overtargeting most firms within a sector and undertargeting a few key firms or links.

Third, firm size is closely related to a firm's customer base: within narrowly defined industries, about half of the variation in firm size relates to the number of customers a firm serves, rather than to how efficient or productive the firm is. Having many customers is what mainly separates large firms from small ones.

Fourth, a firm's position along the production chain, measured by upstreamness or downstreamness, is a separate dimension from its size and centrality. While a firm's aggregate influence is closely captured by its size, its vertical position in the production chain is not. The fact that these patterns are so similar across five otherwise very different economies suggests they reflect fundamental features of how production is organized, rather than country specific institutions.

Fifth, and most consequential for policy, firm-level production networks change the view of how monetary policy reaches firms. Monetary policy does not stop at the firms it hits directly. It travels through their supply chains: when a tightening reduces final demand, firms selling to consumers cut purchases from their suppliers, who in turn cut purchases from their own suppliers. Estimates for Belgium and Estonia show that firms closer to final demand are affected earlier and tend to recover more quickly, whereas firms further upstream experience more delayed and persistent effects. Because countries differ substantially in how production is organized, the same monetary policy shock generates different aggregate responses across them, and upstream firms account for a larger share of that response in countries where production is more vertically extended. Aggregating to the sector level and ignoring this distribution of firms across production stages would therefore miss where the aggregate response is actually coming from.

The paper was developed within the ECB's Challenges for Monetary Policy Transmission in a Changing World (ChaMP) research network. Its harmonized statistics provide a benchmark for calibrating quantitative models of production networks.

Contents

1 Introduction

Production networks play a central role in modern macroeconomics. How shocks propagate across firms, how aggregate fluctuations emerge from microeconomic disturbances, and how policy interventions transmit through the economy all depend on the structure of interfirm linkages. Over the past decade, a large literature has emphasized the importance of supplier-customer relationships for understanding aggregate outcomes, often relying on sector-level input–output tables as the empirical input for theory and quantitative analysis.[1]

At the same time, a large body of work using firm-level data has documented substantial heterogeneity in firm size. Firm size distributions are known to be highly skewed, with economic activity concentrated among a small number of large and often highly productive firms. Moreover, aggregate outcomes can depend critically on the identity of individual firms.[2]

This raises a fundamental question: when studying propagation and aggregation characteristics, how much do we lose by working at the sector level? Sector-level input-output tables treat industries as if they were composed of representative firms linked by average relationships. But if the economically relevant heterogeneity operates mainly within sectors rather than across, sectoral data may miss precisely the margins that matter most for shock transmission. In particular, concentration of economic activity, the structure of supplier–customer linkages, and firms' positions in the production chain may all vary substantially within sectors and be hard to infer from sectoral aggregates alone. Aggregation is costly in two ways: it averages away this within-sector dispersion, and it leaves an across-sector structure that is itself a composition-dependent summary rather than a structural primitive, so even the part of the IO table one does observe conflates technology with the internal distribution of firms.

This paper provides a systematic characterization of firm-to-firm production networks using comprehensive administrative VAT and tax filing data for five European countries: Belgium, Estonia, Hungary, Italy, and Portugal. These data allow us to observe domestic business-to-business transactions at the firm level, covering hundreds of thousands to over a million firms per country and up to tens of millions of bilateral relationships. By linking transaction records to firm characteristics using annual accounts and business registries, we construct large-scale production networks and document their structural, distributional, and aggregation properties in a harmonized and comparable way across countries.

Beyond measurement, we use these networks to show that the documented distinctions are economically consequential, with the transmission of monetary policy as our leading application. Recent work has emphasized that the aggregate effects of monetary policy depend not only on average firm responses, but also on the network position of firms directly and

[1]Early contributions include multi-sector real business cycle models (Long and Plosser, 1983; Horvath, 1998; Dupor, 1999) and growth accounting frameworks with intermediate inputs (Domar, 1961; Hulten, 1978; Jones, 2011). Modern network formulations emphasize how network structure reshapes aggregation and shock propagation (Acemoglu et al., 2012; Carvalho and Gabaix, 2013; Oberfield, 2018; Baqaee and Farhi, 2019, 2020; Carvalho et al., 2021). For excellent surveys, see Carvalho (2014) and Carvalho and Tahbaz-Salehi (2019).

[2]Canonical models of firm dynamics generate highly skewed firm size distributions (Gibrat, 1931; Hopenhayn, 1992; Luttmer, 2007), consistent with empirical regularities including heavy tails (Axtell, 2001). The granularity literature shows that when size dispersion is sufficiently large, idiosyncratic firm-level shocks can have aggregate consequences (Gabaix, 2011; Carvalho and Gabaix, 2013; di Giovanni et al., 2014). For heterogeneity in firm-level productivity see e.g. the survey in Syverson (2011).

indirectly exposed to policy-induced changes in financing conditions, demand, and costs.[3]

Our analysis delivers a set of empirical facts along five dimensions. First, we characterize firms' positions in production networks using various centrality metrics that are consistent with canonical models of shock propagation and aggregate volatility. In linearized environments, Domar weights and Katz-Bonacich centrality summarize the extent to which idiosyncratic shocks to a firm affect aggregate outcomes through input–output linkages. By construction, Katz-Bonacich centrality is a monotone transformation of firm size: in the canonical Cobb-Douglas benchmark the influence vector coincides with the Domar weight (under constant returns and efficiency), so a firm's scale summarizes its first-order aggregate influence. What size does *not* determine is vertical position: we show upstreamness and downstreamness are orthogonal to size and to each other, and are not recoverable from sectoral input–output tables. We also characterize vertical positioning using firm-level measures of upstreamness and downstreamness, which capture firms' distances to final demand and to primary inputs along production chains, but are orthogonal to both firm size and centrality. Moreover, the well-documented positive correlation between upstreamness and downstreamness at the sector level (Antràs and Chor, 2018) essentially vanishes at the firm level, indicating that this association is an artifact of sectoral aggregation rather than a feature of firm-level production.

Second, this heterogeneity extends beyond firm size: network sales, bilateral transaction values, and the number of customers are extremely granular and span several orders of magnitude, consistent with heavy-tailed distributions. This dispersion persists within narrowly defined industries and is remarkably similar across countries, indicating substantial within-industry heterogeneity that cannot be attributed to sectoral composition.

Third, we quantify the origins of firm size heterogeneity through an exact variance decomposition of firm sales into upstream, downstream, and final-demand components. Across all countries and sectors, the extensive margin of customers is the dominant component, accounting for roughly half of within-industry firm size variance. Seller-side characteristics explain a secondary but non-negligible share, while final demand plays a much more modest role.

Fourth, we examine how firm-level production networks relate to standard sector-level input–output representations and show that aggregation fundamentally alters network structure. Sector-level input–output networks are dense and feature sizable within-sector flows, whereas firm-level networks are extremely sparse, with densities on the order of 10^{-5} and the vast majority of potential firm-to-firm links absent. Moreover, the "roundabout production" reflected in diagonal entries of sectoral input–output tables disappears once production is viewed at the level of distinct firms. We further document that firm-level input and output shares vary enormously even within detailed supplier–customer sector pairs, with coefficients of variation typically much above one. This indicates that sector-level technical coefficients

[3]Theoretical contributions show that network structure shapes the slope and composition of aggregate Phillips curves, the sectoral and firm-level incidence of nominal rigidities, and the welfare-relevant trade-offs faced by monetary authorities (Pasten et al., 2020; La'O and Tahbaz-Salehi, 2022; Rubbo, 2023; Höynck, 2025). In networked environments, disaggregated demand and supply channels interact with input linkages in ways that can overturn representative-sector intuitions (Baqaee and Farhi, 2022; Afrouzi and Bhattarai, 2023). Empirically, heterogeneous input linkages generate sharp cross-sectional patterns in responses to monetary shocks (Ghassibe, 2021) and can be detected in asset prices (Ozdagli and Weber, 2025). Variable markups and incomplete pass-through in production networks further amplify heterogeneous transmission of price and cost shocks (Duprez and Magerman, 2018).

mask highly heterogeneous underlying relationships and are misleading proxies when firm-level propagation mechanisms are the object of interest. These patterns are highly stable across countries and industries, suggesting that customer base represents a fundamental driver of firm size that operates independently of sectoral composition or country-specific characteristics.

Finally, we exploit the firm-level production networks to analyze the transmission of monetary policy shocks. We document substantial heterogeneity in firm-level responses that varies systematically with firms' vertical positions in production chains. Upstream firms experience more persistent sales contractions and more negative price responses, with the price gradient weaker than in sales, consistent with the cumulative effects of demand reductions propagating backward along supply chains. Cross-country differences in the distribution of firms across upstream and downstream positions translate into heterogeneous aggregate responses to a common monetary policy shock, highlighting that the vertical organization of production – beyond average network connectivity or firm size – shapes both the magnitude and the incidence of monetary policy transmission.

Overall, the paper makes a single point along several dimensions: while a firm's centrality, or aggregate influence, is well summarized by its size, its vertical position along production chains—which governs how shocks propagate to other firms—is a firm-level object that is only loosely related to firm size and is not recoverable from sector-level representations. Firm size and sectoral input–output tables, the two objects quantitative work typically relies on, each miss economically meaningful and systematic variation in this position. The paper provides a set of robust, cross-country moments that characterize this firm-level structure and establish how it differs systematically from sector-level representations. These moments serve as direct calibration targets for quantitative models of production networks and provide empirical benchmarks for assessing when sector-level input–output tables offer adequate approximations and when firm-level heterogeneity is first-order. The stability of key patterns across five European countries with different economic sizes, industrial compositions, and institutional settings suggests that the documented features represent fundamental properties of firm-level production networks rather than country-specific phenomena. More broadly, our results demonstrate that administrative firm-to-firm transaction data reveal economically meaningful dimensions of heterogeneity that are invisible in standard macroeconomic data and essential for understanding shock propagation, policy transmission, and aggregate dynamics.

This paper contributes to the growing literature that uses production networks to connect micro-level heterogeneity to aggregate dynamics. A long tradition in macroeconomics studies input-output linkages as a propagation mechanism, from multi-sector real business cycle models to modern network formulations (Long and Plosser, 1983; Horvath, 1998; Dupor, 1999). A complementary line of work emphasizes how network structure reshapes standard aggregation results, building on the measurement logic of Domar weights and growth accounting with intermediates (Domar, 1961; Hulten, 1978) and on development and macro frameworks that feature strong complementarities across inputs (Jones, 2011). In the modern network-macro literature, the structure of the production graph is central both for amplification and for how idiosyncratic shocks survive aggregation (Acemoglu et al., 2012; Carvalho, 2014; Carvalho and Gabaix, 2013; Gabaix, 2011; Baqaee and Farhi, 2019; Oberfield, 2018; Carvalho and Tahbaz-Salehi, 2019). Our empirical contribution is motivated by the fact that many of the objects that govern these theoretical mechanisms—firm-level degree, concentration of sales and purchases, and within-sector dispersion in connections and exposure—are typically weakly pinned down when models are calibrated solely to sector-level input-output tables.

A second related literature constructs and analyzes firm-to-firm production networks using administrative or high-coverage micro data, with recent work explicitly calling for systematic, comparable efforts across countries, as emphasized by Pichler et al. (2023). Early contributions leverage establishment-level shipment links and ownership structures for the U.S. (Atalay et al., 2011, 2014), while a series of papers using VAT-based transaction data for Belgium document sparse but highly skewed networks and quantify the aggregate relevance of firm heterogeneity (Dhyne et al., 2015; Magerman et al., 2016). Subsequent work studies how firm-to-firm linkages shape firm outcomes and measured heterogeneity, and how these network primitives map into aggregate dynamics (Bernard et al., 2022). Other studies use transaction networks to quantify the propagation of large shocks and disruptions, including natural disasters and supply-chain disturbances (Barrot and Sauvagnat, 2016; Boehm et al., 2019; Carvalho et al., 2021). In open-economy settings, firm-to-firm linkages also discipline indirect exposure to foreign shocks and the transmission of global disruptions (Tintelnot et al., 2018; Bonadio et al., 2021). Related evidence from other administrative settings highlights the empirical importance of firm-level network exposure for understanding aggregate responses to trade and demand shocks (Huneeus, 2018; Alfaro-Ureña et al., 2022). Bacilieri et al. (2025) discuss a taxonomy of multiple datasets on domestic firm-to-firm networks and emphasize that differences in data construction and coverage can generate large apparent cross-country differences in headline network statistics. Our project harmonizes measurement across multiple countries and documents a set of comparable moments—covering concentration, degree distributions, and the joint distribution of firm size and network position—that can be used directly in quantitative work.

A third body of work motivates why these moments matter by linking network position to firm size and aggregate volatility. Canonical models of firm dynamics generate highly skewed firm size distributions (Gibrat, 1931; Hopenhayn, 1992; Luttmer, 2007), consistent with empirical regularities in the upper tail (Axtell, 2001). Size dispersion implies that granular shocks can have aggregate consequences (Gabaix, 2011; di Giovanni et al., 2014; Carvalho and Gabaix, 2013). Our descriptive facts speak to this interaction by measuring how size, number of partners, and concentration co-vary within and across sectors, and by comparing the implied concentration of influence to what would be inferred from sector-level tables alone.

Finally, our analysis is closely connected to the literature on monetary policy transmission in production networks. Recent work shows that network structure shapes the slope and composition of aggregate Phillips curves, the sectoral and firm-level incidence of nominal rigidities, and the welfare-relevant trade-offs faced by monetary authorities (Pasten et al., 2020; La'O and Tahbaz-Salehi, 2022; Rubbo, 2023; Höynck, 2025). In networked environments, disaggregated demand and supply channels interact with input linkages in ways that can overturn representative-sector intuitions (Baqaee and Farhi, 2022; Afrouzi and Bhattarai, 2023). Empirically, heterogeneous input linkages can generate sharp cross-sectional patterns in monetary shocks (e.g. Ghassibe, 2021) and can be detected in asset prices (Ozdagli and Weber, 2025). Our multi-country moments are designed to be immediately usable in this literature: they provide externally measured restrictions on the dispersion of firm-level exposures and on the mapping between sectoral aggregates and the underlying firm network, helping to discipline quantitative monetary models and to guide the choice of which heterogeneity margins are first-order in practice.

The remainder of the paper is organized as follows. Section 2 describes the data sources and the construction of firm-level production networks. Section 3 and Section 4 document multiple dimensions of firm-level heterogeneity, position in production networks and their covariance. Section 5 provides a variance decomposition of firm sales into network components. Section 6 examines the structural properties of firm-level production networks and their relationship to sector-level input–output representations. Section 7 evaluates the impact of monetary policy shocks on heterogeneous firms in these networks. Section 8 concludes.

2 Data sources and construction

We combine administrative firm-to-firm transaction data with firm-level characteristics to construct large-scale production networks across five European countries for which harmonized VAT-based transaction data are available: Belgium, Estonia, Hungary, Italy, and Portugal. The core data consist of value-added tax (VAT) records reporting domestic business-to-business (B2B) transactions at the firm level, which we link to business registers and balance sheet information to recover firm attributes such as size and sector affiliation.

2.1 Firm-level and firm-to-firm data sources

The backbone of our analysis is administrative VAT data that record domestic transactions between legally distinct firms. For each transaction, the data report the identities of the supplier and the customer, the transaction value, and the reporting period. These records allow us to observe firm-to-firm sales flows directly and to construct directed production networks in which nodes correspond to firms and edges correspond to intermediate input flows.

Individual countries differ in their reporting frequency, ranging from annual aggregates to transactions recorded at the invoice level. We construct annual production networks by aggregating firm-to-firm transaction flows over the calendar year. A directed link from firm i to firm j exists if firm i supplies its output to firm j during the year, with link weights m_{ij} given by the total value of these yearly transactions. Further institutional details on VAT reporting rules and country-specific coverage are provided in Appendix A.

VAT data are particularly well suited for the study of firm-to-firm production networks for three reasons. First, coverage is very broad, encompassing nearly the universe of active firm-to-firm transactions above minimal reporting thresholds. Second, transactions are observed at arm's length, ensuring that recorded flows correspond to market exchanges between distinct legal entities. Third, pecuniary sanctions imposed by tax authorities for late or erroneous reporting result in a very high level of data accuracy and completeness.

Our networks combine administrative layers harmonized across countries. VAT-based B2B records provide the network edges: supplier and customer identities and annual transaction values, aggregated to the calendar year as described above. We link these to firm attributes, including sector classification (NACE Rev. 2, 2008), total sales, and total input expenditures, which are drawn from annual (balance sheet) accounts where available and from firms' own periodic VAT declarations otherwise. We hold each economic concept fixed across countries even where its source differs (annual accounts in Belgium, Italy, and Portugal, VAT-return totals in Estonia, and corporate tax records in Hungary), so that the same firm-level objects enter our network statistics everywhere. Where both are available, VAT declaration totals also serve to cross-validate the transaction flows. Finally, we construct a measure of final-demand sales, including both domestic consumers and exports, as the residual between total firm sales and sales to other firms observed in the B2B network. Appendix A details the country-specific sources.

2.2 Sample coverage and countries

Our analysis focuses on cross-sectional distributions, with 2019 chosen as the base year. This year is available for all countries in the data and precedes the COVID-19 pandemic, ensuring that results are not driven by this large aggregate shock. While institutional details differ across countries, the structure of the underlying data and the construction of production networks are fully harmonized to ensure comparability. All monetary values are expressed in nominal terms within each country and year, in euros for all countries except Hungary, where values are reported in thousands of Hungarian forints. To maintain consistency across analyses, we restrict attention to firms with strictly positive sales and at least one observed firm-to-firm transaction over the year.

Table 1 reports descriptive statistics on the coverage and scale of the firm-to-firm transaction data in 2019. Across countries, the datasets cover hundreds of thousands to over 1.5 million firms, with the vast majority appearing as sellers, buyers, or both. The number of observed firm-to-firm relationships is very large, ranging from approximately 0.8 million in Estonia to nearly 60 million in Italy, underscoring the high dimensionality of the underlying production networks.

Before proceeding to the analysis, we restrict attention in each country and year to the giant connected component (GCC) of the production network, defined as the largest weakly connected component of the directed firm-to-firm transaction graph. This ensures that network measures relying on the global structure of the input–output matrix, in particular centrality, upstreamness, and downstreamness, are well-defined. The restriction has negligible effects on sample coverage: across all countries and years, fewer than 0.5% of firms and fewer than 0.05% of relationships are excluded. All results reported in the remainder of the paper are based on

Table 1: Coverage of VAT transaction data by country (2019).

Country	Firms	Sellers	Buyers	Relationships
Belgium	544,104	383,547	540,368	13,102,712
Estonia	103,592	62,283	93,369	841,823
Hungary	315,259	257,522	226,289	2,122,561
Italy	1,668,485	1,018,578	1,657,712	59,427,029
Portugal	459,548	367,686	458,572	38,735,197

Note: The table reports the number of unique VAT sellers and buyers in each country for the year 2019. Relationships are defined as the existence of a positive trade flow at the yearly level.

the GCC sample.

3 Multi-dimensional granularity in firm-to-firm production networks

We start by documenting several dimensions of granularity and extreme skewness in firm-to-firm production networks that are highly robust across countries. First, the distribution of network sales is highly concentrated among the top firms and firm-to-firm relationships. Second, these distributions span several orders of magnitude and are often heavy-tailed. Third, also the extensive margin of the number of customers per firm is highly dispersed and heavy-tailed. These findings are not primarily driven by sector or country characteristics, and prevail within narrowly defined industries across all countries. These patterns are hard to reconcile with macro models of representative firms within sectors.

3.1 Concentration of firm sales and buyer-seller relationships

A first robust pattern is the extreme concentration of sales within domestic production networks. Panel A of Table 2 reports the share of total network sales accounted for by the largest firms in each country.[4] Across all countries, the top 10% of firms consistently account for around 80–90% of total network sales, while the top 1% alone captures between 45 and 64%. This indicates that a very small subset of firms is responsible for the bulk of value transacted in firm-to-firm production networks. While the exact degree of concentration varies across countries, this pattern is remarkably stable despite substantial differences in economic size and industrial structure. Panel B reports concentration at the level of individual buyer–seller relationships, expressed as the bilateral value of these flows, m_{ij}. Concentration at the link level is even more pronounced: the top 10% of bilateral relationships account for up to 96% of total network sales, while the top 1% still represents between 50 and 80% of this total sales value.

These results show that concentration in production networks operates along at least two distinct dimensions: across firms and across relationships. In both cases, a very small subset of economic units dominates the intensive margin of the production network. These patterns suggest that representative firms or representative buyer–seller relationships can provide a poor approximation of real-world granular production networks. Instead, the identity of both

[4] Firm i's network sales is the sum of transactions to all of its domestic business customers, $S_i^{net} = \sum_j m_{ij}$.

suppliers and customers, as well as the characteristics of the links connecting them, are central for understanding the drivers of microeconomic heterogeneity and aggregate outcomes.

These findings are related to, but distinct from, the canonical firm size granularity hypothesis (Gabaix, 2011). While that literature emphasizes the role of large firms as a source of aggregate fluctuations, the results in Table 2 show that granularity in production networks arises not only from firm size, but also from the concentration of economic activity across buyer–seller relationships. In this sense, firm size alone does not fully characterize how sales and transactions are distributed within production networks. We return to this point and the related Domar weights in Section 4.

For completeness, we also report complementary cumulative distribution functions (CCDFs) of the firm size distribution, together with implied power-law tail estimates, in Figure B.1. These distributions confirm that firm size is highly right-skewed and heavy-tailed across countries.

Table 2: Concentration of firm-level network sales and buyer-seller relationship values.

	Panel A: Network sales		**Panel B: Bilateral sales**	
Country	Top 10%	Top 1%	Top 10%	Top 1%
Belgium	0.89	0.64	0.92	0.72
Estonia	0.81	0.45	0.81	0.50
Hungary	0.86	0.59	0.86	0.61
Italy	0.87	0.61	0.93	0.72
Portugal	0.87	0.63	0.96	0.79

Note: Panel A reports the share of total domestic inter-firm sales observed in the network accruing to the top 10% and top 1% of firms by country for the year 2019. Panel B reports the share of total bilateral sales value accruing to the top 10% and top 1% buyer–seller relationships, ranked by annual transaction value.

3.2 Within-sector heterogeneity

The extreme concentration documented above raises a natural question: to what extent does this heterogeneity simply reflect differences across industries, as opposed to heterogeneity among firms operating within the same industry? Differences in scale, technology, and input intensity across sectors are economically meaningful and expected. Appendix Figure B.2 reports kernel density estimates of firm-level network sales by aggregate industry, confirming substantial sectoral variation in typical scale and dispersion, spanning up to ten orders of magnitude.

However, these patterns are not primarily driven by sectoral characteristics. Even within narrowly defined industries, massive dispersion and skewness remain. Figure 1 plots the distribution of firm-level network sales after demeaning at the NACE 4-digit level and regrouping firms by broad industry. Strikingly, within-sector variation is at least as large as across-sector variation, with substantial overlap in the entire distribution across industries. Firms operating in the same detailed industry can differ in their network sales by several orders of magnitude, while firms from different industries often occupy very similar positions in the distribution.

Two features stand out. First, a large share of the heterogeneity in network sales reflects firm-level differences within detailed industries, and sectoral affiliation is not the main driver of the heterogeneity in firms' network activity. Second, these within-industry distributions are remarkably similar across countries, despite large differences in economic size, industrial composition, and institutional environments. These features suggest that within-industry heterogeneity in network sales reflects common firm-level mechanisms rather than country- or sector-specific features.

These findings have several implications. From a measurement perspective, they imply that sector-level input–output coefficients can mask substantial heterogeneity in the intensity and scale of firm-to-firm relationships, even within narrowly defined industries. From a modeling perspective, they challenge representations of production networks based on representative firms or average sectoral linkages: much of the economically relevant variation in network exposure operates at the firm level within sectors. Finally, the pervasive within-industry dispersion highlights that large firms and highly connected firms are not confined to specific industries, but arise across the entire production structure, potentially shaping aggregate outcomes through their positions in the network.

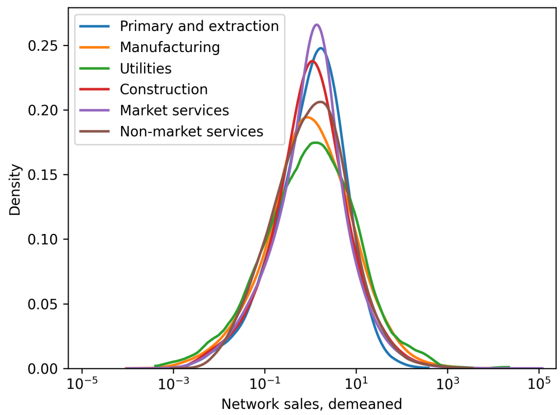
3.3 Heterogeneity in degree distributions

We also document heterogeneity along the extensive margin of firm-to-firm production networks. Figure 2 reports complementary cumulative distribution functions (CCDFs) of the number of customers per firm for each country.[5] The CCDFs are plotted on log–log scales and exhibit pronounced right skewness in all cases, indicating substantial heterogeneity in firms' customer bases. We also report detailed distributional moments by broad industry in Table B.2.

