Production networks, input specificity, and the labor share*

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Abstract

Bargaining power is a key determinant of workers' share of aggregate income, yet difficult to measure empirically. This study proposes input specificity as an important determinant of bargaining power, arguing that the production of harder-to-substitute intermediates strengthens workers' bargaining position. We develop a network-based measure of input specificity and apply it to regional input–output data for European economies. Our results suggest that input specificity varies systematically across regions and is positively associated with the labor share. We find evidence that the relationship between input specificity and the labor share is stronger under coordinated wage bargaining, indicating that institutional settings condition how structural positions in production networks translate into income for workers. From a policy perspective, upgrading strategies that increase input specificity may support higher labor shares, particularly in contexts where institutions enable workers to capture the associated rents.

Keywords: inter-regional inequality; labor share; power resource approach; production network; power law
JEL codes: D63; F14; O18; R11; R15

Highlights

- We propose a network-based measure of input specificity in fragmented production systems.
- European regions and sectors differ systematically in the specificity of their inputs.
- Labor shares are higher in regions supplying more specific and hard-to-substitute inputs.
- Bargaining institutions may condition how input specificity affects labor shares.

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1 Introduction

Economic inequality is a major challenge of the 21st century (Atkinson, 2013). Rising disparities can undermine social cohesion and political stability (Acemoglu and Robinson, 2001; Stiglitz, 2012), hinder innovation (Napolitano et al., 2022), and exacerbate the impact of climate change (Green and Healy, 2022). An important dimension of inequality concerns the functional income distribution, which determines how value added created in the production process is split between labor and capital. While much of the literature focuses on long-run trends in workers' share of aggregate income, substantial cross-sectional variation across regions and sectors persists and remains insufficiently understood. Here we argue that workers' bargaining power arising from their structural position in the production network is an important mechanism underlying this variation.

Bargaining power is widely recognized as a key determinant of labor shares, yet it is notoriously difficult to measure empirically. This paper addresses this challenge by examining how the specificity of supplied intermediate inputs within the production network shapes workers' ability to appropriate value added. When workers producing highly specific and hard-to-substitute inputs suspend production, downstream activities face stronger disruptions, thereby increasing workers' leverage in wage bargaining. Building on this mechanism, this article develops a novel network-based measure of input specificity and provides empirical evidence that higher input specificity is associated with higher labor shares.

Input specificity can affect wages and labor shares through two distinct, but complementary, channels. First, the production and use of specific inputs in the production process often require specific skills, leading to higher wages according to a skill premium (Li, Cai, and Li, 2021). Second, producing specific inputs increases what the Power Resource Approach terms "structural power" (Perrone, Wright, and Griffin, 1984; Wallace, Griffin, and Rubin, 1989; Wright, 2000; Selwyn, 2012; Schmalz, Ludwig, and Webster, 2018; Nowak, 2022), as strikes in such sectors are particularly disruptive for downstream production. Both channels imply that higher input specificity strengthens workers' bargaining position and increases their share of value added. However, to the best of our knowledge, no empirical studies have yet examined whether producing more specific intermediates leads to higher labor shares.

To measure input specificity, we interpret the complex input-output network from the perspective of an individual node. From this vantage point, production relationships can be examined either upstream, tracing a node's suppliers (demand perspective), or downstream, tracing the nodes that use its outputs (supply perspective). Our notion of input specificity adopts the supply perspective, capturing the dependence of other nodes in the production system on the intermediate goods of the focal producer.

To operationalize this approach, we follow the methodology proposed by Zhu et al. (2015) and construct production trees for each node. These trees distill the most relevant linkages from the full input-output network and provide a simplified representation of its local production structure. Production trees can take two limiting forms. In a star-like configuration, a central node supplies many downstream buyers located on the same production layer, reflecting a relatively generic input that is widely used and easily substitutable. In a chain-like configuration, by contrast, nodes are arranged hierarchically, representing tightly linked production stages characterized by low substitutability. The more a production tree resembles a chain rather than a star, the more specific - and less easily replaceable - the intermediate inputs are. This degree of chain-likeness forms the basis of our measure of input specificity.

An important contribution of our paper is the investigation of production structure and the functional income distribution at a disaggregated, regional level. Existing studies on the determinants of the labor share often use national economies as their unit of analysis (e.g., Karabarbounis and Neiman, 2014), which conceals substantial heterogeneity in industrial structure, economic development, and the functional distribution of income. We argue that the regional level is more appropriate to study the role of input specificity, as variation in specificity is plausibly more pronounced at a regional scale. To this end, we employ multiregional input-output data for 248 NUTS-2 regions in 24 European countries from 2000 to 2010 to assess the association between input specificity and the labor share.

We report four main findings. First, our measurement of production structure indicates that theoretical models of vertically fragmented production built on purely chain- or star-like configurations are overly simplistic. Instead, input relationships are better understood as more complex topological structures that lie between these two extremes, consistent with the concept of global production networks advanced by Henderson et al. (2002).

Second, at the descriptive level, we identify significant sectoral differences in production structure and input specificity. Raw materials serve as an almost universal input, resulting in production structures in primary sectors that more closely resemble a star configuration. This finding aligns with the 'inverted pyramid' perspective in ecological economics (Cahen-Fourot et al., 2020), which emphasizes the foundational role of natural resources in sustaining economic activity. In contrast, manufacturing sectors undergo numerous consecutive stages of industrial processing that increase the degree of specificity before final goods reach end-consumer markets. As a result, production trees in these sectors exhibit more chain-like structures.