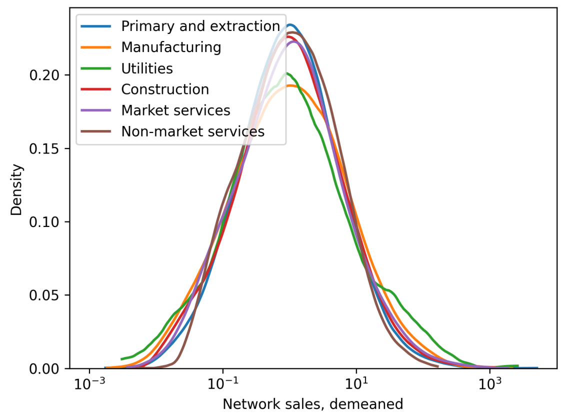
Heterogeneity in the number of buyer–seller relationships across firms is enormous and closely mirrors the concentration patterns observed for network sales and transaction values. The distributions span several orders of magnitude. While a median firm supplies only a handful of business customers, firms in the upper tail serve hundreds of thousands of customers. Even within the upper tail, dispersion remains substantial: firms at the 99th percentile supply up to ten times more customers than firms at the 90th percentile. These patterns underscore that heterogeneity in production networks extends beyond firm size to the structure and scale of firm-level relationships. Estimated tail exponents range between approximately 1.4 and 1.6 across countries, consistent with heavy-tailed distributions.

As with network sales and transaction values, this dispersion is not primarily driven by sector- or country-specific characteristics. Figure B.3 shows that the distributions of customer counts are very similar after demeaning by sector–country averages. Within-industry variation

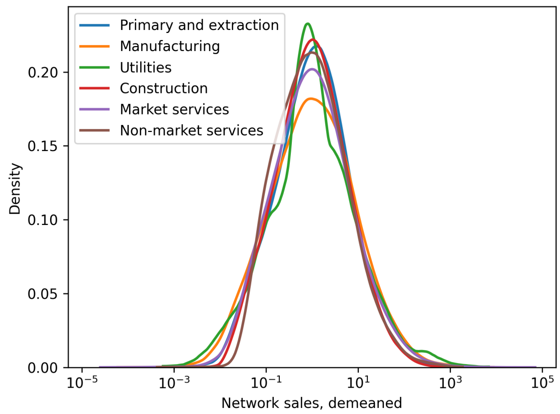
[5]The CCDF of a random variable X is defined as $\Pr(X \geq x) \equiv 1 - F(x)$, where $F(x) = \Pr(X \leq x)$ is the cumulative distribution function. If the distribution of X is consistent with a power-law in the upper tail, then $\Pr(X \geq x) \propto x^{-\alpha}$ for sufficiently large x, where $\alpha > 0$ is the tail exponent. Tail exponents are estimated using a Hill estimator with an endogenously selected lower cutoff, following Clauset et al. (2009).



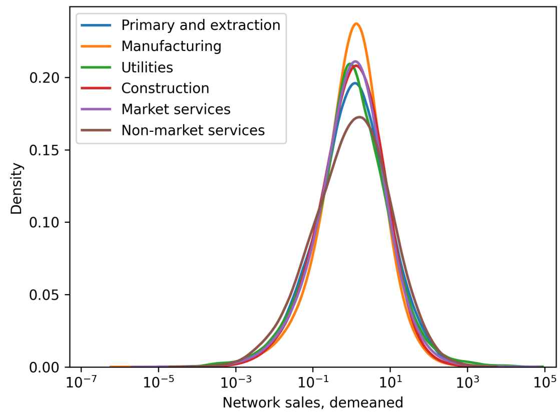
(a) Belgium



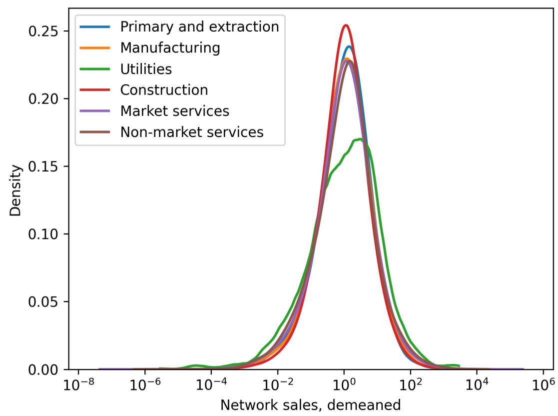
(b) Estonia



(c) Hungary



(d) Italy



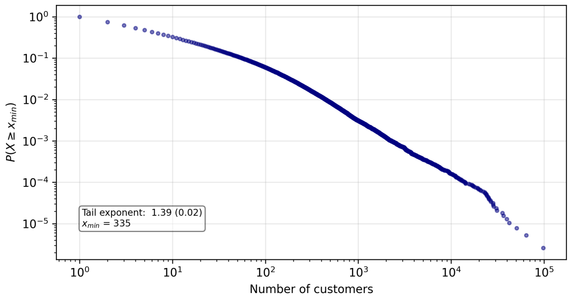
(e) Portugal

Note: The figure reports kernel density estimates of firm-level network sales, demeaned at the NACE 4-digit level, grouped again by high-level industry. The horizontal axis is shown on a logarithmic scale.

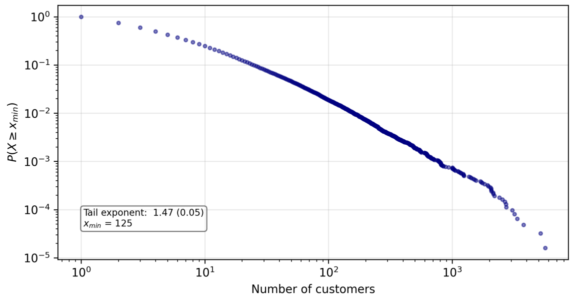
Figure 1: Distribution of firm-level network sales, by industry (NACE 4-digit demeaned).

remains extremely large, spanning a factor of one million to one billion, while differences in dispersion across sectors largely disappear within each country.

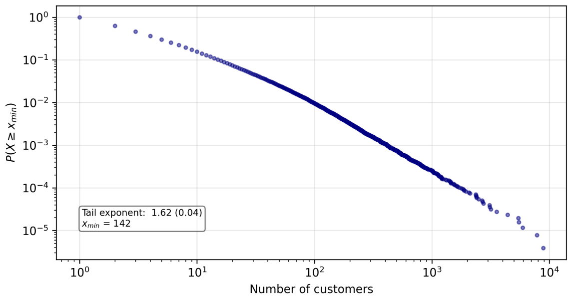
We find qualitatively similar patterns on the supplier side of the network. Figure B.4 reports the distribution of the number of suppliers per firm, which is also highly right-skewed



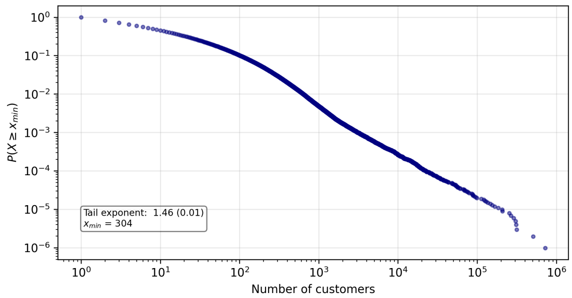
(a) Belgium



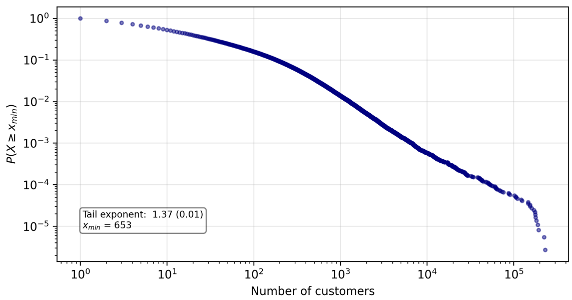
(b) Estonia



(c) Hungary



(d) Italy



(e) Portugal

Note: The figure reports the CCDF of the outdegree distribution for each country. Implied power law exponents are estimated using the Hill estimator with endogenous cutoffs for the tails as in Clauset et al. (2009). Standard errors in parentheses are computed as $\hat{\alpha}/\sqrt{k}$, where k is the number of observations above the endogenous cutoff.

Figure 2: CCDF of the distributions of the number of customers per firm.

and exhibits extreme dispersion across countries, even within industries. However, dispersion on the input side is systematically smaller than on the customer side. This asymmetry reflects the fact that firms typically source from a more limited set of input suppliers than the set of downstream customers they serve. As a result, heterogeneity in buyer–seller relationships is more pronounced along the downstream dimension, reinforcing the role of customer-side exposure in shaping network-level concentration and shock propagation, a point we return to in Section 5.

Table B.1 reports the estimated tail exponents for the number of customers and number of suppliers alongside other firm-level variables, as well as a robustness check using the Gabaix-Ibragimov estimator (Gabaix and Ibragimov, 2011). The two estimators yield consistent results across all variables and countries.

4 Firms' positions in production networks

We now turn to measures of firm centrality and vertical position in production networks. We focus on three metrics grounded in economic theory. The first, Katz-Bonacich centrality, captures a firm's aggregate influence through the network, summarizing how shocks to individual firms propagate to affect aggregate outcomes in canonical production network models. The second and third metrics, upstreamness and downstreamness, quantify firms' distance to final demand and primary inputs, respectively, along production chains. We also examine how these network positions covary with firm size and firm-level network characteristics. Two main findings emerge. First, centrality is extremely right-skewed and spans several orders of magnitude, even within industries, yet it coincides with firm size. Second, vertical position is largely orthogonal to both size and centrality, and upstreamness and downstreamness themselves are uncorrelated at the firm level. These patterns are strikingly stable across all five countries, suggesting fundamental features of firm-level production networks.

4.1 Katz-Bonacich centrality

Hulten's theorem (Hulten, 1978) provides a benchmark for the role of microeconomic shocks in aggregate fluctuations. In competitive economies satisfying the conditions of the second welfare theorem, aggregate productivity growth can be written, to a first order, as a Domar-weighted average of micro-level productivity changes. In particular:

$$\mathrm{d}\ln TFP = \sum_i \lambda_i \mathrm{d}\ln TFP_i \tag{1}$$

where $d\ln TFP_i$ is a shock to producer $i \in N$ and $\lambda_i \equiv S_i/GDP$ is its sales share or Domar weight.[6] This key result is a cornerstone of growth accounting: with homothetic preferences and constant returns to scale production technologies, it provides a first-order approximation of the impact of micro productivity shocks on aggregates. An important negative result is that it also implies that the detailed structure of intermediate input linkages is irrelevant for aggregate outcomes in linear approximations: producers' sales shares are a sufficient statistic, as they fully capture the aggregate impact of input-output linkages by using gross output instead of value added flows.[7] When firm size distributions are sufficiently heavy-tailed, idiosyncratic shocks do not average out even as the number of firms grows large, and GDP volatility becomes proportional to the Herfindahl index of firm sales (Gabaix, 2011).

Acemoglu et al. (2012) show these Domar weights can be decomposed into direct and indirect contributions through the production network using Katz-Bonacich centrality. In their

[6] While Domar weights are no longer sufficient statistics at second order, and in nonlinear or distorted environments (Baqaee, 2018; Baqaee and Farhi, 2019, 2020), together with related objects like Leontief inverse matrices, they do remain key objects in identifying the role of micro units on aggregate outcomes.

[7] Note that $\sum_i \lambda_i \geq 1$, with strict inequality whenever there are intermediate transactions, thereby reflecting the presence of intermediate input linkages and the associated gross-output amplification of micro shocks.

framework, the influence vector satisfies:[8]

$$\lambda = \frac{\alpha}{N} \left[I - (1-\alpha)\Omega \right]^{-1} \mathbf{1} \tag{2}$$

where α is the share of value added in gross output, N is the number of sectors in the economy, Ω is the economy's input-output matrix with elements the input shares m_{ij}/M_j, where M_j is firm j's total intermediate input purchases and $\mathbf{1}$ is a vector of ones.[9]

We compute firm-level Katz-Bonacich centrality following Magerman et al. (2016):

$$v = \frac{\alpha}{Y} \left[I - (1-\alpha)\Omega \right]^{-1} F \tag{3}$$

where Y is the country's GDP and F is the vector of sales to final demand. Hence, it aggregates information on both direct and indirect sales through the production network, as captured by Ω, while also allowing for heterogeneity in firms' exposure to final demand.[10] Furthermore, with Cobb-Douglas preferences and technologies, idiosyncratic shocks to individual producers propagate only downstream, while demand shocks only propagate upstream.

Figure 3 reports the distribution of Katz–Bonacich centrality across firms. Again, several key results stand out. First, Katz–Bonacich centrality is extremely right-skewed in all countries and sectors, indicating that a very small subset of firms accounts for a disproportionate share of aggregate network influence. Second, there is substantial heterogeneity in Katz–Bonacich centrality within sectors, together with a large overlap in centrality values across sectors in each of the countries. While some firms in utilities industries tend to be very central in all countries, firms in virtually all industries can be highly central, and dispersion within sectors is markedly larger than dispersion across sectors. Third, as shown in Table 3 below, firm size (total sales or Domar weights) and Katz-Bonacich centrality are almost perfectly correlated, with Pearson coefficients close to one in every country. This holds by construction: with input shares summing to one and a common value-added share α, the influence vector reduces to the Domar weight, so centrality coincides with firm size up to dispersion in firm-level value-added shares around α.

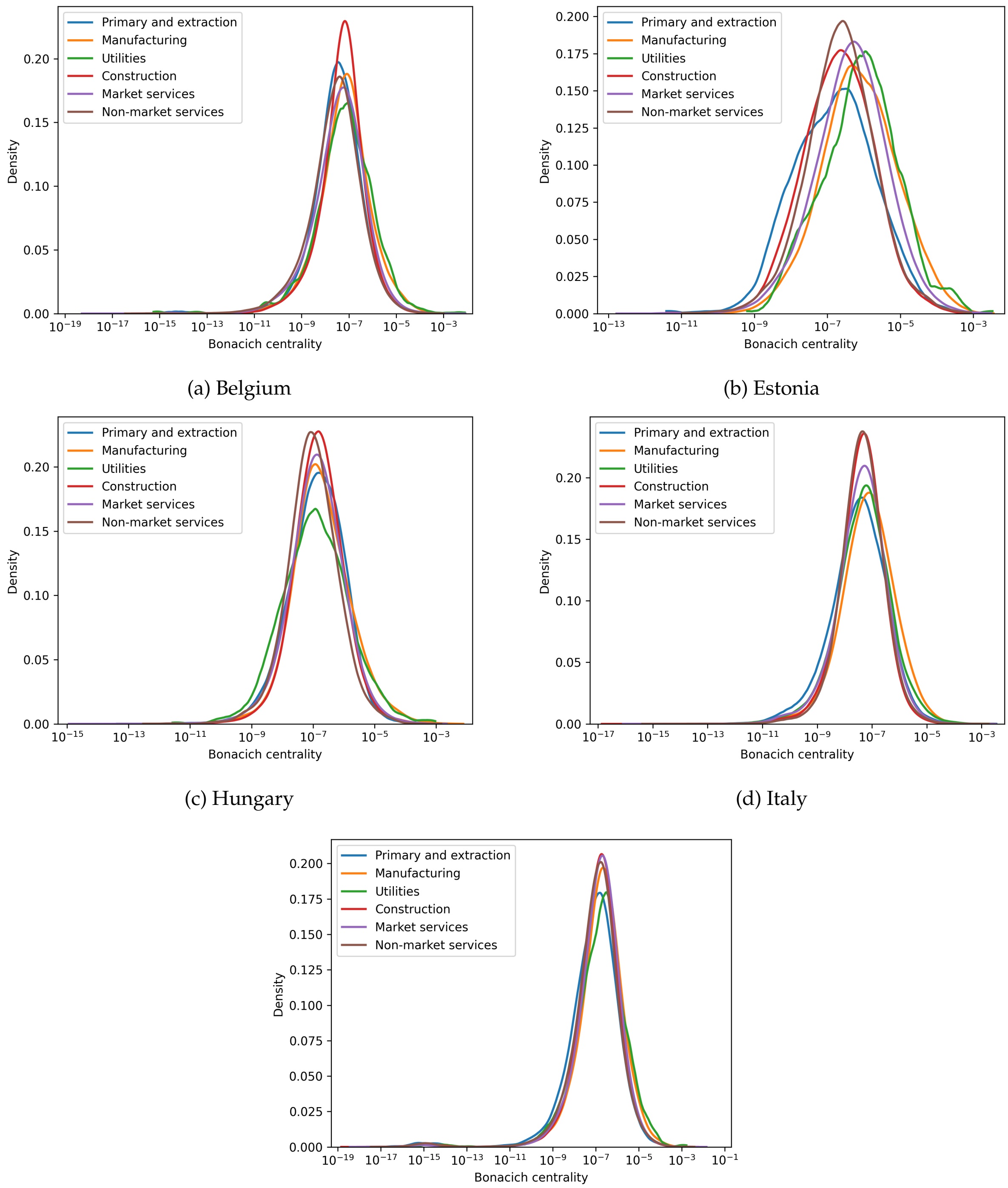
Taken together, these results confirm that firm-level Katz–Bonacich centrality coincides with the Domar weight, so a firm's first-order aggregate influence is summarized by its size.[11] The dimension of network heterogeneity that firm size does *not* capture — firms' vertical positions along supply chains — is the subject of the next subsection.

[8]Focusing on a sequence of economies in the limit as $N \to \infty$, Eq. (2) implies that all heterogeneity is in the production network structure, while each sector sells an equal share of $1/N$ to final demand.

[9]While Gabaix (2011) assumes Hicks-neutral productivity shocks, leading to gross output over GDP as the relevant statistic, Acemoglu et al. (2012) cast their framework in a Harrod-neutral setting, which generates value added shares in GDP as the key object. Rewriting the model with Hicks-neutral shocks recovers the classic Domar weights as the sufficient statistic.

[10]As we do not have information on firms' value added for all countries, we set $\alpha = 0.2$, corresponding to the aggregate labor share in gross output in Belgium.

[11]The Katz–Bonacich centrality should be interpreted as the influence vector of the canonical competitive Cobb–Douglas benchmark. In that benchmark, firm-level influence is summarized by Domar weights. In richer environments with nonlinearities or distortions, however, Domar weights are no longer sufficient statistics for firm-level influence: aggregate effects also depend on substitution elasticities, markups, wedges, and equilibrium reallocation, which are not observed in our VAT data.



(a) Belgium (b) Estonia

(c) Hungary (d) Italy

(e) Portugal

Note: The figure reports kernel density estimates of firm Katz-Bonacich centrality, by high-level industry. The horizontal axis is shown on a logarithmic scale.

Figure 3: Distribution of firm Katz-Bonacich centrality, by high-level industry.

4.2 Upstreamness and downstreamness

Katz-Bonacich centrality measures aggregate influence but is silent on where firms sit along production chains. We characterize firms' vertical positions using measures of upstreamness and downstreamness, which capture their distance to final demand and to factors of production, respectively, along supply chains. These measures extend the sectoral upstreamness and downstreamness metrics introduced by Antràs and Chor (2013) to firm-to-firm production networks, exploiting detailed transaction data rather than sector-level input–output tables.

Firm-level upstreamness measures how far a firm is, on average, from final demand along the supply chain. For firm $i \in N$, upstreamness is defined as:

$$U_i = 1 + \sum_j b_{ij} U_j \tag{4}$$

where $b_{ij} = m_{ij}/S_i$ is the share of firm i's output that goes into firm j, known as the allocation coefficient. Intuitively, firms with high upstreamness sell primarily to other firms that themselves are far from final demand, whereas firms with low upstreamness sell relatively more to final demand or to firms that are close to it. Stacking firms into vectors and letting $\mathbf{B}$ denote the matrix of allocation coefficients with entries b_{ij}, upstreamness can be written in closed form as:

$$\mathbf{U} = [\mathbf{I} - \mathbf{B}]^{-1}\mathbf{1}, \tag{5}$$

where $\mathbf{I}$ is the identity matrix and $\mathbf{1}$ is a vector of ones.

We complement upstreamness with a measure of downstreamness, which measures how many stages of input consumption separate a firm from primary factors of production (i.e. value added). Firms with high downstreamness use inputs that embody longer production chains, while firms with low downstreamness rely more directly on primary inputs or on suppliers close to primary inputs. Similarly to Eq. (4), firm j's downstreamness is defined as

$$D_j = 1 + \sum_i a_{ij} D_i \tag{6}$$

where $a_{ij} = m_{ij}/S_j$ is the amount of firm i's output required to produce one euro of firm j's output, i.e. the technical coefficient. Stacking firms into vectors and denoting $\mathbf{A}$ the matrix of technical coefficients with entries a_{ij}, downstreamness can be written in matrix form as

$$\mathbf{D} = [\mathbf{I} - \mathbf{A}']^{-1}\mathbf{1} \tag{7}$$

where $\mathbf{A}'$ is the transposed matrix of technical coefficients.

These measures are grounded in economic theory. In a general equilibrium model with intermediate goods and input-output linkages, upstreamness and downstreamness emerge naturally from log-linearizing the equilibrium conditions under standard assumptions on production technology and market structure.[12] Specifically, upstreamness arises from goods market clearing conditions, while downstreamness emerges from profit maximization. A key distinction is that upstreamness depends only on *network structure* of production, whereas downstreamness is sensitive to the prevailing *market structure*: under perfect competition and constant returns to scale, downstreamness corresponds to the column sum of the Leontief inverse. Under imperfect competition however, markups enter the pricing equation, requiring mark-

[12] For formal derivations, see Acemoglu et al. (2016) or Magerman and Palazzolo (2026).

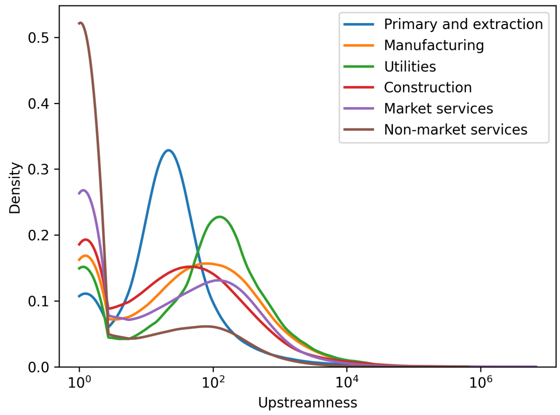
up adjusted cost-based Leontief inverses instead.[13]

Figure 4 reports the distribution of firm upstreamness by high-level industry and country. Three patterns stand out. First, upstreamness varies systematically across industries. Manufacturing and utilities firms generally tend to be located further upstream, while construction and non-market services are closer to final demand. This ranking is stable across countries, despite substantial differences in economic size and industrial structure. One exception is Estonia, where agricultural firms appear relatively more upstream. Second, there is substantial heterogeneity in upstreamness within industries. Even within sector–country pairs, firms differ markedly in their distance to final demand, reflecting heterogeneous production roles and exposure to intermediate versus final markets. Third, this dispersion is not driven by sector–country composition effects. Figure B.5 shows that, after demeaning upstreamness by sector–country averages, within-industry variation remains large and distributions overlap almost completely across sectors. Across all countries, firms in every industry can be located either close to or far from final demand.

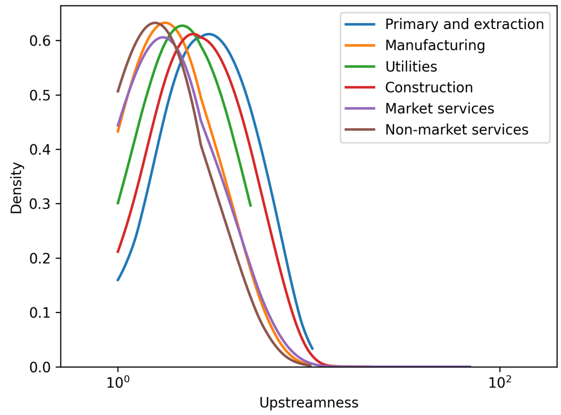
Figure 5 shows that downstreamness exhibits substantial within-industry heterogeneity. Firms with high downstreamness use inputs that embody longer production chains and are therefore further from primary factors, while firms with low downstreamness rely more directly on primary inputs or on suppliers close to primary inputs. In matrix notation, downstreamness corresponds to the column sum of the Leontief inverse and summarizes how quickly a firm's sales are absorbed by final demand rather than propagated further through the network.

As with upstreamness, downstreamness exhibits substantial within-industry heterogeneity (see also Figure B.6). While market services firms tend to be more downstream on average, firms in all industries occupy a wide range of positions along the production chain. This again highlights that firms' network positions are not solely determined by sectoral technologies or a fixed ordering of production stages, but by firm-specific characteristics.

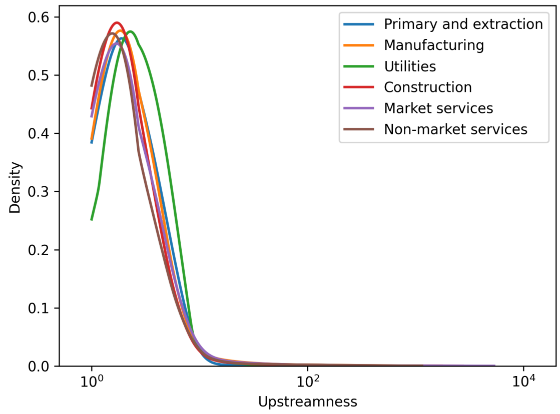
[13]See Baqaee and Farhi (2020) and Magerman and Palazzolo (2026) for such extensions.



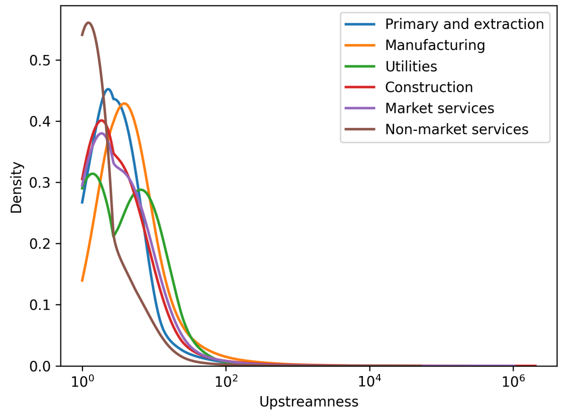
(a) Belgium



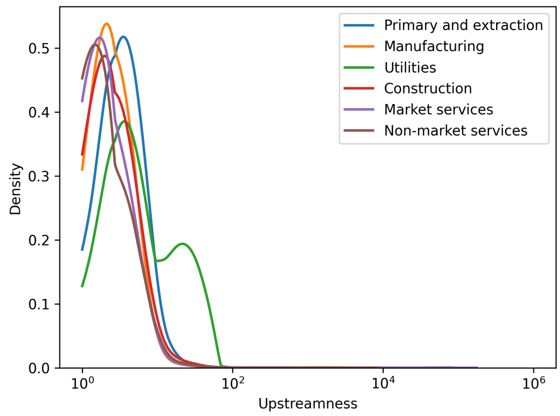
(b) Estonia



(c) Hungary



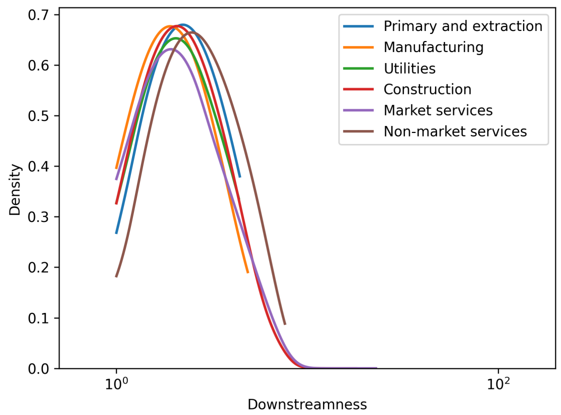
(d) Italy



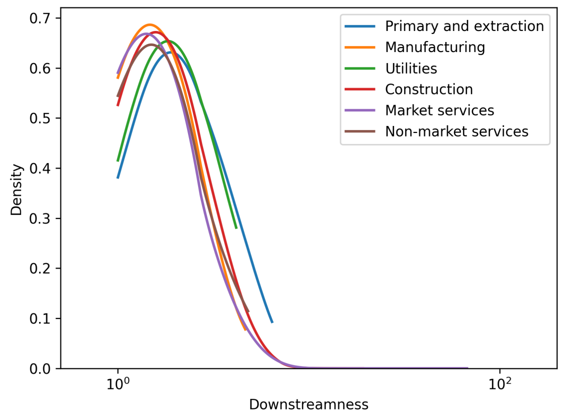
(e) Portugal

Note: The figure reports kernel density estimates of firm upstreamness, by high-level industry. The horizontal axis is shown on a logarithmic scale.

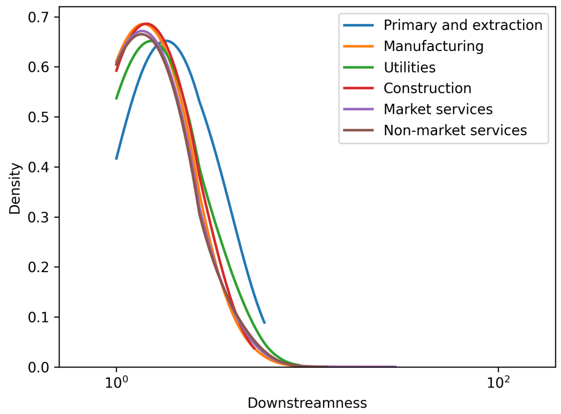
Figure 4: Distribution of firm upstreamness, by high-level industry.



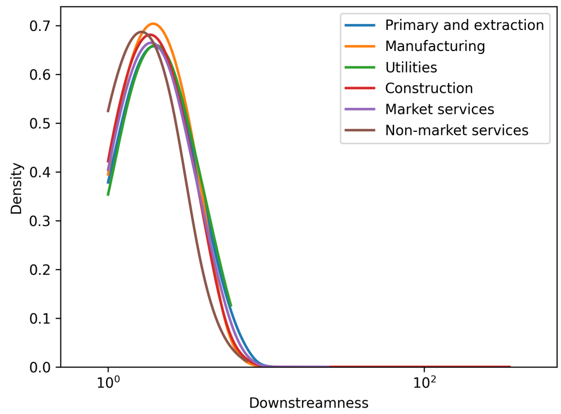
(a) Belgium



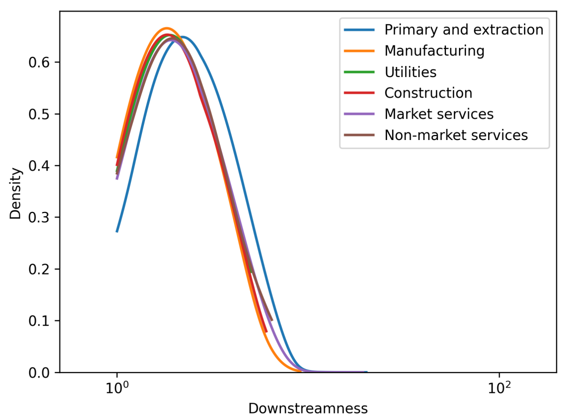
(b) Estonia



(c) Hungary



(d) Italy



(e) Portugal

Note: The figure reports kernel density estimates of firm downstreamness, by high-level industry. The horizontal axis is shown on a logarithmic scale.

Figure 5: Distribution of firm downstreamness, by high-level industry.

4.3 Covariance of firm characteristics in production networks

Having characterized multiple dimensions of firm heterogeneity—size, connectivity, centrality, and vertical position—we now examine how these characteristics covary. Understanding these covariance patterns is essential for three reasons. First, they reveal whether different network dimensions represent distinct margins or reduce to firm size alone. Second, they inform which combinations of firm attributes are empirically plausible when calibrating quantitative models. Third, they indicate which firm characteristics are conditionally informative for predicting network position and influence. Table 3 reports pairwise correlations among key firm characteristics by country. All variables are in natural logarithms and demeaned by NACE two-digit industry, so correlations reflect within-industry covariation. Several robust patterns emerge.

First, intuitively, firm size on the sales and input sides is tightly linked. Total sales S_i are strongly correlated with total input expenditures M_i, with correlation coefficients ranging from 0.85 in Portugal to 0.95 in Italy. Similarly, total sales correlate closely with domestic firm-to-firm sales S_i^{net} (0.74 in Belgium to 0.81 in Estonia), while total input expenditures M_i are highly correlated with domestic firm-to-firm purchases M_i^{net} (0.87 in Hungary to 0.99 in Portugal).

Second, larger firms tend to operate on a broader extensive margin in the production network. Firms with higher sales have more customers ($\text{Corr}(\ln S_i, \ln n_i^c) \sim$ 0.54–0.64), and firms with higher input expenditures have more suppliers ($\text{Corr}(\ln M_i, \ln n_i^s) \sim$ 0.71–0.81). Moreover, firms with many customers also tend to have many suppliers ($\text{Corr}(\ln n_i^c, \ln n_i^s) \sim$ 0.52–0.65). These correlations are sizable but far from mechanical, pointing to substantial heterogeneity in network structure among firms of similar size within the same industry.

Third, a firm's vertical position in the production network, as measured by upstreamness U_i, exhibits little systematic relationship with firm size. Despite large within-industry dispersion in upstreamness, its correlation with sales is weak and sometimes slightly negative ($\text{Corr}(\ln S_i, \ln U_i) \sim -0.09$–0.07). Firm size and downstreamness D_i are likewise weakly related. Moreover, upstreamness and downstreamness are essentially uncorrelated at the firm level ($\text{Corr}(\ln U_i, \ln D_i) \sim -0.03 - 0.17$), in sharp contrast to Antràs and Chor (2018)'s finding of a positive correlation at the sector level. This decoupling underscores that firms' upstream and downstream positions represent distinct dimensions of heterogeneity that are masked by sectoral aggregation.

Finally, Katz–Bonacich centrality is proportional to firm size: v_i correlates near-perfectly with sales (Domar weights) in every country, confirming that the influence vector recovers the Domar weight at the firm level. The heterogeneity that firm size does *not* summarize lies in firms' vertical positions: upstreamness and downstreamness are orthogonal to size and to each other and — unlike the sector-level aggregates in Antràs and Chor (2018) — cannot be inferred from sectoral input–output tables.

Importantly, these correlation patterns are remarkably stable across countries, despite large differences in economic size, industrial structure, and network density. Appendix Figure C.1 reports full correlation heatmaps using raw (non-demeaned) variables in logs; these are very similar to the within-industry correlations reported here, reinforcing that the main covariances are driven by firm-level heterogeneity rather than sector composition.

Overall, these covariance patterns establish that firm size and centrality coincide, while network connectivity and vertical position represent distinct and economically meaningful dimensions of heterogeneity. Because vertical position is orthogonal to size and stable across all five countries, calibrating production network models requires direct measurement of firm-level networks rather than relying on firm size distributions and sectoral input-output tables alone. In Section 5, we exploit this multi-dimensional heterogeneity to decompose firm size variance into its network origins.

Table 3: Correlation matrices by country, demeaned.

Belgium

	$\ln S_i$	$\ln M_i$	$\ln S_i^{net}$	$\ln M_i^{net}$	$\ln n_i^c$	$\ln n_i^s$	$\ln U_i$	$\ln D_i$	$\ln v_i$
$\ln S_i$	1								
$\ln M_i$	0.86	1							
$\ln S_i^{net}$	0.75	0.63	1						
$\ln M_i^{net}$	0.81	0.93	0.60	1					
$\ln n_i^c$	0.55	0.57	0.55	0.58	1				
$\ln n_i^s$	0.71	0.80	0.51	0.83	0.63	1			
$\ln U_i$	0.01	-0.00	0.36	0.01	0.25	0.03	1		
$\ln D_i$	-0.03	0.30	-0.06	0.48	0.14	0.32	-0.03	1	
$\ln v_i$	0.94	0.81	0.67	0.76	0.54	0.68	0.02	-0.03	1

Estonia

	$\ln S_i$	$\ln M_i$	$\ln S_i^{net}$	$\ln M_i^{net}$	$\ln n_i^c$	$\ln n_i^s$	$\ln U_i$	$\ln D_i$	$\ln v_i$
$\ln S_i$	1								
$\ln M_i$	0.89	1							
$\ln S_i^{net}$	0.81	0.87	1						
$\ln M_i^{net}$	0.81	0.88	0.71	1					
$\ln n_i^c$	0.64	0.63	0.72	0.58	1				
$\ln n_i^s$	0.78	0.80	0.69	0.87	0.65	1			
$\ln U_i$	-0.10	0.16	0.36	0.00	0.14	-0.01	1		
$\ln D_i$	0.01	0.26	0.09	0.52	0.04	0.33	0.17	1	
$\ln v_i$	0.93	0.85	0.79	0.75	0.63	0.73	-0.07	-0.01	1

Hungary

	$\ln S_i$	$\ln M_i$	$\ln S_i^{net}$	$\ln M_i^{net}$	$\ln n_i^c$	$\ln n_i^s$	$\ln U_i$	$\ln D_i$	$\ln v_i$
$\ln S_i$	1								
$\ln M_i$	0.94	1							
$\ln S_i^{net}$	0.75	0.70	1						
$\ln M_i^{net}$	0.82	0.87	0.70	1					
$\ln n_i^c$	0.59	0.58	0.66	0.56	1				
$\ln n_i^s$	0.74	0.76	0.59	0.82	0.62	1			
$\ln U_i$	-0.04	-0.04	0.37	0.05	0.19	-0.00	1		
$\ln D_i$	0.06	0.21	0.17	0.54	0.14	0.34	0.17	1	
$\ln v_i$	0.97	0.92	0.72	0.79	0.58	0.72	-0.05	0.04	1

Italy

	$\ln S_i$	$\ln M_i$	$\ln S_i^{net}$	$\ln M_i^{net}$	$\ln n_i^c$	$\ln n_i^s$	$\ln U_i$	$\ln D_i$	$\ln v_i$
$\ln S_i$	1								
$\ln M_i$	0.94	1							
$\ln S_i^{net}$	0.77	0.72	1						
$\ln M_i^{net}$	0.87	0.92	0.67	1					
$\ln n_i^c$	0.59	0.59	0.61	0.59	1				
$\ln n_i^s$	0.74	0.77	0.56	0.80	0.64	1			
$\ln U_i$	0.06	0.05	0.37	0.05	0.22	0.05	1		
$\ln D_i$	0.04	0.22	0.03	0.44	0.15	0.25	-0.01	1	
$\ln v_i$	0.97	0.92	0.75	0.85	0.60	0.73	0.07	0.04	1

Portugal

	$\ln S_i$	$\ln M_i$	$\ln S_i^{net}$	$\ln M_i^{net}$	$\ln n_i^c$	$\ln n_i^s$	$\ln U_i$	$\ln D_i$	$\ln v_i$
$\ln S_i$	1								
$\ln M_i$	0.83	1							
$\ln S_i^{net}$	0.77	0.66	1						
$\ln M_i^{net}$	0.84	0.99	0.67	1					
$\ln n_i^c$	0.54	0.55	0.56	0.55	1				
$\ln n_i^s$	0.63	0.71	0.51	0.72	0.53	1			
$\ln U_i$	-0.03	-0.02	0.37	-0.02	0.08	-0.02	1		
$\ln D_i$	-0.15	0.27	-0.12	0.28	0.05	0.17	-0.01	1	
$\ln v_i$	0.91	0.76	0.76	0.76	0.55	0.59	0.08	-0.16	1

Note: Entries report pairwise correlations of firm-level variables (in logs), demeaned at the NACE 2-digit industry level.

5 Firm size heterogeneity and the role of production networks

Section 4 established that firms differ along multiple network dimensions—size, connectivity, centrality, and vertical position—and that these attributes represent distinct margins of heterogeneity. We now ask a complementary question: among these dimensions, what drives firm size heterogeneity itself? We decompose firm sales into upstream, downstream, and final-demand components, following the exact variance decomposition of Bernard et al. (2022). The goal is to quantify how much within-industry firm size variation is associated with (i) seller-specific fundamentals that affect sales uniformly across customers, (ii) characteristics of a firm's customer base (its size and composition), and (iii) sales outside the domestic production network (final demand and exports). This decomposition exploits the granularity of firm-to-firm transactions in a way that is not feasible with standard firm-level datasets.

We begin by estimating a two-way fixed effects regression on bilateral transactions m_{ij}:

$$\ln m_{ij} = \ln G + \ln \psi_i + \ln \theta_j + \ln \omega_{ij}, \tag{8}$$

where $\ln \psi_i$ is a seller fixed effect, $\ln \theta_j$ a buyer fixed effect, and $\ln \omega_{ij}$ a match-specific residual. The seller effect $\ln \psi_i$ captures sales of firm i to its average customer, controlling for customer size via $\ln \theta_j$, and is therefore closely related to the firm's average market share among its customers. Conversely, $\ln \theta_j$ captures the scale of customer j's purchases, controlling for seller characteristics. The residual $\ln \omega_{ij}$ reflects match-specific factors that lead particular buyer–seller pairs to trade more or less, conditional on seller and buyer characteristics.

Appendix Table C.1 reports the variances and covariances of the estimated seller and buyer fixed effects from Eq. (8). Three patterns stand out. First, the adjusted R^2 ranges from 0.30 to 0.57, indicating that seller and buyer fixed effects explain a substantial share of the variation in firm-to-firm sales. Second, the variance of $\ln \psi_i$ is systematically larger than that of $\ln \theta_j$, suggesting that seller-side heterogeneity plays a dominant role in explaining bilateral transaction values. Third, the correlation between the fixed effects is close to zero (between -0.10 and 0.09), allowing us to interpret seller and buyer heterogeneity as largely distinct dimensions.

Using these estimates, we construct an exact decomposition of firm size into network components. Total sales can be written as the sum of domestic B2B sales and sales to final demand:

$$S_i = \sum_{j \in \mathcal{C}_i} m_{ij} + F_i,$$

where $\mathcal{C}_i$ denotes firm i's set of domestic customers and F_i captures sales to final demand (including exports). Total sales then admit the exact decomposition:

$$\ln S_i = \ln G + \ln \psi_i + \ln n_i^c + \ln \bar{\theta}_i + \ln \Omega_i^c + \ln \beta_i, \tag{9}$$

where G is the grand mean; n_i^c is the number of domestic customers; $\bar{\theta}_i$ is the geometric mean of the buyer fixed effect across those customers; Ω_i^c captures the covariance between buyer size and match quality; and $\beta_i \equiv S_i / S_i^{net}$ measures the importance of sales outside the domestic network relative to domestic network sales.[14]

Each component has a clear economic interpretation. The upstream term ψ_i captures seller-side fundamentals that raise sales uniformly across customers (e.g. productivity, quality, or its supplier base). The downstream terms n_i^c, $\bar{\theta}_i$, and Ω_i^c capture, respectively, the extensive margin of customers, the average scale of those customers, and assortative matching between customer size and match quality. The final-demand term β_i captures variation in sales outside

[14]Note that all elements in Eq. (9) are known: S_i, β_i, n_i^c , and G come directly from the data, while ψ_i, $\bar{\theta}_i$, and Ω_i^c are estimated from Eq. (8).

the domestic production network.

To quantify the contribution of each margin to within-industry firm size dispersion, we first demean all variables by NACE four-digit industry fixed effects. For each component $X_i \in \{\psi_i, n_i^c, \bar{\theta}_i, \Omega_i^c, \beta_i\}$, we then estimate

$$\ln X_i = \alpha_X + \gamma_X \ln S_i + \varepsilon_i.$$

By construction of the exact decomposition, the coefficients γ_X sum to one and can be interpreted as variance shares.

Table 4 reports the resulting variance shares by country. Again, results are remarkably stable across countries. The upstream component ψ_i explains 16–22% of within-industry firm size variance. The downstream components (n_i^c, $\bar{\theta}_i$, and Ω_i^c) account for the majority of dispersion, totaling 68–74%, with the number of customers n_i^c as the dominant contributor (42–51%). Differences in relative final demand β_i contribute only 1–12%. Thus, the single most important advantage of large firms is that they match with many buyers, while heterogeneity in customer characteristics and in sales outside the domestic network plays a smaller role. Appendix C.2 visualizes the decomposition and shows that these patterns are stable throughout the firm size distribution.

Table 4: Firm size decomposition ($\ln S_i$) by country.

	Upstream	Downstream			Final demand
Country	$\ln \psi_i$	$\ln n_i^c$	$\ln \bar{\theta}_i$	$\ln \Omega_i^c$	$\ln \beta_i$
Belgium	0.18	0.46	0.05	0.20	0.12
Estonia	0.21	0.45	0.03	0.21	0.10
Hungary	0.22	0.42	0.04	0.22	0.11
Italy	0.16	0.51	0.05	0.26	0.01
Portugal	0.19	0.49	0.02	0.23	0.07

Note: Entries report variance shares from the firm-size decomposition. All variables are demeaned by NACE four-digit industry averages.

We also perform the decomposition in Eq. (8) separately for each NACE two-digit industry in each country. Table 5 summarizes the distribution of variance shares across sectors, while Table C.2–Table C.5 report full sector-level results. Three regularities emerge. First, downstream components account for the majority of firm size variation in nearly every sector, with the extensive margin of customers ($\ln n_i^c$) consistently explaining the largest share. The coefficient of variation of this component is small and well below one, indicating limited cross-sector dispersion, and suggesting that extensive margin differences in customer relationships are a pervasive and structurally similar driver of firm size across both sectors and countries.

Second, seller-side heterogeneity ($\ln \psi_i$) explains a non-negligible but secondary share of dispersion within industries, and is relatively stable across countries within a given sector. Customer interaction effects ($\ln \Omega_i^c$) also show limited cross-sector dispersion. In contrast, the average customer size component ($\ln \bar{\theta}_i$) has a small mean contribution but exhibits more dispersion in some cases, most notably in Estonia. This points to substantial heterogeneity in the quality of downstream partners in specific sectors, even though this margin contributes little to firm size on average.

Finally, the final-demand component ($\ln \beta_i$) displays the largest cross-sector heterogeneity. While its average contribution is modest, its coefficient of variation exceeds one in all countries and is particularly high in Italy, indicating substantial sectoral variation in exposure to final demand and exports even though this margin plays a smaller role on average.

Overall, two conclusions stand out. First, downstream network margins dominate firm size heterogeneity across countries and sectors. Second, the similarity of sector-level decompositions across countries points to common structural features of production networks—rather than country-specific institutions or market size—as central determinants of firm size distributions.

Table 5: Cross-country summary statistics of sector-level decompositions.

	$\ln \psi_i$	$\ln n_i^c$	$\ln \bar{\theta}_i$	$\ln \Omega_i^c$	$\ln \beta_i$
Belgium					
Mean	0.18	0.42	0.05	0.22	0.13
CV	0.55	0.35	0.89	0.34	1.10
Estonia					
Mean	0.21	0.40	0.02	0.21	0.16
CV	0.68	0.39	2.37	0.39	1.13
Hungary					
Mean	0.20	0.38	0.03	0.22	0.16
CV	0.38	0.32	0.72	0.28	1.17
Italy					
Mean	0.17	0.47	0.05	0.27	0.04
CV	0.67	0.27	0.66	0.29	3.11
Portugal					
Mean	0.21	0.43	0.02	0.26	0.09
CV	0.56	0.34	1.00	0.35	1.29

Note: Mean shows the unweighted mean variance component across all NACE 2-digit sectors for each country. CV denotes the coefficient of variation for each component.

6 Network structure and implications for aggregation

This section documents structural properties of firm-level production networks that are largely invisible in standard sector-level input–output (IO) representations, and that matter for aggregation and calibration. We establish three facts. First, sector IO networks are effectively dense, whereas firm-to-firm networks are extremely sparse. Second, the "roundabout" structure implied by sizable diagonal elements in sector IO tables largely vanishes once production is viewed at the level of legally distinct firms. Third, within narrowly defined supplier–customer sector pairs, firm-level input and output shares exhibit massive dispersion, so that sector-pair averages are weak proxies for underlying micro linkages. Together, these results emphasize that firm-level production networks are fundamentally different objects from sectoral IO tables.

6.1 Network sparsity and aggregation

We start by comparing network topology across levels of aggregation. For each country, we aggregate all observed firm-to-firm flows within each supplier–customer sector pair and construct sectoral networks at both the NACE 4-digit and NACE 2-digit levels. We then benchmark these sectoral networks against the underlying firm-to-firm network.[15]

Let N denote the number of nodes and E the number of directed links, where a link corresponds to a strictly positive intermediate input flow. Allowing for self-loops, network density is then given by:[16]

$$\rho = \frac{E}{N^2}.$$

Table 6 shows a sharp change in how nodes and links scale as the level of aggregation is refined. Across countries, the number of nodes increases by a factor of 6–8 when moving from NACE–2 to NACE–4, and by several orders of magnitude when moving from NACE–4 sectors to firms. By contrast, the number of links increases by only one to two orders of magnitude across these levels. As a direct consequence, density collapses with disaggregation.

At the sectoral level (NACE–2 and NACE–4), IO networks are effectively dense: the number of observed links grows roughly on the order of the square of the number of nodes, $E = O(N^2)$, so densities remain high even as the number of sectors increases. In contrast, firm-level production networks are extremely sparse, with densities on the order of 10^{-5}. In other words, more than 99.99% of all potential firm-to-firm links are absent. As the number of firms reaches the hundreds of thousands or millions, the number of observed links grows approximately linearly with N, implying $\rho = O(1/N)$.

A related aggregation issue concerns within-sector sourcing. Column (5) of Table 6 reports the share of total intermediate inputs that a node sources from itself.[17] At the NACE–2 level,

[15] These bottom-up sector networks are constructed to study disaggregation and aggregation properties. They are not directly comparable to official national-accounts IO tables for several reasons, discussed in Appendix D.

[16] For an edge-related notion of sparsity, see (Minetti et al., 2025).

[17] The within share is computed as the sum of diagonal technical coefficients relative to the sum of all coefficients, $\sum_r a_{rr} / \sum_r \sum_s a_{rs}$, where $a_{rs} = m_{rs}/S_s$ is the technical coefficient for entry (r, s), m_{rs} denotes intermediate sales from r to s, and S_s is gross output of s.

this within share ranges from about 8% in Portugal to 22% in Italy, consistent with the sizable diagonal entries typically observed in sector IO tables and commonly interpreted as "round-about" production within sectors.

As production networks become more disaggregated, this within share declines sharply. At the NACE–4 level it ranges between 0.5% and 8.3%. At the firm level, by construction of the VAT data, self-loops are absent because transactions are observed only between legally distinct entities.[18]

Taken together, these results show that sectoral input–output tables can mask the sparse and heterogeneous structure of production networks at the micro level. This distinction is not merely descriptive. Dense and sparse networks belong to fundamentally different classes of graphs and are typically generated by very different network formation processes, ranging from approximately Poisson degree distributions in dense networks to heavy-tailed degree distributions in sparse ones. In random graphs, a small change in density relates to phase transitions that fundamentally change the topological features of these networks.

[18] Intra-firm trade can still exist, and is often documented for cross-border flows of multinational corporations. Some countries in the data also report whether VAT entities are part of VAT units that jointly submit consolidated accounts. Transactions across VAT entities within these units can then be seen as intra-firm domestic flows. However, it is up to the firm to choose its legal boundaries and how to organize its activities. For example, some establishments of a retail chain might be integrated and operate under one VAT number, while another chain might be organized into franchise locations, each with a separate VAT number.

Table 6: Input–output statistics across countries and levels of aggregation.

Level	Nodes (N)	Links (E)	Density (ρ)	Within share
Panel A: Belgium				
NACE-2	78	5,762	0.95	0.172
NACE-4	564	172,295	0.54	0.005
Firms	544,104	13,102,712	4.4×10^{-5}	0
Panel B: Estonia				
NACE-2	81	5,280	0.80	0.101
NACE-4	537	70,072	0.24	0.005
Firms	103,592	841,823	7.8×10^{-5}	0
Panel C: Hungary				
NACE-2	87	5,870	0.78	0.159
NACE-4	583	99,260	0.29	0.070
Firms	315,259	2,122,561	2.1×10^{-5}	0
Panel D: Italy				
NACE-2	83	6,257	0.91	0.222
NACE-4	709	293,213	0.58	0.083
Firms	1,668,485	59,427,029	2.1×10^{-5}	0
Panel E: Portugal				
NACE-2	82	6,264	0.93	0.079
NACE-4	575	204,482	0.62	0.049
Firms	459,548	38,735,197	1.8×10^{-4}	0

Notes: The table reports directed, unweighted production-network statistics at different levels of aggregation. For sector-level networks, links are defined by strictly positive sales values. Density is defined as the share of directed non-zero entries in the adjacency matrix, including self-loops. The within share is computed as $\sum_r a_{rr} / \sum_{r,s} a_{rs}$, where a_{rs} is the technical coefficient for entry (r, s), and reflects the value-weighted importance of within-sector intermediate input use. For firm-level networks, nodes correspond to firms and links correspond to observed firm-to-firm transactions. Within shares are mechanically zero.

6.2 Heterogeneity in input and output shares

We next quantify heterogeneity in firm-level sourcing and sales shares within narrowly defined sector pairs, and assess how informative sector-level IO coefficients are about underlying firm-to-firm relationships.

For each firm j, we compute the input share sourced from supplier i as $\omega_{ij} \equiv m_{ij}/M_j$. Normalizing by total expenditures ensures that these shares account for purchases outside the observed domestic B2B network (e.g. imports). These firm-level shares are the direct analogue of cost-based technical coefficients corrected for markups, as in Baqaee and Farhi (2020). We then group firm pairs by supplier–customer sector pairs (at the NACE 2-digit or 4-digit level) and compute, within each sector pair, (i) the average input share and (ii) the coefficient of variation (CV) across firm pairs. The CV provides a scale-free measure of relative dispersion and summarizes the degree of heterogeneity in firm-level sourcing behavior conditional on sector affiliation.

Table 7 summarizes the distribution of these moments across countries. Two results stand out. First, average sector-pair input shares are small—typically on the order of 1–5%, even at coarse levels of aggregation. Second, dispersion within sector pairs is extremely large: CVs are typically well above one and can exceed seven, implying that firm-level input shares within a given sector pair vary by multiples of their sector-pair average.

Table 7: Distribution of average input sourcing shares (2019).

	Mean	SD	p10	p25	p50	p75	p90
Panel A: Belgium							
Avg. share (NACE-2 pairs)	0.02	0.03	0.0012	0.004	0.0116	0.025	0.046
Avg. share (NACE-4 pairs)	0.02	0.05	0.0001	0.001	0.0049	0.017	0.044
CV (NACE-2 pairs)	3.36	1.77	1.52	2.20	3.01	4.12	5.58
CV (NACE-4 pairs)	1.98	1.23	0.82	1.21	1.69	2.47	3.47
Panel B: Estonia							
Avg. share (NACE-2 pairs)	0.05	0.08	0.0017	0.008	0.0275	0.066	0.129
Avg. share (NACE-4 pairs)	0.05	0.12	0.0004	0.002	0.0106	0.047	0.140
CV (NACE-2 pairs)	2.09	1.04	0.98	1.38	1.91	2.61	3.43
CV (NACE-4 pairs)	1.35	0.73	0.53	0.88	1.27	1.68	2.23
Panel C: Hungary							
Avg. share (NACE-2 pairs)	0.04	0.06	0.0015	0.007	0.0220	0.048	0.085
Avg. share (NACE-4 pairs)	0.03	0.08	0.0003	0.001	0.0082	0.032	0.086
CV (NACE-2 pairs)	2.22	1.08	1.07	1.47	2.05	2.75	3.58
CV (NACE-4 pairs)	1.45	0.77	0.61	0.96	1.34	1.80	2.40
Panel D: Italy							
Avg. share (NACE-2 pairs)	0.01	0.01	0.0010	0.002	0.0054	0.011	0.020
Avg. share (NACE-4 pairs)	0.01	0.02	0.0001	0.001	0.0021	0.007	0.017
CV (NACE-2 pairs)	3.84	1.92	1.82	2.63	3.56	4.66	6.06
CV (NACE-4 pairs)	2.17	1.40	0.90	1.29	1.82	2.71	3.83
Panel E: Portugal							
Avg. share (NACE-2 pairs)	0.01	0.02	0.0010	0.003	0.0075	0.016	0.030
Avg. share (NACE-4 pairs)	0.01	0.03	0.0001	0.001	0.0029	0.010	0.027
CV (NACE-2 pairs)	4.28	2.88	1.75	2.53	3.60	5.16	7.57
CV (NACE-4 pairs)	2.36	2.03	0.91	1.30	1.85	2.81	4.22

We perform an analogous exercise on the output side. For each supplier firm i, we compute output shares to customer j as m_{ij}/S_i, and again aggregate firm pairs by sector pairs. Table 8 reports the distribution of average output shares and their dispersion. The patterns closely mirror those on the input side: average output shares are small, but within-pair heterogeneity is very large, with CVs comparable to those observed for input shares.

These results imply that sector-level IO coefficients provide, at best, a very coarse summary of underlying firm-to-firm production linkages. Sector-level models collapse all firm-level relationships within a sector pair into a single average coefficient, yet the data show that within-pair dispersion is often larger than differences across sector pairs. As a result, sectoral IO tables can be misleading proxies for firm-level production linkages when concentration, network structure, or firm-level propagation mechanisms are the relevant objects of interest. These results are in line with the conclusions of Diem et al. (2024), who show that aggregating firm-level production networks entails a substantial loss of economic predictability.

Table 8: Distribution of average output sourcing shares (2019).

	Mean	SD	p10	p25	p50	p75	p90
Panel A: Belgium							
Avg. share (NACE-2 pairs)	0.02	0.05	0.0013	0.004	0.0109	0.026	0.056
Avg. share (NACE-4 pairs)	0.02	0.07	0.0002	0.001	0.0035	0.014	0.049
CV (NACE-2 pairs)	4.22	2.81	1.56	2.42	3.73	5.27	7.45
CV (NACE-4 pairs)	2.31	1.90	0.80	1.22	1.79	2.81	4.33
Panel B: Estonia							
Avg. share (NACE-2 pairs)	0.05	0.08	0.0016	0.008	0.0264	0.065	0.123
Avg. share (NACE-4 pairs)	0.05	0.11	0.0003	0.002	0.0088	0.041	0.125
CV (NACE-2 pairs)	2.22	1.25	1.01	1.41	1.98	2.68	3.76
CV (NACE-4 pairs)	1.42	0.86	0.54	0.91	1.31	1.74	2.38
Panel C: Hungary							
Avg. share (NACE-2 pairs)	0.06	0.08	0.0016	0.013	0.0401	0.080	0.133
Avg. share (NACE-4 pairs)	0.05	0.11	0.0003	0.002	0.0130	0.052	0.140
CV (NACE-2 pairs)	2.26	1.34	1.12	1.52	2.05	2.67	3.58
CV (NACE-4 pairs)	1.52	0.86	0.63	1.00	1.39	1.87	2.51
Panel D: Italy							
Avg. share (NACE-2 pairs)	0.01	0.03	0.0005	0.002	0.0057	0.013	0.029
Avg. share (NACE-4 pairs)	0.01	0.04	0.0001	0.000	0.0017	0.007	0.022
CV (NACE-2 pairs)	5.71	4.42	2.11	3.17	4.60	6.72	10.37
CV (NACE-4 pairs)	2.70	2.41	0.93	1.36	2.04	3.26	5.06
Panel E: Portugal							
Avg. share (NACE-2 pairs)	0.01	0.04	0.0003	0.002	0.0054	0.016	0.032
Avg. share (NACE-4 pairs)	0.01	0.05	0.0000	0.000	0.0015	0.007	0.026
CV (NACE-2 pairs)	5.93	5.37	1.95	3.02	4.43	6.80	11.28
CV (NACE-4 pairs)	2.85	2.99	0.92	1.36	2.02	3.31	5.37

7 Transmission of monetary policy shocks through firm-to-firm networks

The preceding sections established that firms differ along several network dimensions and that these dimensions are largely invisible in sector-level data. We now show that this heterogeneity is consequential for a first-order macroeconomic question: how monetary policy transmits through the economy. The vehicle is the firm's position in the production network. Section 4 showed that, in production networks with the structure we consider, demand shocks propagate upstream along firm-to-firm linkages, so that a firm's distance from final demand governs its exposure to a monetary shock operating through demand. A firm's upstreamness is therefore a leading statistic for its response, and the cross-country differences in the upstreamness distribution documented in Section 4 should translate into differences in aggregate transmission, even across countries facing a common monetary policy.

We develop this argument in three steps. First, we summarize the estimation of heterogeneous firm-level responses to euro area monetary policy shocks in the Belgian production network, on which the calibration builds. Second, we re-estimate these responses independently on Estonian data, providing out-of-sample evidence that the relationship between upstreamness and monetary policy responses is a structural feature of production networks rather than a Belgian characteristic. Finally, we combine the estimated response functions with the measured distribution of firms across production stages in each country, quantifying how cross-country differences in network structure generate heterogeneous aggregate responses to a common shock.

7.1 A summary of the Belgian application

The calibration exercise in this section requires two inputs: an estimate of how firm-level responses to monetary policy shocks vary with position in the production network, and the distribution of firms across these positions in each country. The second input comes directly from the networks constructed in Section 4. For the first, we draw on the estimation of Dhyne et al. (2026), who study the transmission of euro area monetary policy shocks through the Belgian firm-to-firm production network.[19] This subsection summarizes the elements of that estimation that the calibration requires: the empirical specification, the estimated impulse response functions, and the mechanism that links them to firms' vertical positions. We refer to Dhyne et al. (2026) for the full set of results, robustness checks, and extensions.

The estimation combines quarterly firm-level real sales from VAT declarations (2002Q1–2023Q4) with producer prices at the firm-product level from Statbel (2001–2024), matched to the Belgian production network described in Section 2. Monetary policy shocks are identified from the high-frequency series of ECB policy surprises of Jarociński and Karadi (2020), which isolate the unanticipated component of policy decisions within narrow windows around Governing Council announcements, aggregated to quarterly frequency. A one standard deviation contractionary shock corresponds to approximately 5 basis points.

Firm-level responses are estimated with local projections in which the monetary policy shock is interacted with the firm's upstreamness, computed as in Eq. (5). Following Dhyne et al. (2026), upstreamness is measured not from the contemporaneous network but from a three-year moving average: the firm-to-firm network is aggregated over years t, $t-1$, and $t-2$, the allocation matrix is constructed from these pooled flows, and a single measure $\bar{U}_{i,t}$ is computed from the resulting network. This limits the sensitivity of measured vertical position to firms entering or exiting the network in a given year while preserving the cross-sectional

[19] Dhyne et al. (2026) was developed in parallel to this project. That paper focuses on the identification and estimation of heterogeneous firm-level responses in Belgium. On the other hand, the contribution of this paper is the harmonized cross-country measurement and comparison of monetary policy effects as shaped by countries' production-network structures.

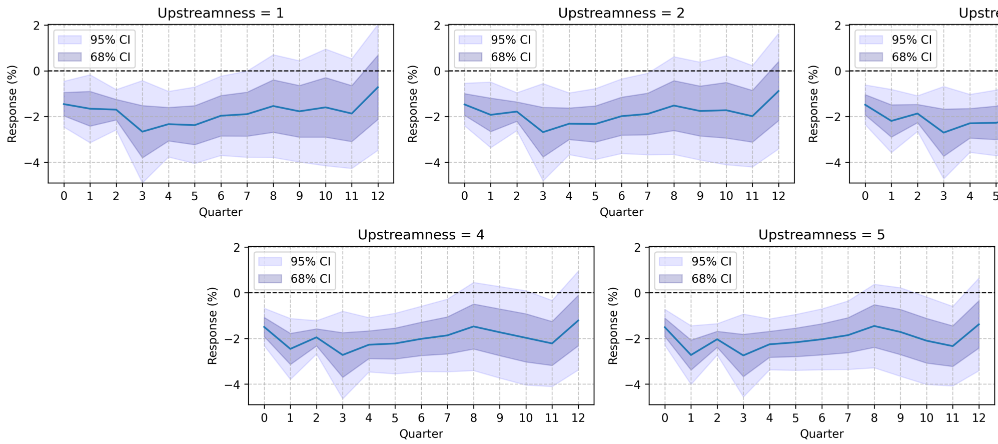


Figure 6: IRFs to a monetary policy shock on firm sales by upstreamness (Dhyne et al. (2026))

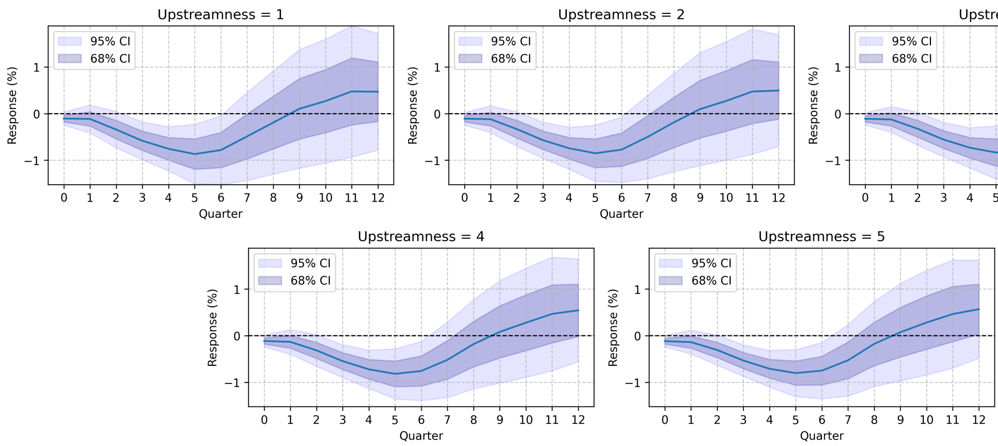


Figure 7: IRFs to a monetary policy shock on prices by upstreamness (Dhyne et al. (2026))

ranking of firms. The specification at horizon h is

$$\Delta^h \log Y_{i,t+h} = \alpha_i + \kappa_{q(t)} + \beta_h \,\mathrm{MP}_t + \lambda_h \,\bar{U}_{i,t-1} + \delta_h \,(\mathrm{MP}_t \times \bar{U}_{i,t-1}) + \gamma_h X_{i,t} + \epsilon_{i,t+h}, \tag{10}$$

where $\Delta^h \log Y_{i,t+h} \equiv \log Y_{i,t+h} - \log Y_{i,t-1}$, MP_t is the monetary policy surprise normalized to unit variance, $\bar{U}_{i,t-1}$ is the moving-average upstreamness measured over the window ending in $t-1$, $X_{i,t}$ contains four lags of the outcome and of the shock together with controls including the sectoral frequency of price changes, α_i denotes firm or firm-product fixed effects and $\kappa_{q(t)}$ denotes quarter-of-year fixed effects. Using the window ending in $t-1$ ensures that network positions are predetermined relative to the outcome. The total marginal effect of the shock for firm i at horizon h is $\beta_h + \delta_h \bar{U}_{i,t-1}$. [20]

Figure 6 and Figure 7 report the estimated impulse response functions for sales and prices, evaluated at upstreamness values ranging from 1 (closest to final demand) to 5. A one-standard-deviation contractionary shock lowers real sales by about 1.5% on impact, deepening to a

[20] Dhyne et al. (2026) additionally smooth the horizon-specific coefficients across h using cubic B-spline basis functions. We use the unsmoothed coefficients throughout, both here and in the calibration, to maintain comparability with the Estonian estimation in the following section, which is conducted at monthly frequency without smoothing, and to keep the aggregation transparent: the smoothing borrows information across horizons, so smoothed coefficients would blur the horizon-specific contributions that the calibration decomposes.

trough of roughly 2.5% around the third quarter. The magnitude of the peak contraction is broadly similar across positions; what varies systematically with vertical position is its *persistence*. Firms selling primarily to final demand ($U = 1$) recover fastest, with sales returning toward zero by the end of the three-year horizon, whereas the most upstream firms ($U = 5$) remain depressed for longer, staying further below baseline at the end of the horizon. Prices adjust more slowly and by less: they decline gradually to a trough of about 0.8–0.9% around the fifth to sixth quarter, then revert, returning to baseline by roughly the eighth to ninth quarter. The peak price decline is slightly larger for firms further from final demand, though this gradient is weaker than for sales.

This gradient is the empirical counterpart of the backward propagation of demand shocks discussed in Section 4: in production networks, a contraction in final demand travels upstream through firm-to-firm linkages, so that upstreamness, rather than centrality, is the relevant exposure statistic for a monetary shock operating through demand. When tightening reduces final demand, firms selling to final consumers cut purchases of intermediate inputs, lowering demand for their suppliers, and so on along the chain. A firm far from final demand is therefore exposed both to the direct effect of the shock on its own financing conditions and to the cumulated demand reductions of all its downstream customers. The variance decomposition of Section 5 indicates why this cumulation is quantitatively powerful: the customer extensive margin is the dominant source of firm size, so upstream firms typically serve many buyers and aggregate their simultaneous contractions, generating more persistent responses than those of firms selling mainly to final demand.

Dhyne et al. (2026) test this mechanism directly by decomposing each firm's total response into a direct component and an indirect component transmitted through the demand responses of its downstream customers. For upstream firms, the indirect component accounts for the vast majority of the contraction in both sales and prices, while the direct component is small and short-lived. Moreover, for firms close to final demand, the two are of comparable magnitude. The dominance of indirect demand effects for upstream firms is the property that the calibration below exploits: it implies that a firm's response to a common monetary shock is well summarized by its position in the domestic production network.

7.2 The transmission of monetary policy shocks in the Estonian production network

Having established our methodology for estimating heterogeneous monetary policy effects across production network positions, we now apply this framework to Estonian data. Unlike Belgium, Estonia lacks firm-level producer price information but provides VAT declarations at monthly frequency (detailed in A.2). We therefore re-estimate Eq. (10) for real sales at the monthly level, exploiting the higher temporal granularity of the Estonian administrative records.[21] As in the previous section, we control for firm fixed effects, four lags of the monetary policy shock and real sales and we use Driscoll-Kraay standard errors. Moreover, we consider a total period of 3 years (i.e. 36 months) after the shock, to match the 12 quarters of the Belgian

[21] Using the monthly monetary policy shock series from Jarociński and Karadi (2020), a one-standard-deviation increase in the shock corresponds to approximately 3 basis points.

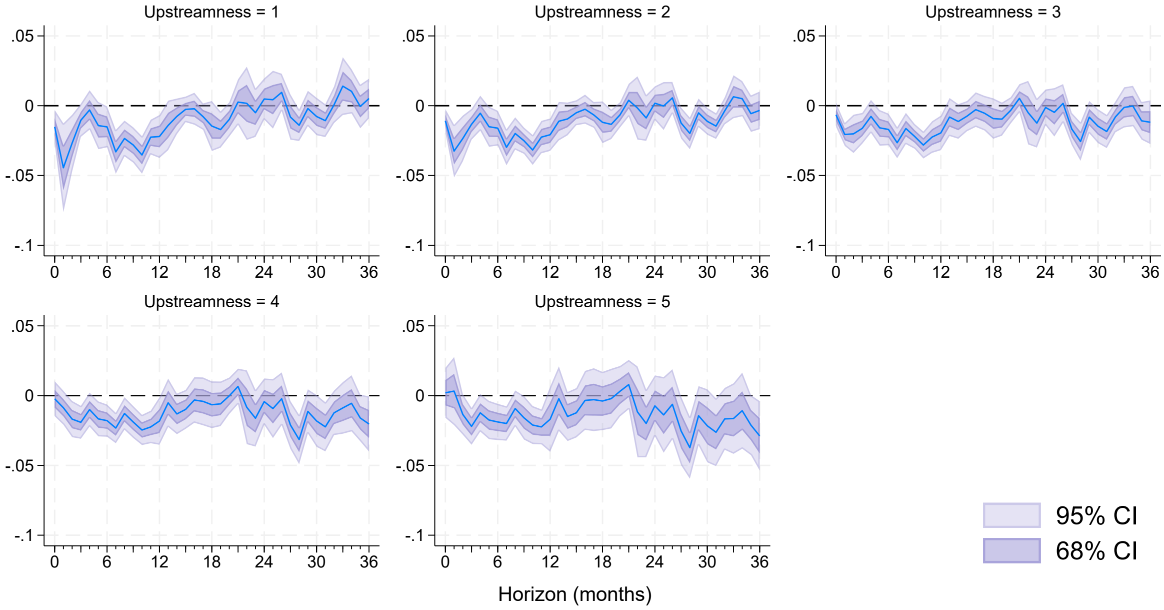


Figure 8: IRFs to a monetary policy shock on firm sales by upstreamness (Estonia).

estimation.

The Estonian results, presented in Figure 8, align with the Belgian patterns documented earlier. The impulse response functions reveal distinct temporal dynamics across production network positions. Firms selling directly to final consumers ($U^c_{i,y} = 1$) exhibit the strongest responses on impact and especially after one month, with sales declining by approximately 4-5%, consistent with immediate demand effects documented by Dhyne et al. (2026). These downstream responses begin reverting after 18-20 months. Notably, this is precisely when more upstream firms (upstreamness equal to 5) experience their largest sales declines, reaching peak effects of 3-4% around 28 months after the shock. This delayed but persistent upstream response confirms the propagation through the production network via backward demand linkages: the initial monetary contraction reduces downstream demand, which then transmits through supply chains with a lag, generating amplified and more persistent effects among upstream producers as downstream firms begin to recover.

7.3 Counterfactual calibration to other countries

As documented in Section 4, the five countries in our sample differ markedly in the distribution of firms across upstream and downstream positions in the production network. If the same firm-level relationship between upstreamness and monetary policy responses holds across countries, these differences in network structure should translate into systematic cross-country variation in the aggregate effects of a common ECB monetary policy shock. We evaluate this prediction by combining the estimated firm-level response functions from Belgium with the observed distributions of upstreamness in each country. This calibration exercise allows us to quantify how the aggregate effects of monetary policy are driven by the distribution of firms across production stages, and how cross-country differences in network structure and industrial composition generate heterogeneous transmission of a common monetary policy shock.

Our calibration proceeds in three steps. First, we take the estimated impulse response functions from Belgium as given. For each horizon h, the local projection in Eq. (10) delivers a baseline coefficient β_h and an interaction coefficient δ_h that captures how the response varies with upstreamness. Together these coefficients summarize the dynamic relationship between monetary policy shocks and firm outcomes as a function of network position.

Second, we apply these impulse response functions to firms in the other countries using their measured upstreamness. In the estimation above, upstreamness is lagged to make network position predetermined relative to the monetary policy shock and the subsequent firm-level response. In the cross-country calibration, by contrast, we use each country's observed moving-average upstreamness distribution in year y. Let $\bar{U}^c_{i,y}$ denote the moving-average upstreamness of firm i in country c, constructed from the network aggregated over years y, $y-1$, and $y-2$. The implied firm-level impulse response at horizon h is

$$\mathrm{IRF}^c_{i,y}(h) = \beta_h + \delta_h\,\bar{U}^c_{i,y}, \tag{11}$$

This step should therefore be interpreted as a counterfactual aggregation using observed network positions, rather than as a re-estimation of the causal response in each country. It preserves the horizon-specific dynamics estimated on Belgian data while allowing cross-country heterogeneity in responses to arise from differences in firms' positions within domestic production networks.

Third, we aggregate firm-level responses to the country level using sales weights. Let $w^c_{i,y}$ denote firm i's share of total sales in country c and year y, with $\sum_i w^c_{i,y} = 1$. The aggregate response in country c, year y, and horizon h is

$$A^c_y(h) = \sum_i w^c_{i,y}\,\mathrm{IRF}^c_{i,y}(h) = \beta_h + \delta_h \sum_i w^c_{i,y}\bar{U}^c_{i,y} = \beta_h + \delta_h\,\bar{U}^c_y, \tag{12}$$

where $\bar{U}^c_y \equiv \sum_i w^c_{i,y}\bar{U}^c_{i,y}$ is the sales-weighted average upstreamness in country c and year y. Under this linear specification, the aggregate response depends on the upstreamness distribution only through its sales-weighted mean, so cross-country differences in $A^c_y(h)$ are driven entirely by differences in average upstreamness across domestic production networks.

To characterize the contribution of firms at different production stages, we decompose the aggregate response by upstreamness groups. Let $\mathcal{G}$ denote a partition of firms into groups based on upstreamness. The contribution of group $g \in \mathcal{G}$ to the aggregate response in country c, year y, and horizon h is

$$A^c_{g,y}(h) = \sum_{i \in g} w^c_{i,y}\,\mathrm{IRF}^c_{i,y}(h), \tag{13}$$

and the corresponding contribution share is

$$\sigma^c_{g,y}(h) = \frac{A^c_{g,y}(h)}{A^c_y(h)}. \tag{14}$$

By construction, $\sum_{g\in\mathcal{G}} \sigma^c_{g,y}(h) = 1$ for any (c, y, h) such that $A^c_y(h) \neq 0$. Our calibration aver-

Table 9: Average contribution of upstreamness groups to the aggregate response to a monetary policy shock.

	Upstreamness classes				
	$U^c_{i,y} = 1$	$1 < U^c_{i,y} \leq 2$	$2 < U^c_{i,y} \leq 3$	$3 < U^c_{i,y} \leq 4$	$U^c_{i,y} > 4$
Panel A: Belgium					
Average contribution, sales	0.00	0.47	0.17	0.07	0.29
Average contribution, prices	0.00	0.53	0.18	0.08	0.21
Panel B: Estonia					
Average contribution, sales	0.04	0.60	0.23	0.09	0.03
Average contribution, prices	0.06	0.76	0.15	0.02	0.02
Panel C: Hungary					
Average contribution, sales	0.02	0.57	0.25	0.11	0.05
Average contribution, prices	0.03	0.65	0.20	0.08	0.04
Panel D: Italy					
Average contribution, sales	0.01	0.25	0.16	0.12	0.46
Average contribution, prices	0.00	0.11	0.08	0.08	0.73
Panel E: Portugal					
Average contribution, sales	0.09	0.34	0.20	0.16	0.21
Average contribution, prices	0.04	0.19	0.16	0.15	0.46

Notes: The table reports the average contribution of firms at different positions in the production network to the aggregate response to a monetary policy shock. Upstreamness classes are defined based on integer values of firm-level upstreamness. For each group, contributions are computed as the ratio of the sales-weighted response of the group to the total sales-weighted aggregate response, and then averaged across years and horizons.

ages contribution shares across years for each country and horizon:

$$\bar{\sigma}^c_g(h) = \frac{1}{T_c} \sum_{y=1}^{T_c} \sigma^c_{g,y}(h), \tag{15}$$

where T_c is the number of years available to estimate the response for country c. This procedure isolates the typical contribution of firms at different stages of the production network to the aggregate response at each horizon, abstracting from year-specific fluctuations in aggregate conditions. The resulting decomposition quantifies how differences in network structure and industrial composition across countries translate into heterogeneous aggregate transmission of a common ECB monetary policy shock, conditional on the impulse response function estimated in Belgium.

Results Table 9 implies striking cross-country heterogeneity in how monetary policy shocks propagate through production networks under this counterfactual calibration, revealing systematic patterns related to economy size and industrial structure. The decomposition by upstreamness position highlights fundamental differences in supply chain architecture across European economies.

The starkest contrast emerges between Italy and the smaller economies. In Italy, the most upstream firms ($U^c_{i,y} > 4$) account for nearly half of the sales response and over 70% of the price response, a degree of upstream concentration unmatched by any other country in the sample. This reflects a production structure in which a substantial mass of economic activity sits far from final demand, consistent with Italy's deep manufacturing base and the long supply chains it generates.

Belgium exhibits a markedly different pattern from Italy. The aggregate response is predominantly driven by firms at moderate distances from final demand, with firms sitting between 1 and 2 steps away from final demand accounting for roughly half of both the sales and price responses. On the other hand, the most upstream firms ($U^c_{i,y} > 4$) contribute a non-negligible but secondary share of around 20–30%. This pattern is consistent with Belgium's smaller economic size and greater trade openness, which limit the length of domestic supply chains and concentrate economic mass closer to final demand relative to Italy.

Among the smaller economies, Estonia stands out as the sharpest contrast to Italy. The aggregate response is extremely concentrated among firms close to final demand: the $1 < U^c_{i,y} \leq 2$ class alone accounts for roughly 60% of the sales response and over 75% of the price response, while the most upstream firms ($U^c_{i,y} > 4$) contribute less than 5%. This pattern points to a domestic production structure characterized by short supply chains, with limited economic mass operating far from final demand, which is consistent with Estonia's small economic size and high degree of openness to international trade.

Portugal occupies a genuinely intermediate position. Unlike Estonia, where the response is concentrated among firms close to final demand, Portugal shows a more evenly spread contribution profile across upstreamness classes. The most upstream firms ($U^c_{i,y} > 4$) account for roughly 20% of the sales response but nearly half of the price response, suggesting that extreme upstream firms play a limited role in quantity adjustment but a more significant one in price transmission. Together, Estonia and Portugal bracket a pattern in which smaller, more open economies exhibit shorter domestic supply chains and less upstream concentration in monetary transmission relative to larger, more industrially complex economies such as Italy.

Hungary closely mirrors the Estonian pattern. The aggregate response is dominated by firms at moderate distances from final demand, with the $1 < U^c_{i,y} \leq 2$ class accounting for roughly 57% of the sales response and 65% of the price response. The most upstream firms ($U^c_{i,y} > 4$) contribute less than 5% to either margin, placing Hungary firmly among the smaller economies where domestic supply chains are short and monetary transmission operates primarily through firms close to final demand rather than through extreme upstream propagation.

These patterns carry important implications for monetary policy effectiveness. In large economies like Italy, monetary-policy-induced declines in final demand are transmitted backward along longer domestic supply chains, potentially amplifying effects through cumulative upstream responses. Conversely, in smaller economies with flatter production structures, transmission operates more uniformly across network positions.

Once again, these results underscore that the transmission of monetary policy through firm-to-firm production networks is fundamentally shaped by specific network structures. While the propagation mechanisms appear robust across countries, the magnitude and persistence of these effects likely vary with structural features such as supply chain length, intensity of transactions, economy size, and sectoral composition. Understanding how these dimensions interact with trade openness and global value chain integration to shape cross-country heterogeneity in transmission patterns remains an important avenue for future research.

8 Conclusion

This paper documents a set of robust empirical facts on firm-to-firm production networks across five European economies using comprehensive administrative VAT and tax-filing data. By constructing large-scale firm-level production networks and combining them with firm characteristics, we show that a firm's vertical position—where it sits along production chains—is a distinct dimension of heterogeneity that is largely orthogonal to firm size and invisible in sector-level input–output representations, whereas its centrality, or aggregate influence, essentially coincides with size. These patterns are remarkably stable across countries and have direct implications for how aggregation, shock propagation, and firm heterogeneity should be modeled.

First, we characterize firms' positions in production networks. Katz–Bonacich centrality is extremely right-skewed and dispersed even within narrowly defined industries, and coincides closely with firm size (Domar weights), confirming that a firm's aggregate influence is well summarized by its scale. Firms also differ in their vertical position: upstreamness and downstreamness exhibit substantial within-industry dispersion and are largely orthogonal to firm size and to each other. This indicates that scale, network connectivity, and vertical position capture distinct aspects of firm behavior, challenging models that assign representative centrality or vertical position at the sector level and motivating firm-level treatments of production stages.

Second, using an exact variance decomposition of firm size, we show that firm size is itself shaped by the network. Across all countries and sectors, the extensive margin of customers is the single largest contributor to within-industry variation in firm sales, accounting for roughly half of total variance. Seller-side fundamentals play a secondary but non-negligible role, while final demand explains only a modest share on average. These patterns are strikingly stable across countries and sectors, pointing to common structural features of production networks—rather than country-specific institutions—as central determinants of firm size distributions.

Third, this heterogeneity extends beyond firm size along several dimensions. Network sales, transaction values, and the number of customers all exhibit heavy-tailed distributions spanning multiple orders of magnitude, even within narrowly defined industries. Once variables are demeaned by detailed industry fixed effects, within-industry dispersion remains large and distributions overlap almost perfectly across sectors and countries, so this granularity reflects fundamental firm-level differences rather than sectoral composition or country-specific institutions.

Fourth, we show that firm-level production networks are structurally very different from sector-level input–output tables. While sectoral IO networks are dense and feature sizable diagonal elements often interpreted as roundabout production, firm-to-firm networks are extremely sparse, with densities on the order of 10^{-5}, and the roundabout structure of the economy largely disappears once production is viewed at the level of legally distinct firms. Moreover, firm-level input and output shares vary enormously even within the same NACE 4-digit supplier–customer pair, with coefficients of variation well above one. As a result, sector-level technical coefficients provide, at best, a coarse summary of underlying firm-to-firm relationships, and can be misleading proxies when firm-level interactions, concentration, or propagation mechanisms are of interest.

Finally, these distinctions are economically relevant for a first-order policy question. Firm-level responses to monetary policy shocks vary systematically with vertical position: upstream firms experience more persistent sales contractions and more negative price responses than firms close to final demand, with the price gradient weaker than in sales. This heterogeneity cannot be captured by sector-level aggregates, and cross-country differences in the distribution of firms across production stages generate heterogeneous aggregate responses to a common monetary policy shock, even among countries subject to the same policy.

Overall, the paper provides a set of harmonized, cross-country moments on the structure of firm-level production networks. These moments serve as direct calibration targets for quantitative models and as empirical benchmarks for assessing when sector-level approximations are adequate and when firm-level detail is first-order.

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A Data sources and construction

This appendix provides additional details on the various data sources and their construction to obtain a comparable cross-country analysis.

A.1 Belgium

Belgian B2B data are collected by the National Bank of Belgium (NBB) using VAT client lists submitted to Belgian tax authorities. The dataset contains information on invoices issued by Belgian non-financial corporations to other non-financial corporations. Every business registered and liable for VAT must file an annual list of its Belgian customers with the tax authorities, including the annual transaction value in euros between two businesses. Each business submits its list by March 31 of the year following the reference year, using the online INTERVAT application. For each pair of counterparties, the dataset provides the reference year, the VAT identification number of the supplier, the VAT identification number of the buyer, and the gross annual transaction value from annual VAT client lists. Only transactions equal to or greater than 250 euros are retained, as this is the statutory threshold for mandatory reporting.

The dataset is then enriched with firm-level information from the NBB's annual business accounts, which provides insight on total sales and total input expenditures, and the National Accounts Institute register, which provides data regarding the sector NACE classification and location of firms. The dataset comprises exclusively transactions where both the supplier and buyer are non-financial corporations, excluding self-employed persons, financial institutions, public institutions, and non-profit associations from the production network. The dataset covers all sectors, from primary industries, manufacturing and utilities to construction, business services and other services.

To ensure data quality, individual transaction flows are checked for consistency with total amounts of sales or purchases declared by businesses in their VAT returns or annual accounts. For the 3.3% of observations that are inconsistent, corrections are applied following a step-by-step methodology that adjusts outliers in totals, corrects transactions larger than total sales, uses moving averages for correction, and adjusts totals when all flows are consistent from one side.

A.2 Estonia

The Estonian B2B data are collected by the Estonian Tax and Customs Board for VAT purposes. Firms must register for VAT and submit monthly returns once their annual sales exceed 40,000 euros, while firms with smaller turnover may register voluntarily. The VAT return consists of a main form reporting total monthly sales and inputs, and an appendix – introduced in 2015 – that records business-to-business (B2B) transactions above a monthly partner-specific threshold of 1,000 euros. For the period from 2015 to 2024, the dataset contains roughly 30 million firm-to-firm records in total. About 50 thousand firms submit B2B data each month, and in 2024 about 110 thousand firms reported positive annual sales in 2024 in their VAT main forms.

We apply light data cleaning by removing a small number of extreme observations in the B2B data that are either implausibly large (exceeding 1 billion euros) or exceed 100 million euros and are also at least 100 times larger than the monthly total sales reported in the VAT main form. This procedure is sufficient to eliminate artificial spikes in the series of aggregate monthly sales. We further exclude monthly B2B transactions below the reporting threshold, as well as observations with missing or non-positive firm-level monthly sales. Finally, we restrict the sample to resident firms and exclude sole proprietors. For more details on the data source and data preparations, see Kulikov and Paulus (2026).

A.3 Hungary

The Hungarian B2B trade network is constructed using firm-level VAT reports collected by the National Tax and Customs Administration of Hungary. All entities holding a VAT number are required to submit VAT reports, with reporting frequency – monthly, quarterly, or annually – determined by firm size, economic activity, and the amount of VAT reported in previous years. For annual analyses, monthly and quarterly reports are aggregated to the yearly level. For each reported trade relationship, the dataset contains the reporting period; anonymized VAT identifiers of the trading partners; the total value of transactions during the reporting period; the associated VAT amount; the number of invoices; and any subsequent corrections to the originally reported data.

The VAT reporting system was introduced in 2014 and subsequently underwent two major reforms, resulting in three distinct reporting regimes. From 2015 to 2018Q2, a reporting threshold of HUF 1 million applied, defined in terms of the total VAT amount associated with all transactions between two entities within a reporting period. During this first regime, firms were required to report both their sales and purchase partners. Between 2018Q3 and 2020Q2, three key changes were implemented: (i) the reporting threshold was reduced to HUF 100,000; (ii) bidirectional reporting was abolished, and only purchases were required to be reported; and (iii) the threshold was applied at the level of individual invoices rather than the aggregate transaction value between two entities within a reporting period. As a result, only invoices with a VAT amount exceeding HUF 100,000 were subject to reporting. From 2020Q3 onward, the reporting threshold was eliminated entirely, requiring all domestic B2B transactions to be reported.

The following data cleaning and processing procedures were applied. We exclude trade links with zero or negative reported transaction values and remove self-loops. We also correct for evident reporting errors, most notably those arising from misplaced decimal points in the reported tax rates. Finally, the VAT data are enriched with additional firm-level characteristics, including NACE industry classifications, annual turnover, and material costs, which are obtained from corporate tax reports collected by the National Tax and Customs Administration of Hungary.

A.4 Italy

Italian B2B data are collected by the Italian Revenue Agency (Agenzia delle Entrate) and shared with the Banca d'Italia based on a specific agreement for research purposes. The dataset contains information on invoices issued by Italian firms and public entities to Italian counterparties (firms, public entities, and consumers). For each pair of counterparties, it provides the quarterly cumulative amount of invoices and VAT, as well as the number of invoices issued. If the invoice issuer (supplier) or the payer (customer) is a legal entity or a public entity, the datasetis enriched with the sector (NACE) code, and the province of location, sourced from Business Registries (Infocamere). For invoices involving sole proprietorships, whether as supplier or buyer, the data are aggregated at the sector level (2-digit NACE) and anonymized by excluding the tax identification code and the province. Invoicing to final consumers (individuals) is aggregated at the level of the supplier. For complementary information see Astuti and Piras (2026).

Balance sheet information on the universe of limited liability companies in Italy comes from Cerved Group. Sole proprietorships, financial and real estate companies, small household producers, or unincorporated partnerships are not covered. These data include standard company accounts, such as total sales and total input expenditure, for the period of interest.

A.5 Portugal

Portuguese B2B data comes from the e-Fatura system, made available by the Instituto Nacional de Estatística (INE) under the collaboration protocol with the Banco de Portugal. The e-Fatura database contains information on invoices issued by resident firms, reported to the Autoridade Tributária (AT) for tax purposes, including the taxable value of transactions (exclusive of VAT), the economic activity of the issuer, and limited information on the purchaser, which is then further enriched with Banco de Portugal databases. The data provided, correspond to monthly extracts and are subject to a sequence of data validation and treatment procedures carried out by INE prior to dissemination. These procedures are designed to improve data quality while preserving aggregate consistency. In particular, INE performs: (i) identification and imputation of extreme outliers in positive taxable values, notably observations exceeding predefined absolute and relative thresholds; (ii) treatment of large negative taxable values, which typically reflect accounting corrections to previously misreported invoices, through temporal reallocation when symmetric values can be identified in recent months; and (iii) imputation of missing values for a limited set of economically relevant firms, based on firm-specific historical patterns The version of the data used in this paper corresponds to the first available release for each reference month. Although subsequent transmissions may include more complete information, later versions are not formal revisions but rather enrichments of the original dataset. As a result, the analysis prioritizes internal consistency across time rather than full exhaustiveness for any given month.

Information on purchasers is partial. For transactions involving domestic corporate purchasers, the buyer's tax identifier is available. Transactions involving domestic individuals or foreign purchasers are reported in aggregated form, without individual identifiers and are then removed for the analysis. Moreover, the country of the purchaser may be missing or invalid in some records; in such cases, INE assigns a null value following ISO 3166-1 alpha-2 standards. The identification of foreign purchasers is therefore subject to measurement limitations, which should be taken into account when interpreting results involving cross-border transactions

The e-Fatura data may contain residual measurement error stemming from reporting mistakes, delayed corrections, or incomplete information, particularly for foreign transactions. While the cleaning procedures implemented by INE mitigate the most severe issues, the data should be interpreted as an administrative proxy for economic activity rather than a fully audited accounting dataset. For this project, further cleaning procedures are implemented.

For this project, additional data cleaning and harmonization procedures are implemented to build a consistent dataset of domestic firm-to-firm transactions suitable for network analysis. First, B2B transactions are restricted to identifiable domestic corporate relationships by retaining only observations for which the purchaser is in Portugal and a valid purchaser tax identifier is available. Transactions involving foreign purchasers, aggregated purchasers (consumers), or missing purchaser identifiers are excluded. Transaction records are then assigned to calendar years based on the reference date. Bilateral transactions are subsequently aggregated at the annual seller–buyer level, summing taxable values to obtain yearly sales flows for each firm pair. Seller–buyer pairs with non-positive net annual sales are excluded, as these typically reflect accounting corrections or residual reporting noise rather than economically meaningful trade relationships. The resulting B2B dataset therefore consists exclusively of positive annual domestic sales flows between uniquely identified firms.

Firm-level metadata are processed separately using the monthly files, which have been enriched with items from the Central Balance Sheet Database. A restricted set of firm attributes is kept, and observations are assigned to calendar years based on the reference date. Records with missing firm identifiers are removed, and when multiple observations exist for the same firm within a given year, the most recent observation is retained, ensuring a single firm-year record. Sectoral classification is harmonized by extracting a five-digit CAE code from the reported CAE string and mapping it to two- and four-digit NACE groupings using an CAE hierarchy table. When no hierarchy match is available, two- and four-digit NACE sector codes are constructed by truncation of the extracted five-digit code. The final firm-year dataset contains one observation per firm per year with consistent sectoral identifiers.

Finally, firm-level metadata are merged onto the bilateral transaction data for both sellers and buyers using tax identifiers. Transactions for which firm information is missing on either side of the link are excluded. The resulting dataset consists of identifiable domestic B2B relationships between firms with valid identifiers and harmonized sectoral classifications, forming the basis for the construction of firm-to-firm production and exposure networks.

B Additional results: granularity

Figure B.1 reports the complementary cumulative distribution functions (CCDFs) of firm size for each country in the sample. Firm size is measured as total sales in their annual accounts or business registry data. Let X denote firm size. The CCDF of X is defined as

$$\Pr(X \geq x) \;\equiv\; 1 - F(x),$$

where $F(x) = \Pr(X \leq x)$ is the cumulative distribution function. For any value x, the CCDF reports the probability that a randomly selected firm has size at least as large as x. Empirically, this corresponds to the fraction of firms in the sample whose total sales exceed x. If firm size is consistent with a power-law distribution in the upper tail, then

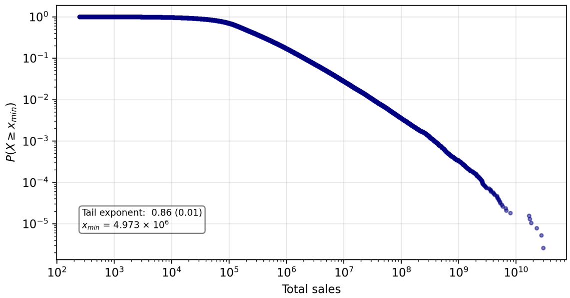
$$\Pr(X \geq x) \;\propto\; x^{-\alpha},$$

for sufficiently large x, where $\alpha > 0$ is the tail exponent. Taking logarithms yields

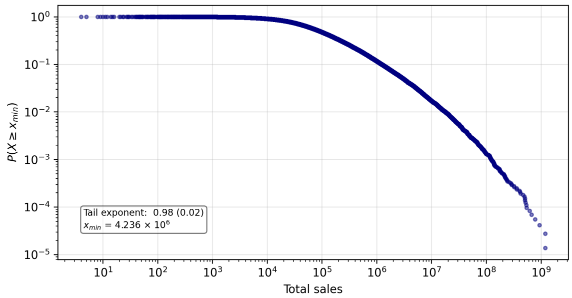
$$\log \Pr(X \geq x) \;=\; -\alpha \log x + c,$$

so that the slope of the CCDF in log–log space corresponds to $-\alpha$. The CCDFs are plotted on log–log scales and exhibit pronounced right skewness in all cases, with a small number of very large firms coexisting with a large mass of small firms. This pattern is remarkably stable across countries despite substantial differences in economic size and industrial structure.

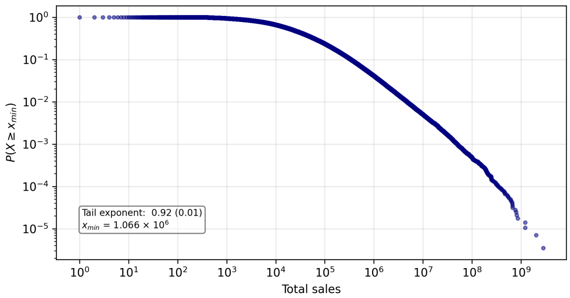
For descriptive purposes, we also report implied power-law tail exponents obtained using a Hill estimator with an endogenously selected lower cutoff for the tail, following the procedure in Clauset et al. (2009). Estimated tail exponents range between approximately 0.85 and 1.15 across countries.



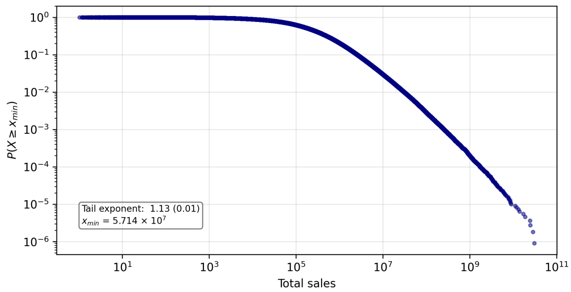
(a) Belgium



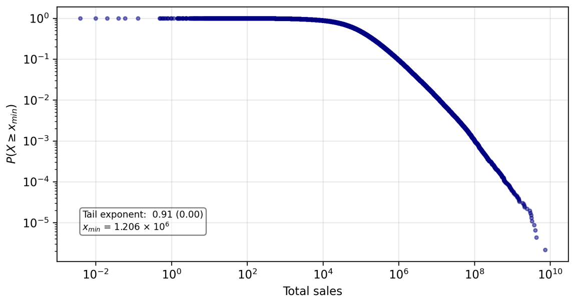
(b) Estonia



(c) Hungary



(d) Italy



(e) Portugal

Note: The figure reports the CCDF of the firm size distribution for each country. Implied power law exponents are estimated using the Hill estimator with endogenous cutoffs for the tails as in Clauset et al. (2009). Standard errors in parentheses are computed as $\hat{\alpha}/\sqrt{k}$, where k is the number of observations above the endogenous cutoff.

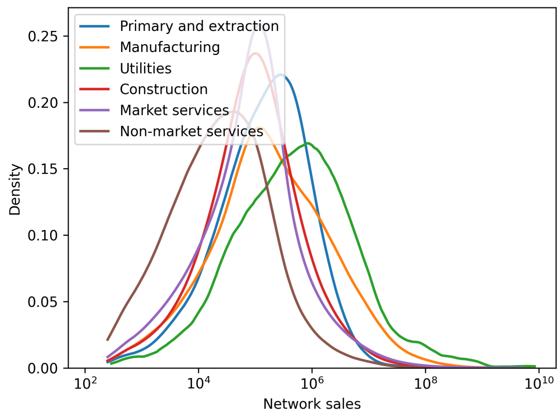
Figure B.1: CCDF of the distributions of total sales.

Figure B.2 reports kernel density estimates of firm-level network sales for each country, disaggregated by broad industry groups. Network sales are defined as the value of inter-firm transactions observed in the domestic production network. Industries are defined based on the NACE Rev. 2 (2008) classification at the 2-digit division level: Primary and extraction (NACE 01–09), Manufacturing (NACE 10–33), Utilities (NACE 35–39), Construction (NACE 41–43), Market services (NACE 45–82), and Non-market services (NACE 84–96). The horizontal axis is shown on a logarithmic scale. Firms in utilities and manufacturing tend to exhibit higher average network sales than firms in construction or non-market services.

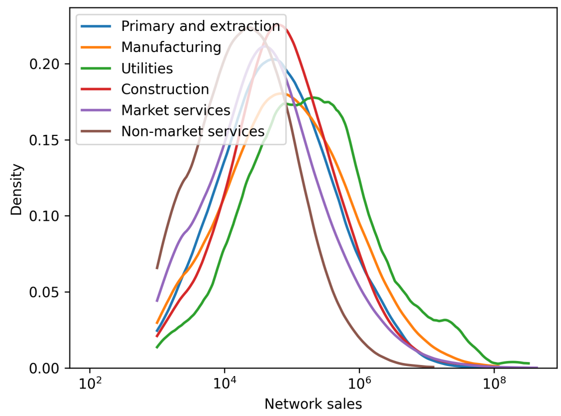
Table B.1: Tail Exponents by Country and Variable

	Belgium		Estonia		Hungary		Italy		Portugal	
Variable	Hill	GI	Hill	GI	Hill	GI	Hill	GI	Hill	GI
Total sales	0.8646 (0.0063)	0.9089 (0.0006)	0.9757 (0.0186)	1.0792 (0.0033)	0.9224 (0.0088)	0.9561 (0.0008)	1.1293 (0.0148)	1.1565 (0.0010)	0.9144 (0.0047)	0.9659 (0.0005)
Total inputs	0.8557 (0.0067)	0.8991 (0.0006)	0.9967 (0.0172)	1.0858 (0.0029)	0.9115 (0.0081)	0.9431 (0.0007)	1.0930 (0.0131)	1.1244 (0.0010)	0.9186 (0.0055)	0.9723 (0.0005)
Network sales	0.9795 (0.0112)	1.0285 (0.0011)	1.0345 (0.0210)	1.1180 (0.0035)	1.0027 (0.0139)	1.0419 (0.0016)	1.0924 (0.0111)	1.1152 (0.0006)	0.8783 (0.0050)	0.9327 (0.0005)
Network inputs	0.9605 (0.0089)	1.0140 (0.0008)	0.9847 (0.0189)	1.0675 (0.0034)	0.9321 (0.0084)	0.9760 (0.0006)	1.1162 (0.0146)	1.1303 (0.0011)	0.9186 (0.0055)	0.9723 (0.0005)
Domar weights	0.8646 (0.0063)	0.9089 (0.0006)	0.9757 (0.0186)	1.0792 (0.0033)	0.9224 (0.0088)	0.9561 (0.0008)	1.1293 (0.0148)	1.1565 (0.0010)	0.9144 (0.0047)	0.9659 (0.0005)
Number of customers	1.3901 (0.0185)	1.3871 (0.0011)	1.4704 (0.0493)	1.4989 (0.0062)	1.6241 (0.0427)	1.6315 (0.0024)	1.4570 (0.0084)	1.4219 (0.0009)	1.3713 (0.0145)	1.3563 (0.0011)
Number of suppliers	1.7805 (0.0091)	1.9202 (0.0010)	1.8169 (0.0479)	1.9908 (0.0092)	1.8337 (0.0353)	1.9543 (0.0040)	2.4025 (0.0266)	2.4333 (0.0015)	1.9987 (0.0097)	2.0636 (0.0004)
Centrality	0.9776 (0.0119)	1.0302 (0.0012)	1.3772 (0.0796)	1.4615 (0.0229)	0.9209 (0.0076)	0.9643 (0.0008)	1.1471 (0.0170)	1.1660 (0.0011)	1.2187 (0.0299)	1.2222 (0.0027)

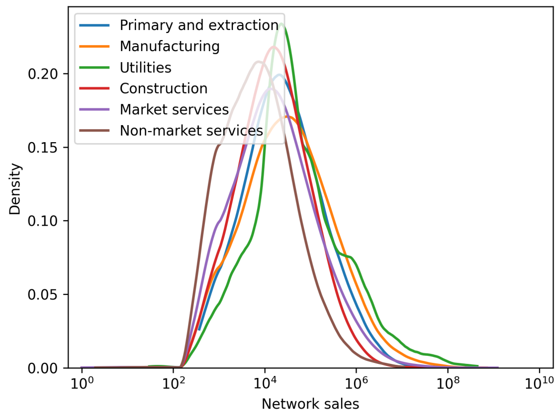
Notes: Hill refers to the Hill estimator as implemented in Clauset et al. (2009). GI refers to the Gabaix and Ibragimov (2011) estimator. Standard errors in parentheses.



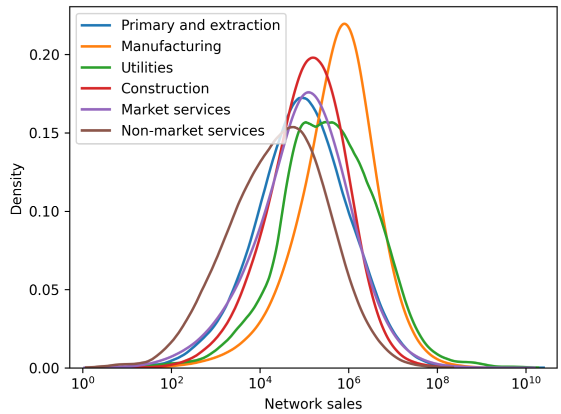
(a) Belgium



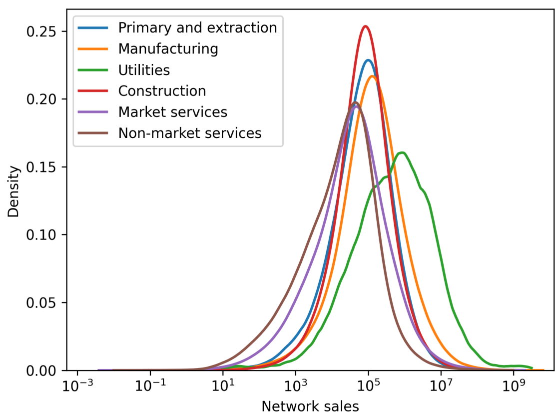
(b) Estonia



(c) Hungary



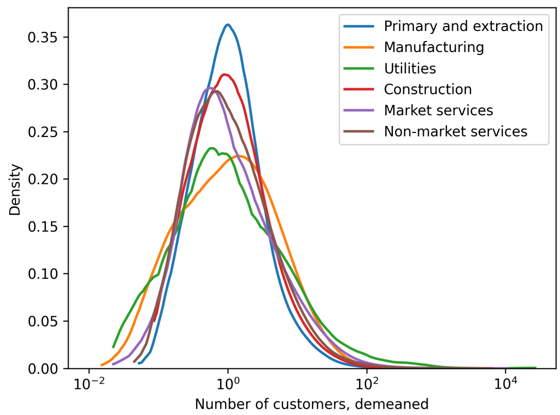
(d) Italy



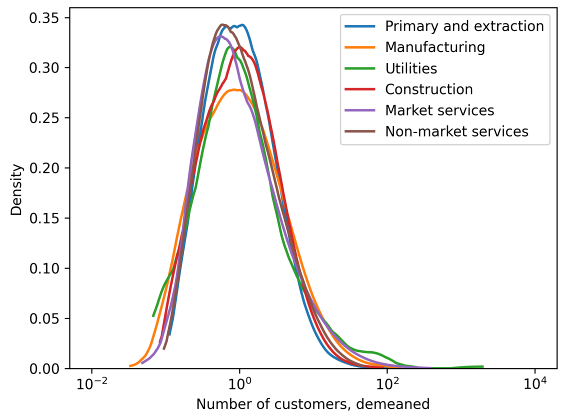
(e) Portugal

Note: The figure reports kernel density estimates of firm-level sales within the domestic production network, by high-level industry for the year 2019. The horizontal axis is shown on a logarithmic scale. Distributions are demeaned by their industry average for each NACE 4-digit industry in each country.

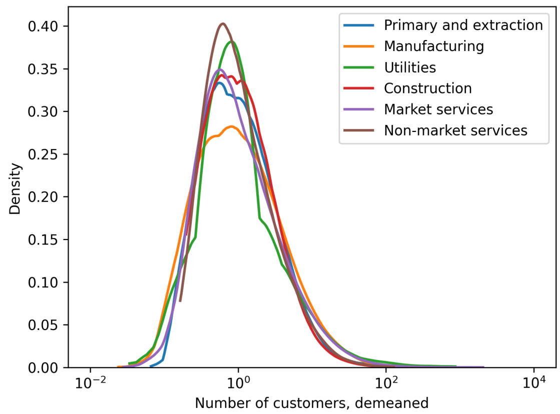
Figure B.2: Distribution of firm-level network sales, by industry (NACE 4-digit demeaned).



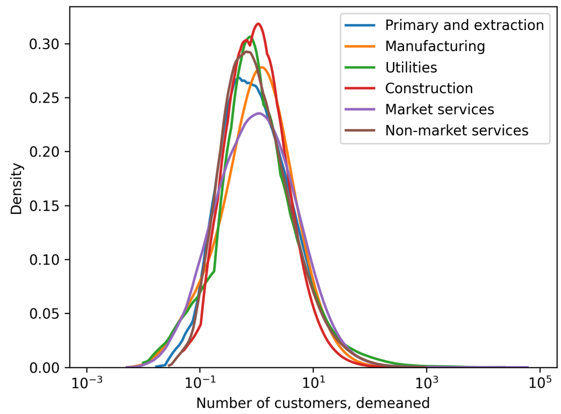
(a) Belgium



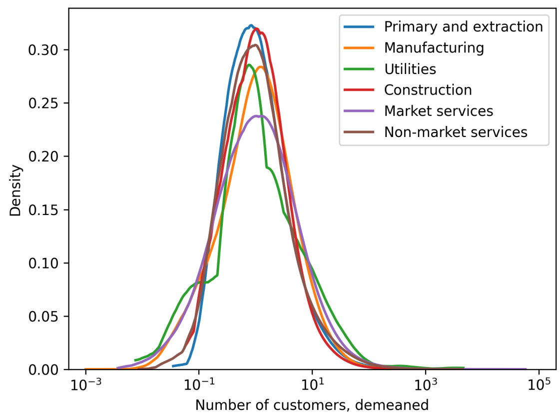
(b) Estonia



(c) Hungary



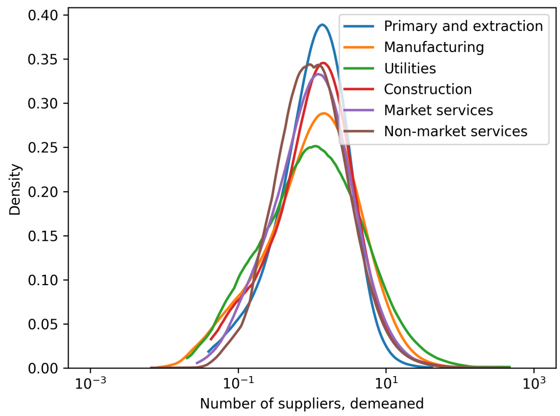
(d) Italy



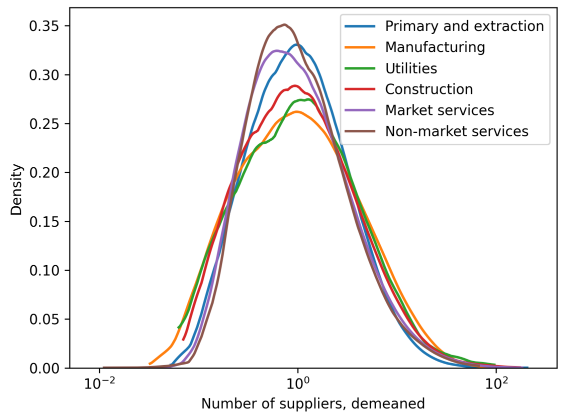
(e) Portugal

Note: The figure reports kernel density estimates of the number of customers per seller, by high-level industry. The horizontal axis is shown on a logarithmic scale. Distributions are demeaned by their industry average for each NACE 4-digit industry in each country.

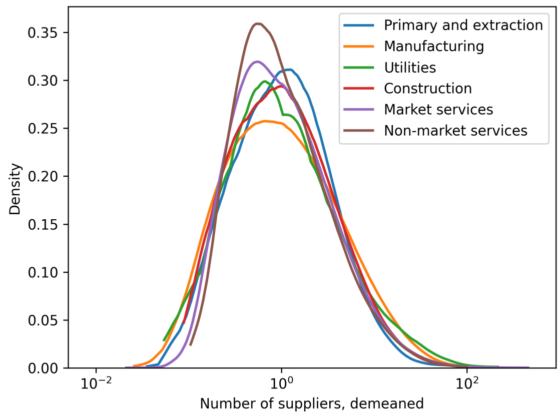
Figure B.3: Distribution of the number of customers per firm, by industry (NACE 4-digit demeaned).



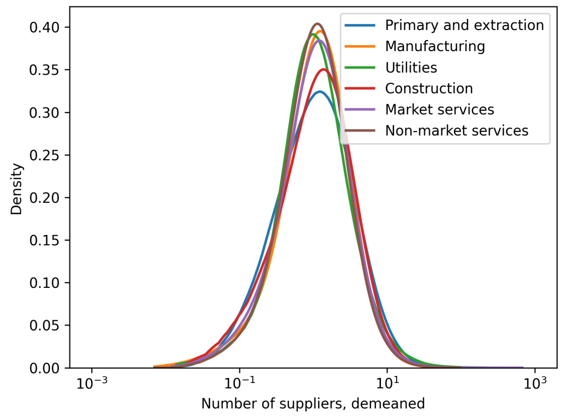
(a) Belgium



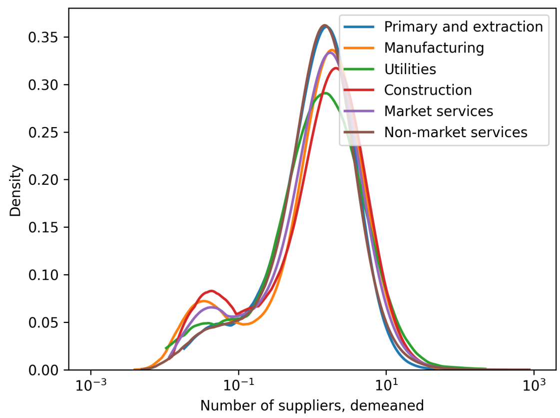
(b) Estonia



(c) Hungary



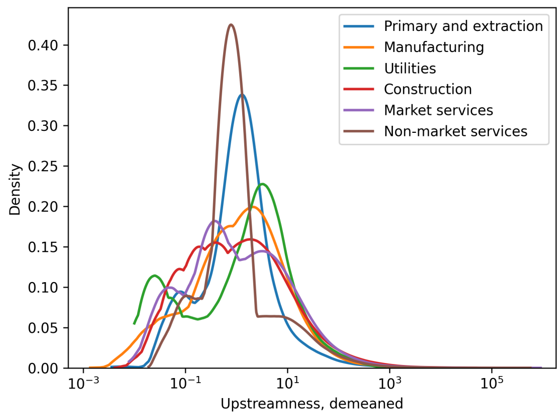
(d) Italy



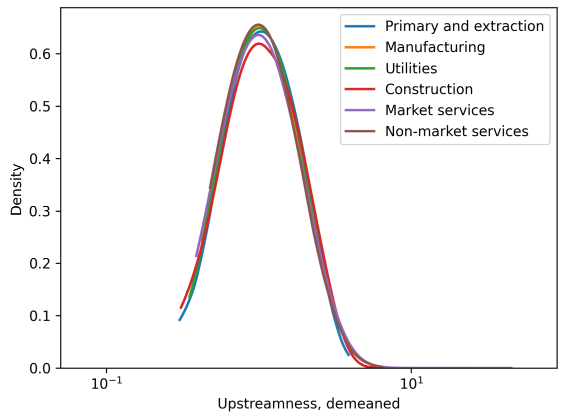
(e) Portugal

Note: The figure reports kernel density estimates of the number of suppliers per customer, by high-level industry. The horizontal axis is shown on a logarithmic scale. Distributions are demeaned by their NACE 4-digit industry average for each industry in each country.

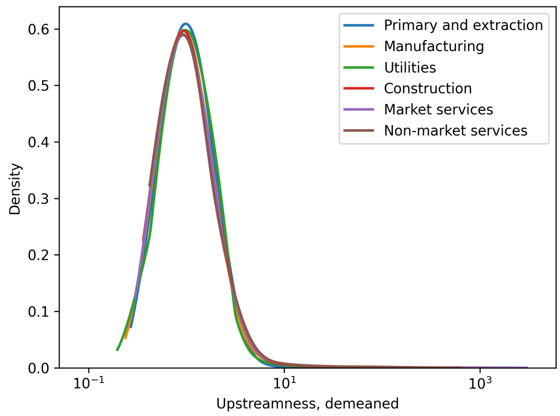
Figure B.4: Distribution of the number of suppliers per firm, by industry (NACE 4-digit demeaned).



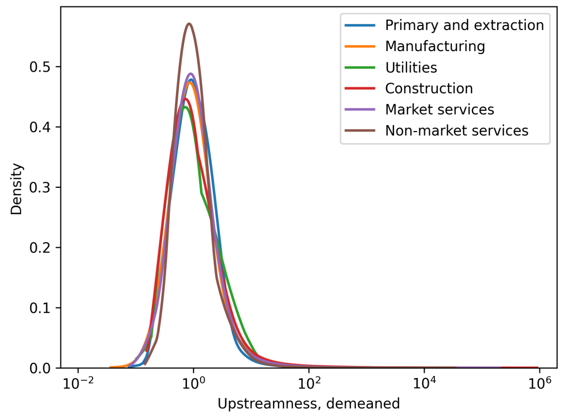
(a) Belgium



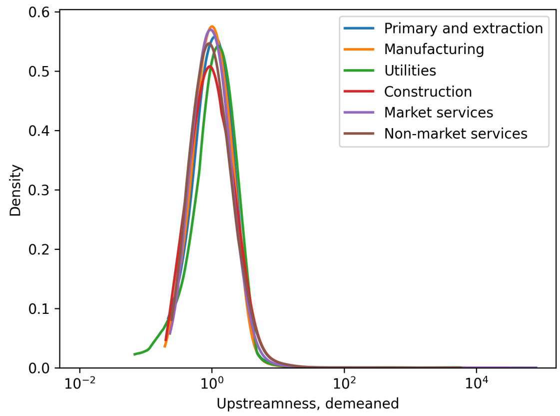
(b) Estonia



(c) Hungary



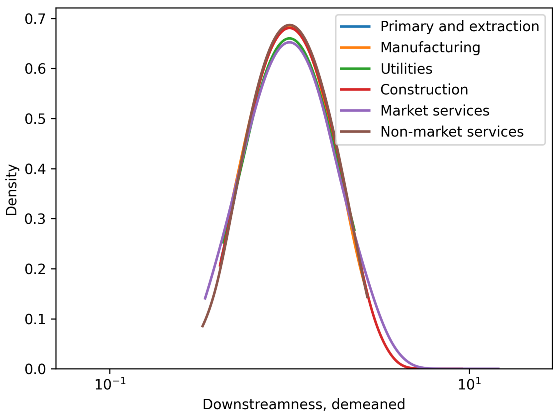
(d) Italy



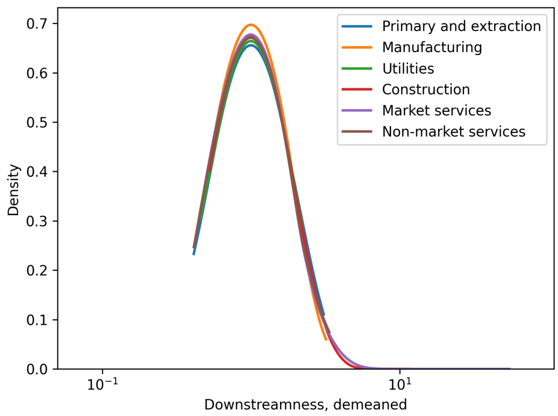
(e) Portugal

Note: The figure reports kernel density estimates of firm upstreamness, by high-level industry and demeaned by sector-country averages. The horizontal axis is shown on a logarithmic scale.

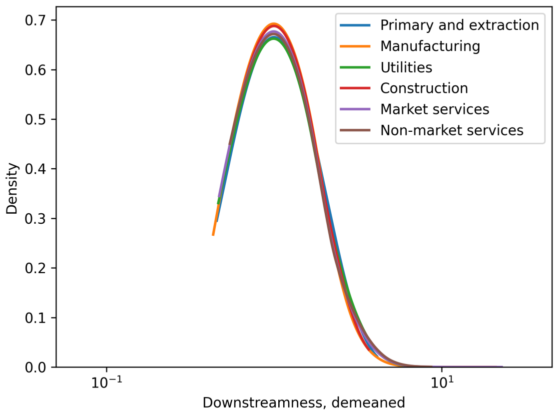
Figure B.5: Distribution of firm upstreamness, by industry (NACE 4-digit demeaned).



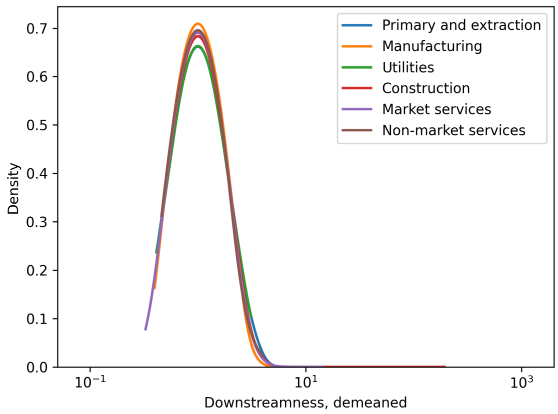
(a) Belgium



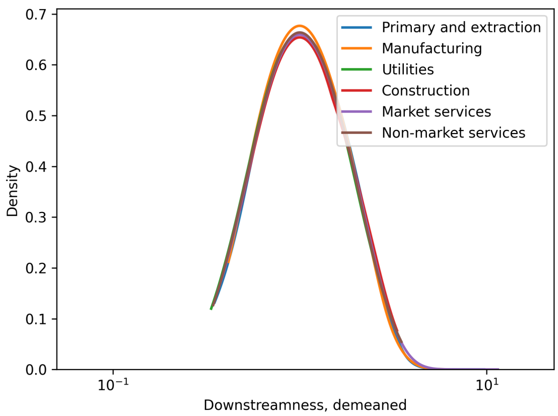
(b) Estonia



(c) Hungary



(d) Italy



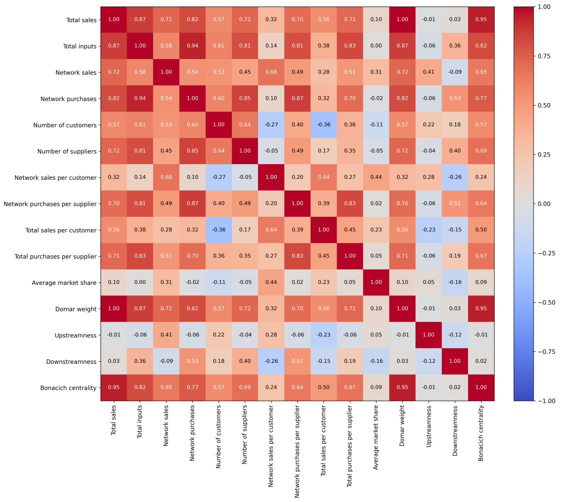
(e) Portugal

Note: The figure reports kernel density estimates of firm downstreamness, by high-level industry and demeaned by sector-country averages. The horizontal axis is shown on a logarithmic scale.

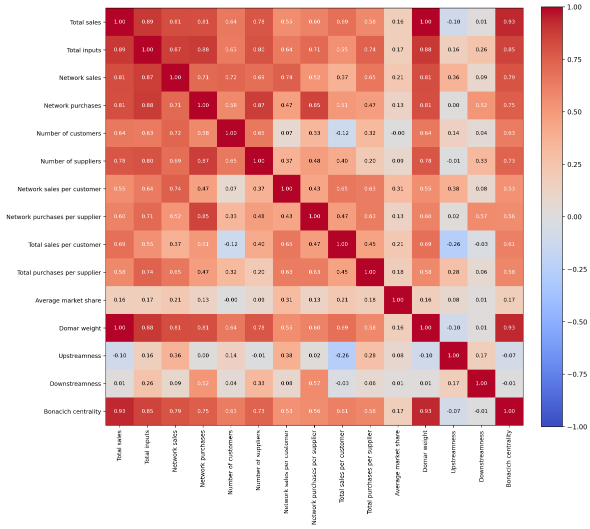
Figure B.6: Distribution of firm downstreamness, by industry and country (NACE 4-digit demeaned).

C Additional results: firm size correlations

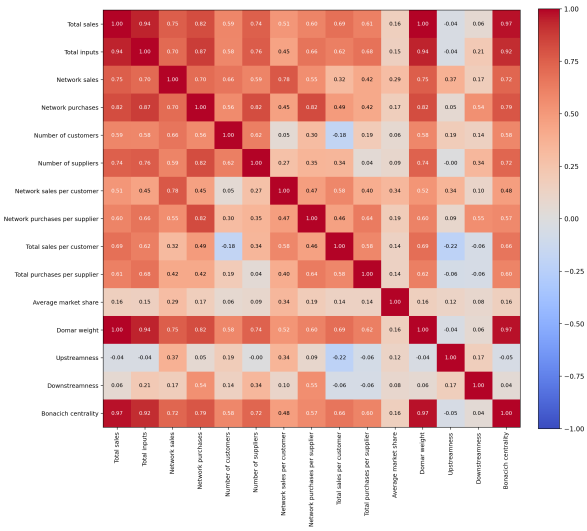
Figure C.1 reports heatmaps of the correlation matrix for each country. Variables are raw (non-demeaned) and correlations are based on their values in natural logs.



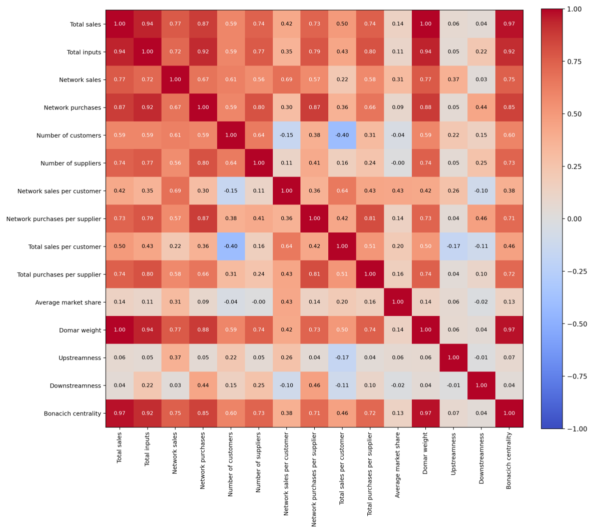
(a) Belgium



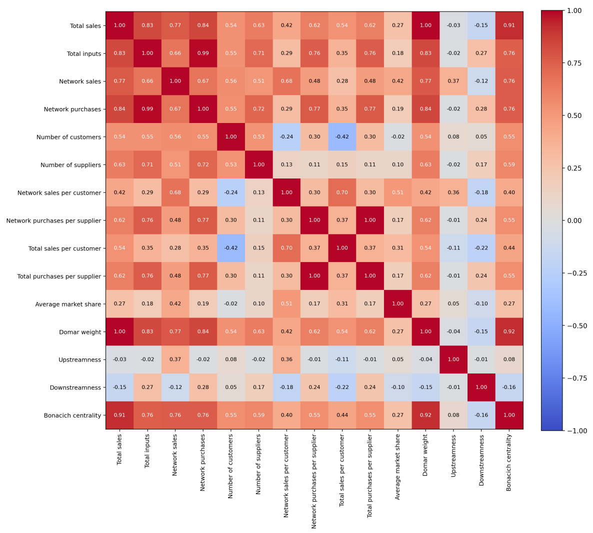
(b) Estonia



(c) Hungary



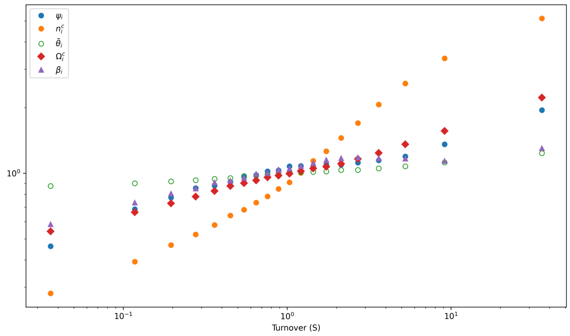
(d) Italy



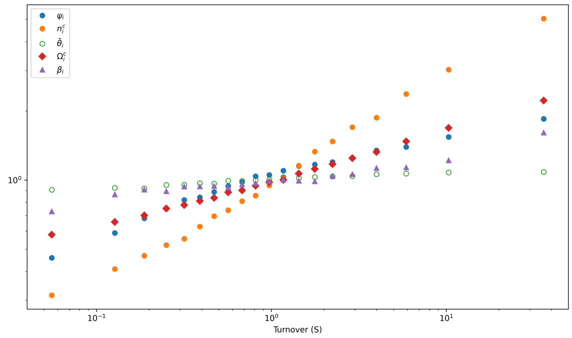
(e) Portugal

Note: The figure reports correlation coefficients across key firm and firm-to-firm variables. All variables are denoted in natural logs.

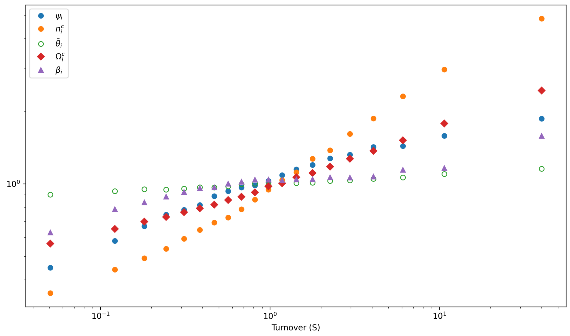
Figure C.1: Heatmaps of correlations across firm size heterogeneity and production network variables.



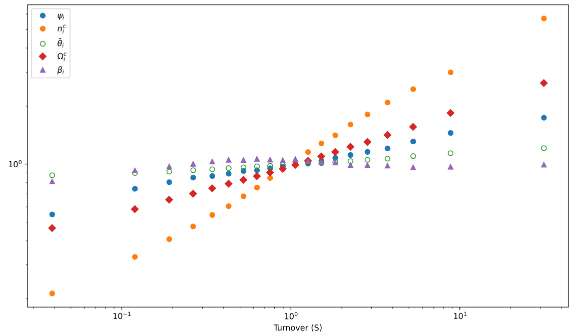
(a) Belgium



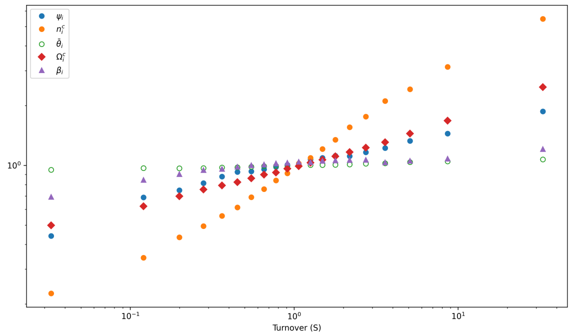
(b) Estonia



(c) Hungary



(d) Italy



(e) Portugal

Note: The binned scatter plots group firms into 20 equally sized bins by log firm total sales. All variables are demeaned by NACE four-digit industry averages.

Figure C.2: Firm size variance decomposition (NACE 4-digit demeaned.)

D Bottom-up versus national-accounts IO tables

These bottom-up input–output tables are not directly comparable to official input–output tables for several reasons. First, official input–output tables are constructed within national accounts to describe, in a consistent accounting framework, how goods and services are supplied and used in an economy during a given period. They start from supply and use tables (SUTs), which map, for each product, total supply, decomposed into domestic production and imports, and total use, distinguishing between intermediate consumption and final uses. Products are valued at basic prices in the supply table and at purchasers' prices in the use table, with trade and transport margins and taxes explicitly accounted for. Supply and use tables are jointly balanced to ensure that total supply equals total demand for each product, using a combination of survey data, administrative sources, business accounts, and national accounts constraints, often through iterative adjustment procedures such as Reconciliation, Adjustment, Scaling, or RAS. To obtain industry–industry input–output tables, statistical offices apply product–technology or industry–technology assumptions to transform the product-by-industry structure of the SUTs into symmetric input–output matrices. By contrast, our bottom-up tables start from observed firm-to-firm transactions in gross value terms and do not exploit product-level supply–use balancing or technology assumptions.

Second, we recover only the intermediate input–output matrices, as comprehensive information on value added and final demand components is not available in the firm-to-firm data.

Third, for all sector pairs we compute gross output flows. In official input–output tables, several so-called margin industries (such as wholesale, retail, transportation, and distribution) are recorded in terms of margins rather than gross transaction values. This convention avoids mechanically inflating the size of these sectors, since a large share of transactions would otherwise pass through them without reflecting additional production.

As a result, our tables should be interpreted as network-based representations of intermediate production linkages rather than as substitutes for official national accounts. We view them as high-resolution empirical objects that discipline the structure of firm-level production networks. Accordingly, we focus on their aggregate properties and implications for network measures, rather than on direct cell-by-cell comparisons with official input–output matrices.

Table B.2: Customer links per firm by sector and country (2019).

Sector	N	Mean	SD	p_{10}	p_{50}	p_{90}	p_{95}	p_{99}	p_{99}/p_{90}
Panel A: Belgium									
Primary and extraction	11,825	10.2	29.1	0	4	19	38	124	6.5
Manufacturing	26,806	43.8	170.5	0	8	104	184	495	4.8
Utilities	1,916	177.2	2426.8	0	4	177	362	1807	10.2
Construction	71,077	13.2	56.4	0	4	27	48	158	5.9
Market services	370,936	27.0	314.2	0	2	38	94	398	10.5
Non-market services	61,463	8.5	190.5	0	0	11	26	114	10.4
All	544,104	24.1	306.8	0	2	35	83	343	9.8
Panel B: Estonia									
Primary and extraction	4,717	6.3	13.2	1	3	14	21	49	3.5
Manufacturing	6,557	16.6	44.8	1	5	37	66	186	5.0
Utilities	475	44.9	284.4	1	5	57	124	711	12.6
Construction	10,503	9.5	18.4	1	4	21	33	77	3.7
Market services	44,684	12.0	69.6	0	2	20	42	164	8.2
Non-market services	4,943	6.1	15.2	0	2	14	25	61	4.3
All	103,592	8.1	54.4	0	1	15	29	110	7.3
Panel C: Hungary									
Primary and extraction	7,723	6.6	16.6	0	2	14	23	64	4.6
Manufacturing	18,791	13.8	75.9	0	4	29	55	156	5.4
Utilities	1,950	27.5	209.3	1	2	24	64	539	22.5
Construction	23,598	5.7	13.3	0	3	12	19	50	4.2
Market services	112,605	9.7	55.9	0	2	17	36	131	7.7
Non-market services	7,636	4.1	11.7	0	1	9	16	44	4.8
All	315,259	6.7	43.9	0	2	12	23	85	7.1
Panel D: Italy									
Primary and extraction	16,360	30.2	556.2	0	4	53	100	358	6.8
Manufacturing	124,632	83.1	319.4	2	27	191	321	817	4.3
Utilities	13,853	176.1	3645.9	0	3	146	304	1876	12.9
Construction	102,995	16.9	63.3	0	4	37	66	203	5.5
Market services	426,715	86.9	1898.6	1	12	151	281	862	5.7
Non-market services	58,880	15.8	105.1	0	2	30	64	243	8.1
All	1,668,485	35.6	1047.8	0	1	56	125	459	8.2
Panel E: Portugal									
Primary and extraction	16,689	11.9	45.7	0	3	22	45	168	7.6
Manufacturing	43,897	59.9	387.9	0	13	132	234	642	4.9
Utilities	1,704	362.4	4795.4	1	5	322	880	5317	16.5
Construction	45,017	14.8	85.8	0	4	29	53	168	5.8
Market services	279,092	117.3	1560.4	0	8	204	410	1424	7.0
Non-market services	73,149	25.6	250.6	0	2	29	80	447	15.4
All	459,548	84.3	1261.5	0	6	137	295	1074	7.8

Note: The table reports the distribution of the number of customer links per firm in 2019. Percentiles are computed within each country–sector cell. The last column reports the ratio p_{99}/p_{90} as a summary measure of upper-tail thickness.

Table B.3: Supplier links per firm by sector and country (2019).

Sector	N	Mean	SD	p_{10}	p_{50}	p_{90}	p_{95}	p_{99}	p_{99}/p_{90}
Panel A: Belgium									
Primary and extraction	11,825	26.8	28.5	4	20	55	70	126	2.3
Manufacturing	26,806	58.9	110.5	3	25	146	226	493	3.4
Utilities	1,916	69.3	253.2	2	16	146	219	883	6.1
Construction	71,077	33.0	61.3	2	20	68	99	235	3.5
Market services	370,936	21.2	41.9	2	10	50	75	171	3.4
Non-market services	61,463	13.8	44.1	1	5	29	46	131	4.5
All	544,104	24.1	53.4	2	11	55	84	205	3.7
Panel B: Estonia									
Primary and extraction	4,717	10.2	20.9	1	4	24	41	87	3.6
Manufacturing	6,557	19.8	39.3	1	6	55	87	179	3.3
Utilities	475	22.8	51.6	1	7	53	88	274	5.2
Construction	10,503	13.8	39.7	0	5	31	51	141	4.5
Market services	44,684	8.1	24.8	0	3	17	30	88	5.2
Non-market services	4,943	11.0	36.4	0	2	21	46	157	7.5
All	103,592	8.1	26.0	1	2	17	32	99	5.8
Panel C: Hungary									
Primary and extraction	7,723	12.9	24.9	0	5	31	50	109	3.5
Manufacturing	18,791	18.2	47.5	0	4	45	82	205	4.6
Utilities	1,950	19.8	74.8	0	3	44	91	282	6.4
Construction	23,598	10.4	25.4	0	4	25	41	99	4.0
Market services	112,605	7.8	25.5	0	2	17	30	88	5.2
Non-market services	7,636	5.4	15.0	0	2	11	22	69	6.3
All	315,259	8.6	29.2	0	2	18	33	117	6.5
Panel D: Italy									
Primary and extraction	16,360	42.2	75.3	4	21	98	141	306	3.1
Manufacturing	124,632	114.6	142.4	16	76	245	340	657	2.7
Utilities	13,853	64.8	117.4	6	23	165	247	526	3.2
Construction	102,995	52.2	71.9	5	33	116	160	309	2.7
Market services	426,715	58.3	100.5	7	36	124	176	365	2.9
Non-market services	58,880	43.7	60.5	7	29	89	128	271	3.0
All	1,668,485	35.6	79.0	1	12	90	139	310	3.4
Panel E: Portugal									
Primary and extraction	16,689	58.9	70.6	5	41	125	172	328	2.6
Manufacturing	43,897	108.8	168.1	2	65	249	359	719	2.9
Utilities	1,704	140.8	305.5	4	53	325	514	1286	4.0
Construction	45,017	82.8	129.1	2	52	186	260	510	2.7
Market services	279,092	81.5	156.3	2	48	177	254	567	3.2
Non-market services	73,149	85.6	160.7	4	52	182	250	552	3.0
All	459,548	84.3	154.6	2	50	184	263	578	3.1

Note: The table reports the distribution of the number of supplier links per firm in 2019. Percentiles are computed within each country–sector cell. The last column reports the ratio p_{99}/p_{90} as a summary measure of upper-tail thickness.

Table C.1: (Co-)variance of seller and buyer fixed effects.

Country	N	$\frac{\mathrm{var}(\ln\psi_i)}{\mathrm{var}(\ln\psi_i + \ln\theta_j)}$	$\frac{\mathrm{var}(\ln\theta_j)}{\mathrm{var}(\ln\psi_i + \ln\theta_j)}$	$\frac{2\,\mathrm{cov}(\ln\psi_i, \ln\theta_j)}{\mathrm{var}(\ln\psi_i + \ln\theta_j)}$	R^2	Adjusted R^2
Belgium	12,957,849	0.66	0.28	0.05	0.43	0.39
Estonia	793,501	0.68	0.43	-0.10	0.40	0.30
Hungary	1,957,588	0.67	0.44	-0.11	0.43	0.31
Italy	58,972,808	0.76	0.15	0.09	0.53	0.51
Portugal	38,652,683	0.89	0.06	0.05	0.57	0.57

Note: N denotes the number of buyer–seller observations used in the two-way fixed effects regression of $\ln m_{ij}$.

Table C.2: Sector-level firm size decomposition, Belgium (2019).

NACE2 (sector)	N	$\ln \beta_i$	$\ln \psi_i$	$\ln n_i^c$	$\ln \bar{\theta}_i$	$\ln \Omega_i^c$
01 – Crop and animal production	8,364	-0.01	0.30	0.34	0.07	0.30
02 – Forestry and logging	360	0.12	0.18	0.41	0.03	0.27
03 – Fishing and aquaculture	62	0.13	0.29	0.14	0.10	0.35
08 – Other mining and quarrying	111	0.06	0.13	0.47	0.03	0.31
09 – Mining support services	11	0.06	0.51	0.03	0.37	0.02
10 – Food products	3,220	0.02	0.24	0.39	0.06	0.30
11 – Beverages	474	-0.03	0.25	0.46	0.03	0.28
12 – Tobacco products	15	0.24	0.17	0.24	0.04	0.31
13 – Textiles	690	0.16	0.15	0.44	0.03	0.22
14 – Wearing apparel	271	0.05	0.28	0.49	-0.01	0.18
15 – Leather products	46	0.27	0.17	0.42	0.00	0.14
16 – Wood products	934	-0.02	0.16	0.60	0.04	0.22
17 – Paper products	183	0.09	0.23	0.37	0.06	0.26
18 – Printing and media reproduction	2,021	0.01	0.17	0.57	0.05	0.20
19 – Coke and refined petroleum	13	-0.07	0.42	0.26	0.07	0.33
20 – Chemicals	538	0.19	0.27	0.20	0.08	0.26
21 – Pharmaceuticals	91	0.22	0.15	0.16	0.10	0.38
22 – Rubber and plastics	632	0.15	0.21	0.37	0.05	0.23
23 – Non-metallic minerals	1,091	-0.01	0.15	0.62	0.03	0.22
24 – Basic metals	182	0.17	0.26	0.25	0.05	0.27
25 – Fabricated metal products	4,020	0.02	0.15	0.52	0.06	0.25
26 – Computer and electronic products	269	0.33	0.19	0.24	0.07	0.17
27 – Electrical equipment	416	0.11	0.14	0.44	0.06	0.25
28 – Machinery and equipment	948	0.19	0.08	0.42	0.06	0.24
29 – Motor vehicles	287	0.12	0.22	0.27	0.09	0.30
30 – Other transport equipment	81	0.17	0.24	0.25	0.03	0.31
31 – Furniture	1,015	0.01	0.17	0.58	0.04	0.20
32 – Other manufacturing	773	0.27	0.16	0.34	0.05	0.17
33 – Repair and installation	1,662	0.02	0.12	0.56	0.07	0.23
35 – Electricity and gas	492	0.09	0.25	0.37	0.00	0.29
36 – Water supply	24	0.16	-0.07	0.62	-0.01	0.30
37 – Sewerage	132	-0.15	0.15	0.48	0.05	0.47
38 – Waste management	622	0.06	0.13	0.50	0.04	0.27
39 – Remediation services	62	-0.01	0.26	0.46	0.05	0.23
41 – Construction of buildings	10,459	0.14	0.26	0.30	0.05	0.24
42 – Civil engineering	1,426	0.03	0.20	0.39	0.10	0.29
43 – Specialised construction	36,852	-0.04	0.16	0.58	0.07	0.23
45 – Motor vehicle trade and repair	10,387	0.01	0.09	0.63	0.02	0.24
46 – Wholesale trade	25,979	0.07	0.23	0.47	0.04	0.19
47 – Retail trade	26,521	0.42	-0.03	0.48	-0.00	0.13
49 – Land transport	6,765	0.06	0.07	0.51	0.04	0.31
50 – Water transport	146	0.17	0.30	0.20	0.04	0.29
51 – Air transport	147	0.23	0.19	0.37	0.02	0.19
52 – Warehousing and transport support	2,177	0.14	0.09	0.43	0.05	0.29
53 – Postal and courier activities	885	0.05	0.13	0.54	0.04	0.25
55 – Accommodation	1,482	0.22	0.04	0.53	0.05	0.16
56 – Food and beverage services	10,778	0.56	-0.02	0.31	0.06	0.10
58 – Publishing	921	0.07	0.14	0.56	0.02	0.22
59 – Film and TV production	2,257	0.08	0.29	0.33	0.05	0.26
60 – Broadcasting	183	-0.01	0.24	0.35	0.08	0.34
61 – Telecommunications	478	0.10	0.14	0.45	0.05	0.25
62 – IT services	12,285	0.08	0.21	0.47	0.09	0.16
63 – Information services	1,478	0.08	0.23	0.46	0.06	0.16
68 – Real estate	9,386	0.20	0.29	0.28	0.06	0.17
69 – Legal and accounting	12,956	0.08	0.05	0.83	0.01	0.03
70 – Head offices and consultancy	29,092	0.09	0.38	0.26	0.08	0.18
71 – Architecture and engineering	9,641	0.05	0.23	0.46	0.08	0.17
72 – Scientific R&D	406	0.22	0.25	0.29	0.05	0.19
73 – Advertising and market research	4,477	0.04	0.22	0.46	0.08	0.21
74 – Other professional services	4,416	0.10	0.21	0.47	0.05	0.18
75 – Veterinary activities	977	0.44	-0.03	0.49	0.01	0.09
77 – Rental and leasing	2,388	0.03	0.15	0.59	0.05	0.18
78 – Employment activities	1,215	0.01	0.19	0.61	0.07	0.12
79 – Travel agencies	732	0.36	0.09	0.42	0.01	0.13
80 – Security services	390	0.00	0.07	0.62	0.05	0.25
81 – Building services	6,337	0.02	0.16	0.55	0.06	0.21
82 – Office administration support	5,870	0.07	0.25	0.43	0.07	0.18
85 – Education	2,108	0.16	0.07	0.59	0.05	0.13
86 – Human health	1,049	0.45	0.26	0.17	-0.01	0.13
87 – Residential care	117	0.57	0.14	0.15	0.03	0.11
88 – Social work	317	-0.08	0.12	0.65	0.05	0.27
90 – Creative and entertainment	3,520	0.06	0.29	0.39	0.05	0.22
91 – Libraries and museums	80	0.26	0.02	0.50	0.03	0.20
92 – Gambling and betting	92	0.42	0.14	0.22	0.01	0.21
93 – Sports and recreation	5,251	0.17	0.17	0.46	0.03	0.17
94 – Membership organisations	1,148	0.27	0.24	0.30	0.02	0.16
95 – Repair of computers and goods	642	0.06	0.11	0.60	0.04	0.20
96 – Other personal services	2,497	0.38	0.08	0.37	0.02	0.14

Table C.3: Sector-level firm size decomposition, Estonia (2019).

NACE2 (sector)	N	$\ln \beta_i$	$\ln \psi_i$	$\ln n_i^c$	$\ln \bar{\theta}_i$	$\ln \Omega_i^c$
01 – Crop and animal production	1,896	0.00	0.31	0.38	0.01	0.30
02 – Forestry and logging	1,218	0.01	0.25	0.42	0.03	0.29
03 – Fishing and aquaculture	98	0.07	0.33	0.28	0.05	0.27
08 – Other mining and quarrying	100	0.05	0.07	0.58	0.05	0.25
09 – Mining support services	5	0.22	0.31	0.13	0.08	0.26
10 – Food products	370	0.03	0.24	0.42	0.04	0.28
11 – Beverages	65	-0.11	0.22	0.58	-0.01	0.32
13 – Textiles	144	0.20	0.20	0.41	0.01	0.18
14 – Wearing apparel	179	0.39	0.15	0.25	0.05	0.15
15 – Leather products	34	0.14	0.18	0.32	0.06	0.30
16 – Wood products	785	0.19	0.19	0.34	0.05	0.23
17 – Paper products	39	0.25	0.17	0.37	-0.00	0.21
18 – Printing and media reproduction	251	0.03	0.15	0.63	0.01	0.18
20 – Chemicals	55	0.18	0.21	0.39	-0.03	0.25
21 – Pharmaceuticals	7	0.44	0.34	0.08	-0.05	0.20
22 – Rubber and plastics	157	0.23	0.09	0.41	0.03	0.24
23 – Non-metallic minerals	145	0.06	0.19	0.52	0.00	0.23
25 – Fabricated metal products	1,009	0.17	0.17	0.42	0.04	0.21
26 – Computer and electronic products	51	0.41	0.13	0.18	0.04	0.24
27 – Electrical equipment	85	0.37	0.10	0.32	0.05	0.16
28 – Machinery and equipment	123	0.40	0.07	0.31	0.06	0.16
29 – Motor vehicles	56	0.28	0.11	0.36	0.02	0.22
30 – Other transport equipment	36	0.38	0.26	0.17	0.04	0.14
31 – Furniture	568	0.22	0.13	0.38	0.05	0.21
32 – Other manufacturing	129	0.34	0.21	0.32	-0.01	0.15
33 – Repair and installation	468	0.14	0.19	0.40	0.06	0.21
35 – Electricity and gas	174	-0.02	0.35	0.47	0.00	0.20
36 – Water supply	54	0.11	0.13	0.62	-0.00	0.15
37 – Sewerage	27	-0.11	0.41	0.24	0.07	0.40
38 – Waste management	114	0.08	0.09	0.51	0.04	0.27
39 – Remediation services	5	-0.31	0.71	0.25	-0.30	0.65
41 – Construction of buildings	2,660	0.02	0.34	0.33	0.05	0.27
42 – Civil engineering	754	-0.05	0.21	0.48	0.05	0.30
43 – Specialised construction	4,640	-0.03	0.24	0.49	0.06	0.24
45 – Motor vehicle trade and repair	2,039	0.03	0.10	0.62	0.01	0.25
46 – Wholesale trade	4,034	0.09	0.19	0.51	0.00	0.20
47 – Retail trade	2,118	0.26	0.07	0.52	0.00	0.14
49 – Land transport	2,422	0.08	0.16	0.47	0.03	0.25
50 – Water transport	12	0.17	0.17	0.45	0.03	0.17
51 – Air transport	9	0.70	0.14	-0.00	0.03	0.13
52 – Warehousing and transport support	693	0.23	0.12	0.43	0.03	0.20
53 – Postal and courier activities	69	0.18	0.08	0.62	0.03	0.09
55 – Accommodation	383	0.20	0.06	0.59	0.04	0.11
56 – Food and beverage services	932	0.31	0.05	0.40	0.09	0.14
58 – Publishing	215	-0.05	0.25	0.59	-0.04	0.24
59 – Film and TV production	446	0.07	0.27	0.39	0.06	0.22
60 – Broadcasting	11	-0.01	-0.02	0.77	-0.02	0.28
61 – Telecommunications	89	0.31	0.18	0.31	0.01	0.18
62 – IT services	1,223	0.12	0.25	0.41	0.05	0.17
63 – Information services	222	0.29	0.14	0.41	0.04	0.12
64 – Financial services	118	0.39	0.19	0.31	0.01	0.10
66 – Auxiliary financial services	59	0.25	0.24	0.31	0.03	0.18
68 – Real estate	2,922	0.04	0.37	0.39	0.03	0.17
69 – Legal and accounting	922	0.21	0.12	0.51	0.05	0.10
70 – Head offices and consultancy	1,122	0.20	0.33	0.28	0.04	0.15
71 – Architecture and engineering	1,543	0.00	0.24	0.51	0.06	0.20
72 – Scientific R&D	93	0.22	0.19	0.37	0.06	0.15
73 – Advertising and market research	623	0.03	0.23	0.51	0.06	0.18
74 – Other professional services	949	0.12	0.21	0.47	0.05	0.15
75 – Veterinary activities	47	0.72	0.10	0.05	0.07	0.06
77 – Rental and leasing	615	0.10	0.19	0.47	0.06	0.18
78 – Employment activities	257	0.10	0.31	0.35	0.06	0.19
79 – Travel agencies	65	0.36	0.18	0.29	0.05	0.12
80 – Security services	47	0.00	0.08	0.66	0.04	0.22
81 – Building services	685	-0.07	0.24	0.54	0.05	0.23
82 – Office administration support	447	0.13	0.29	0.38	0.05	0.15
84 – Public administration	51	0.05	0.32	0.39	0.08	0.16
85 – Education	462	0.10	0.11	0.53	0.04	0.22
86 – Human health	87	0.35	0.08	0.42	0.00	0.15
87 – Residential care	6	0.46	0.31	-0.04	-0.01	0.28
88 – Social work	14	-0.17	1.02	0.06	-0.27	0.36
90 – Creative and entertainment	665	0.10	0.13	0.57	0.03	0.17
91 – Libraries and museums	43	0.09	0.01	0.67	0.03	0.21
93 – Sports and recreation	642	0.16	0.16	0.46	0.04	0.17
94 – Membership organisations	225	0.03	0.31	0.40	0.01	0.25
95 – Repair of computers and goods	151	0.04	0.22	0.46	0.05	0.21
96 – Other personal services	300	0.28	0.30	0.26	0.01	0.15

Table C.4: Sector-level firm size decomposition, Hungary (2019).

NACE2 (sector)	N	$\ln \beta_i$	$\ln \psi_i$	$\ln n_i^c$	$\ln \bar{\theta}_i$	$\ln \Omega_i^c$
01 – Crop and animal production	3,999	0.11	0.21	0.39	0.02	0.28
02 – Forestry and logging	601	0.00	0.23	0.54	0.01	0.22
03 – Fishing and aquaculture	47	0.31	0.14	0.30	0.07	0.18
08 – Other mining and quarrying	145	-0.08	0.23	0.52	0.03	0.30
09 – Mining support services	32	-0.04	0.43	0.23	0.05	0.33
10 – Food products	979	0.02	0.22	0.46	0.03	0.27
11 – Beverages	394	-0.15	0.25	0.53	0.07	0.30
13 – Textiles	220	0.26	0.17	0.35	0.05	0.16
14 – Wearing apparel	231	0.31	0.20	0.33	-0.02	0.18
15 – Leather products	55	0.51	0.10	0.23	0.03	0.14
16 – Wood products	862	0.03	0.19	0.47	0.03	0.27
17 – Paper products	219	0.04	0.21	0.49	0.03	0.23
18 – Printing and media reproduction	699	-0.09	0.27	0.52	0.03	0.28
19 – Coke and refined petroleum	6	0.01	0.21	0.51	0.02	0.25
20 – Chemicals	264	0.15	0.22	0.40	0.02	0.21
21 – Pharmaceuticals	49	0.29	0.13	0.28	0.04	0.26
22 – Rubber and plastics	934	0.11	0.24	0.37	0.05	0.24
23 – Non-metallic minerals	567	0.00	0.20	0.55	0.02	0.23
24 – Basic metals	127	0.28	0.26	0.20	0.07	0.19
25 – Fabricated metal products	3,145	0.16	0.21	0.35	0.05	0.24
26 – Computer and electronic products	463	0.27	0.22	0.21	0.06	0.25
27 – Electrical equipment	351	0.27	0.19	0.28	0.03	0.22
28 – Machinery and equipment	1,137	0.19	0.16	0.37	0.03	0.24
29 – Motor vehicles	246	0.28	0.23	0.13	0.08	0.28
30 – Other transport equipment	67	0.20	0.21	0.25	-0.00	0.35
31 – Furniture	717	0.17	0.17	0.45	0.01	0.20
32 – Other manufacturing	265	0.31	0.22	0.26	0.04	0.18
33 – Repair and installation	1,144	0.02	0.24	0.44	0.05	0.26
35 – Electricity and gas	353	0.04	0.22	0.40	0.06	0.28
36 – Water supply	101	0.17	0.07	0.57	0.02	0.18
37 – Sewerage	65	-0.01	0.14	0.56	0.06	0.24
38 – Waste management	446	0.05	0.17	0.38	0.05	0.35
39 – Remediation services	50	0.05	0.24	0.42	0.02	0.28
41 – Construction of buildings	4,926	0.28	0.20	0.28	0.04	0.19
42 – Civil engineering	1,875	0.21	0.18	0.33	0.04	0.24
43 – Specialised construction	8,745	0.10	0.25	0.38	0.05	0.22
45 – Motor vehicle trade and repair	4,333	-0.02	0.17	0.55	0.04	0.26
46 – Wholesale trade	11,392	0.03	0.19	0.55	0.01	0.22
47 – Retail trade	6,956	0.20	0.11	0.50	0.01	0.18
49 – Land transport	3,533	0.06	0.14	0.49	0.01	0.30
50 – Water transport	30	0.25	-0.00	0.51	-0.00	0.24
51 – Air transport	15	0.69	0.14	0.07	0.05	0.05
52 – Warehousing and transport support	1,173	0.05	0.16	0.45	0.04	0.29
53 – Postal and courier activities	159	0.11	0.13	0.55	-0.02	0.24
55 – Accommodation	624	0.31	0.07	0.45	0.04	0.13
56 – Food and beverage services	1,337	0.41	0.15	0.24	0.05	0.16
58 – Publishing	573	0.05	0.24	0.42	0.05	0.24
59 – Film and TV production	792	0.05	0.34	0.31	0.04	0.26
60 – Broadcasting	134	-0.02	0.27	0.41	0.00	0.33
61 – Telecommunications	267	0.13	0.15	0.41	0.06	0.25
62 – IT services	2,909	0.05	0.29	0.38	0.07	0.21
63 – Information services	465	0.11	0.22	0.41	0.07	0.19
64 – Financial services	367	0.20	0.19	0.40	0.04	0.17
65 – Insurance	14	0.89	0.12	0.01	-0.04	0.02
66 – Auxiliary financial services	221	0.45	0.20	0.22	0.00	0.13
68 – Real estate	5,744	0.14	0.29	0.32	0.05	0.20
69 – Legal and accounting	2,431	0.02	0.31	0.45	0.04	0.18
70 – Head offices and consultancy	3,290	0.08	0.31	0.36	0.06	0.19
71 – Architecture and engineering	5,226	0.07	0.31	0.36	0.05	0.21
72 – Scientific R&D	643	0.16	0.26	0.35	0.04	0.19
73 – Advertising and market research	1,333	-0.08	0.34	0.42	0.06	0.26
74 – Other professional services	1,191	0.12	0.29	0.37	0.03	0.20
75 – Veterinary activities	86	0.13	0.14	0.62	-0.03	0.15
77 – Rental and leasing	896	0.03	0.22	0.51	0.05	0.18
78 – Employment activities	344	0.43	0.04	0.33	0.04	0.15
79 – Travel agencies	184	0.52	0.02	0.28	0.02	0.16
80 – Security services	925	-0.04	0.30	0.42	0.06	0.25
81 – Building services	1,547	0.02	0.32	0.35	0.05	0.26
82 – Office administration support	1,369	0.12	0.22	0.38	0.07	0.20
84 – Public administration	57	-0.14	0.27	0.55	0.06	0.26
85 – Education	615	0.32	0.12	0.35	0.05	0.16
86 – Human health	230	0.66	0.09	0.16	0.03	0.07
88 – Social work	29	0.24	0.18	0.34	-0.00	0.25
90 – Creative and entertainment	856	0.09	0.25	0.41	0.03	0.22
91 – Libraries and museums	55	0.09	0.24	0.50	-0.02	0.19
92 – Gambling and betting	9	0.59	0.06	0.14	0.06	0.15
93 – Sports and recreation	789	0.16	0.26	0.33	0.04	0.21
94 – Membership organisations	201	0.29	0.13	0.36	0.03	0.18
95 – Repair of computers and goods	374	-0.02	0.27	0.44	0.06	0.26
96 – Other personal services	289	0.19	0.23	0.40	0.00	0.17

Table C.5: Sector-level firm size decomposition, Italy (2019).

NACE2 (sector)	N	$\ln \beta_i$	$\ln \psi_i$	$\ln n_i^c$	$\ln \bar{\theta}_i$	$\ln \Omega_i^c$
01 – Crop and animal production	9,108	-0.01	0.21	0.43	0.05	0.32
02 – Forestry and logging	522	-0.06	0.31	0.37	0.07	0.31
03 – Fishing and aquaculture	803	-0.02	0.34	0.37	0.03	0.28
06 – Extraction of crude petroleum and natural gas	12	-0.00	-0.02	0.67	-0.06	0.42
08 – Other mining and quarrying	1,165	-0.02	0.14	0.54	0.02	0.31
09 – Mining support services	15	0.20	0.31	0.13	0.09	0.26
10 – Food products	10,711	-0.13	0.24	0.52	0.09	0.28
11 – Beverages	1,415	-0.03	0.24	0.48	0.08	0.24
12 – Tobacco products	11	-0.08	0.09	0.20	0.11	0.69
13 – Textiles	3,772	0.04	0.09	0.57	0.04	0.26
14 – Wearing apparel	5,521	0.06	0.12	0.51	0.04	0.27
15 – Leather products	4,185	0.13	0.02	0.41	0.06	0.39
16 – Wood products	3,602	-0.04	0.17	0.62	0.04	0.20
17 – Paper products	1,869	0.02	0.24	0.51	0.07	0.16
18 – Printing and media reproduction	4,089	-0.06	0.31	0.44	0.08	0.24
19 – Coke and refined petroleum	147	-0.05	0.32	0.44	0.06	0.23
20 – Chemicals	3,024	0.04	0.27	0.45	0.05	0.19
21 – Pharmaceuticals	429	0.14	0.23	0.38	-0.03	0.28
22 – Rubber and plastics	5,477	0.06	0.19	0.49	0.05	0.21
23 – Non-metallic minerals	5,797	-0.01	0.23	0.54	0.03	0.21
24 – Basic metals	1,470	0.08	0.31	0.37	0.06	0.18
25 – Fabricated metal products	25,388	0.02	0.17	0.48	0.06	0.27
26 – Computer and electronic products	3,392	0.09	0.13	0.45	0.06	0.27
27 – Electrical equipment	3,907	0.10	0.10	0.52	0.05	0.24
28 – Machinery and equipment	12,438	0.19	0.08	0.44	0.05	0.25
29 – Motor vehicles	1,607	0.07	0.15	0.32	0.08	0.38
30 – Other transport equipment	1,646	0.08	0.12	0.35	0.07	0.38
31 – Furniture	4,906	0.06	0.12	0.56	0.03	0.24
32 – Other manufacturing	3,978	0.07	0.12	0.51	0.05	0.25
33 – Repair and installation	7,499	-0.01	0.19	0.46	0.08	0.29
35 – Electricity and gas	3,150	0.06	0.24	0.43	-0.00	0.27
36 – Water supply	286	0.04	-0.06	0.87	-0.05	0.19
37 – Sewerage	656	-0.13	0.32	0.40	0.06	0.34
38 – Waste management	3,953	0.04	0.15	0.43	0.06	0.33
39 – Remediation services	303	-0.04	0.15	0.49	0.09	0.32
41 – Construction of buildings	33,455	0.06	0.29	0.29	0.08	0.28
42 – Civil engineering	3,895	-0.01	0.20	0.38	0.06	0.37
43 – Specialised construction	37,089	-0.08	0.21	0.51	0.08	0.29
45 – Motor vehicle trade and repair	21,072	-0.08	0.07	0.68	0.01	0.32
46 – Wholesale trade	78,071	-0.02	0.19	0.57	0.03	0.23
47 – Retail trade	49,735	0.03	-0.00	0.67	-0.00	0.31
49 – Land transport	16,611	0.01	0.06	0.57	0.03	0.34
50 – Water transport	483	0.10	-0.05	0.57	0.03	0.34
51 – Air transport	80	0.05	0.02	0.45	0.05	0.43
52 – Warehousing and transport support	9,273	-0.03	0.09	0.53	0.05	0.37
53 – Postal and courier activities	660	-0.14	0.28	0.50	0.06	0.30
55 – Accommodation	13,569	0.00	0.14	0.59	0.04	0.22
56 – Food and beverage services	31,884	0.00	-0.12	0.84	0.01	0.27
58 – Publishing	2,918	0.01	0.19	0.48	0.03	0.29
59 – Film and TV production	3,030	0.05	0.28	0.33	0.07	0.26
60 – Broadcasting	776	-0.01	0.32	0.34	0.07	0.27
61 – Telecommunications	1,374	0.02	0.19	0.44	0.04	0.30
62 – IT services	15,021	-0.00	0.23	0.48	0.11	0.19
63 – Information services	13,787	-0.00	0.20	0.54	0.08	0.19
64 – Financial services	9	-0.11	0.44	0.26	0.11	0.30
66 – Auxiliary financial services	3,131	0.40	0.11	0.21	0.07	0.20
68 – Real estate	8,311	0.04	0.18	0.47	0.08	0.23
69 – Legal and accounting	4,137	0.08	0.07	0.59	0.05	0.21
70 – Head offices and consultancy	16,429	0.03	0.29	0.39	0.09	0.20
71 – Architecture and engineering	11,987	-0.03	0.23	0.45	0.11	0.24
72 – Scientific R&D	1,674	0.10	0.26	0.34	0.07	0.22
73 – Advertising and market research	6,345	-0.00	0.24	0.44	0.11	0.21
74 – Other professional services	9,836	-0.01	0.24	0.49	0.08	0.21
75 – Veterinary activities	156	0.42	-0.04	0.43	0.01	0.18
77 – Rental and leasing	4,563	-0.01	0.12	0.61	0.05	0.23
78 – Employment activities	477	-0.03	0.13	0.69	0.08	0.14
79 – Travel agencies	4,579	0.10	0.23	0.46	-0.01	0.22
80 – Security services	1,342	-0.01	-0.03	0.75	0.02	0.28
81 – Building services	8,735	-0.09	0.22	0.45	0.08	0.34
82 – Office administration support	7,844	-0.01	0.20	0.45	0.07	0.29
85 – Education	5,995	0.21	0.08	0.47	0.05	0.18
86 – Human health	4,981	0.34	-0.01	0.35	0.04	0.28
87 – Residential care	1,150	0.04	0.16	0.33	0.08	0.38
88 – Social work	2,689	0.03	0.32	0.27	0.05	0.32
90 – Creative and entertainment	2,313	0.02	0.25	0.47	0.06	0.21
91 – Libraries and museums	353	0.05	-0.04	0.61	0.07	0.30
92 – Gambling and betting	679	0.62	-0.01	0.27	-0.04	0.15
93 – Sports and recreation	6,590	0.22	0.08	0.43	0.05	0.23
95 – Repair of computers and goods	1,480	-0.11	0.19	0.52	0.05	0.35
96 – Other personal services	4,038	-0.05	0.27	0.52	0.04	0.21

Table C.6: Sector-level firm size decomposition, Portugal (2019).

NACE2 (sector)	N	$\ln \beta_i$	$\ln \psi_i$	$\ln n_i^c$	$\ln \bar{\theta}_i$	$\ln \Omega_i^c$
01 – Crop and animal production	9,224	0.01	0.38	0.29	0.02	0.30
02 – Forestry and logging	1,676	-0.03	0.29	0.38	0.04	0.32
03 – Fishing and aquaculture	143	0.21	0.35	0.17	0.03	0.24
08 – Other mining and quarrying	513	0.06	0.08	0.56	0.01	0.30
09 – Mining support services	8	-0.15	0.18	0.14	0.09	0.73
10 – Food products	4,972	-0.08	0.23	0.53	0.01	0.31
11 – Beverages	1,005	-0.01	0.16	0.46	0.01	0.38
13 – Textiles	1,689	0.13	0.18	0.40	0.02	0.27
14 – Wearing apparel	3,445	0.39	0.04	0.29	0.01	0.27
15 – Leather products	1,749	0.39	-0.06	0.32	0.01	0.34
16 – Wood products	2,208	0.08	0.25	0.39	0.02	0.27
17 – Paper products	346	0.04	0.27	0.46	0.03	0.21
18 – Printing and media reproduction	1,621	-0.02	0.27	0.52	0.01	0.22
19 – Coke and refined petroleum	12	0.01	0.11	0.45	0.04	0.40
20 – Chemicals	518	0.06	0.33	0.34	0.03	0.24
21 – Pharmaceuticals	74	0.14	0.18	0.32	0.03	0.33
22 – Rubber and plastics	829	0.15	0.27	0.29	0.04	0.26
23 – Non-metallic minerals	1,952	0.09	0.22	0.47	0.00	0.21
24 – Basic metals	196	0.13	0.36	0.25	0.03	0.24
25 – Fabricated metal products	6,354	0.10	0.23	0.39	0.02	0.25
26 – Computer and electronic products	166	0.27	0.22	0.26	0.04	0.21
27 – Electrical equipment	411	0.18	0.19	0.37	0.03	0.23
28 – Machinery and equipment	1,032	0.18	0.16	0.39	0.02	0.24
29 – Motor vehicles	381	0.28	0.24	0.05	0.05	0.37
30 – Other transport equipment	139	0.32	0.12	0.20	0.01	0.35
31 – Furniture	2,073	0.12	0.18	0.44	0.02	0.24
32 – Other manufacturing	1,212	0.13	0.23	0.43	0.02	0.20
33 – Repair and installation	2,170	0.03	0.26	0.38	0.04	0.28
35 – Electricity and gas	329	-0.01	0.35	0.34	0.03	0.29
36 – Water supply	142	0.04	0.02	0.79	-0.02	0.18
37 – Sewerage	45	-0.04	0.38	0.27	0.02	0.37
38 – Waste management	641	0.01	0.12	0.47	0.02	0.38
39 – Remediation services	6	0.00	0.01	0.90	0.05	0.04
41 – Construction of buildings	14,869	0.12	0.30	0.31	0.04	0.23
42 – Civil engineering	1,644	0.02	0.22	0.38	0.04	0.35
43 – Specialised construction	13,696	-0.01	0.22	0.48	0.03	0.27
45 – Motor vehicle trade and repair	13,822	0.01	0.12	0.64	0.00	0.23
46 – Wholesale trade	26,453	-0.02	0.22	0.56	0.01	0.22
47 – Retail trade	40,487	0.00	0.08	0.70	-0.00	0.23
49 – Land transport	15,933	-0.05	0.24	0.51	-0.00	0.30
50 – Water transport	134	0.15	0.02	0.54	0.01	0.28
51 – Air transport	41	0.18	0.06	0.41	-0.00	0.35
52 – Warehousing and transport support	1,574	-0.02	0.13	0.52	0.01	0.35
53 – Postal and courier activities	369	0.01	0.35	0.41	-0.02	0.24
55 – Accommodation	5,540	0.23	-0.00	0.54	0.01	0.23
56 – Food and beverage services	27,572	0.04	0.06	0.81	-0.01	0.10
58 – Publishing	1,101	0.02	0.15	0.56	0.01	0.27
59 – Film and TV production	1,263	0.08	0.27	0.36	0.02	0.27
60 – Broadcasting	277	0.01	0.27	0.39	-0.00	0.32
61 – Telecommunications	402	0.12	0.15	0.46	0.02	0.26
62 – IT services	4,443	0.10	0.31	0.38	0.05	0.16
63 – Information services	475	0.18	0.28	0.34	0.04	0.17
68 – Real estate	13,049	0.25	0.22	0.33	0.03	0.16
69 – Legal and accounting	10,640	0.02	0.19	0.66	0.04	0.08
70 – Head offices and consultancy	7,353	0.08	0.35	0.33	0.05	0.19
71 – Architecture and engineering	6,952	0.09	0.26	0.41	0.05	0.19
72 – Scientific R&D	434	0.10	0.22	0.41	0.03	0.24
73 – Advertising and market research	2,583	0.01	0.36	0.38	0.04	0.22
74 – Other professional services	4,208	0.08	0.28	0.42	0.03	0.19
75 – Veterinary activities	1,107	0.44	-0.10	0.53	-0.01	0.14
77 – Rental and leasing	1,515	-0.03	0.22	0.55	0.02	0.24
78 – Employment activities	418	-0.01	0.33	0.43	0.03	0.22
79 – Travel agencies	2,111	0.04	0.44	0.40	-0.00	0.12
80 – Security services	366	0.01	0.16	0.59	0.02	0.22
81 – Building services	2,611	-0.02	0.27	0.50	0.04	0.22
82 – Office administration support	4,511	0.05	0.27	0.41	0.03	0.24
84 – Public administration	1,270	0.11	0.19	0.48	-0.00	0.22
85 – Education	3,717	0.29	0.30	0.27	0.01	0.13
86 – Human health	17,307	0.26	-0.11	0.36	0.10	0.39
87 – Residential care	816	0.16	0.18	0.23	0.08	0.35
88 – Social work	1,066	0.35	0.26	0.17	0.02	0.20
90 – Creative and entertainment	2,026	0.06	0.24	0.46	-0.00	0.25
91 – Libraries and museums	116	0.15	-0.02	0.61	-0.01	0.27
92 – Gambling and betting	204	-0.04	0.38	0.43	-0.01	0.25
93 – Sports and recreation	5,926	0.14	0.25	0.40	-0.00	0.22
94 – Membership organisations	4,843	0.15	0.27	0.36	0.01	0.21
95 – Repair of computers and goods	794	-0.08	0.18	0.58	0.01	0.30
96 – Other personal services	4,271	0.04	0.23	0.51	0.01	0.21

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