Third, our analysis uncovers considerable regional heterogeneity in input specificity. The European periphery tends to rely on inputs with above-average specificity while supplying less specific intermediates. In contrast, core regions, characterized by above-average value-added, exhibit the opposite pattern: they source less specific inputs but produce more specialized intermediates. This finding complements previous research on the relatively lower production complexity of peripheral regions - a related but distinct concept (Gräbner et al., 2020). When comparing regions in Central and Eastern Europe with those in Western Europe, much of the observed heterogeneity in input specificity disappears. Given the persistently higher labor share in Western Europe, this pattern suggests that differences in labor shares across these regions cannot be explained by input specificity alone and may instead reflect institutional differences in how structural positions within production networks translate into income for workers.

Fourth, we conduct panel regressions to examine the relationship between input specificity and the labor share. Consistent with our hypothesis, we find a significantly positive relationship across various specifications, implying that regions producing more specific inputs tend to exhibit higher labor shares. Given the slow-moving nature of both variables, however, the relationship appears structural and thus better explains cross-sectional differences in labor shares than their evolution over time. We also find suggestive evidence that the relationship is stronger under coordinated wage bargaining. This finding might help explain the persistent East–West divide in labor shares, as coordinated multi-employer bargaining is common in Western Europe, whereas single-employer bargaining dominates in most Central and Eastern European countries.

The remainder of this paper is organized as follows: Section 2 reviews related literature and situates our study in the power resources approach. Section 3 introduces our regional data, while we explain our methodology in more detail in Section 4. Section 5 documents regional and sectoral differences in production tree structures and uses regression analysis to examine their relationship with the labor share. Section 6 concludes, discusses our study's limitations, and posits avenues for further research.

2 Theoretical Background and Related Literature

After being famously constant for most of recorded history (Kaldor, 1961), the recent secular decline in the U.S. labor share has revived scholarly interest in the functional income distribution and its determinants (see, for example, Bergholt, Furlanetto, and Maffei-Faccioli, 2022; Elsby, Hobijn, and Sahin, 2013). Two broad strands of explanation have emerged. The neoclassical approach highlights investment and technological factors, whereas the political economy perspective focuses on bargaining power as a key determinant of labor shares (Stockhammer, 2017).

One view in the neoclassical tradition emphasizes the role of capital accumulation in explaining shifts in the functional income distribution. Piketty (2014) highlights the increase in aggregate savings, while Karabarbounis and Neiman (2014) argue that a drop in the price of investment goods may have increased the capital-output ratio, thereby depressing the labor share (cf. Bentolila and Saint-Paul, 2003; Young and Lawson, 2014; Young and Tackett, 2018). However, this influential line of argument relies on the assumption that the elasticity of substitution between capital and labor exceeds one - a premise that appears empirically questionable (see Gechert et al., 2022, for a recent meta-analysis).

Another strand in the neoclassical literature emphasizes technological change as a key determinant of income shares. Building on a task-based model in the spirit of Acemoglu and Autor (2011), Acemoglu and Restrepo (2018) argue that automation can reduce the labor share by displacing workers from existing tasks. Yet their analysis also shows that this effect is potentially offset by the long-run tendency of technological progress to encourage the creation of new, more complex tasks in which labor has a comparative advantage. More recently, Autor et al. (2020) and Kehrig and Vincent (2021) shed light on the microeconomic origins of the income distribution. They attribute the decline in the labor share to the rise of "superstar" firms under intense global competition, which sustain high profit margins while allocating a relatively small share of value added to labor.

The political economy tradition emphasizes power asymmetries and argues that the decline in workers' bargaining power - partly driven by globalization - has contributed to the fall in the aggregate labor share (Stockhammer, 2017). A notable recent contribution is Stansbury and Summers (2020), who argue that declining worker power accounts for nearly the entire fall in the U.S. labor share. Yet even within this literature, the relationship between production structure and the functional income distribution remains largely unexplored, except for studies focusing on offshoring (Guschanski and Onaran, 2022; Guschanski and Onaran, 2023). This omission is striking, as power asymmetries within global value chains - such as the distinction between buyer-driven and seller-driven structures - are well documented (Dallas, Ponte, and Sturgeon, 2019), and in some cases analyzed using methodologies similar to ours (Iliopoulos, 2022). Nevertheless, previous studies have not examined how power relations arising from production structures influence the functional income distribution (Selwyn, 2012).

By contrast, our empirical analysis integrates the *power resources approach* (Wright, 2000; Silver, 2003) into the broader context of increasingly integrated transnational production networks. Such an approach complements standard models of offshoring, automation, and the capital-output ratio by arguing that labor can - under certain conditions - capture a larger share of value added through the systematic leverage of structural, associational, and institutional power. While our explanatory attempt is based on technology, namely the topology of the production network, our approach is firmly grounded in the political economy strand, as it focuses on the (technological and other) determinants of labor's bargaining power.

We focus on *structural power* which resides in workers' potential to disrupt production by withholding essential inputs or technical know-how. When downstream production depends on specialized inputs that are challenging to replace, even small groups of workers can secure higher shares of value added (Wright, 2000). This structural dimension of power is conceptually distinct from *associational power*, which stems from collective organization and union membership. Finally, *institutional power* reflects how political, legal, and regulatory

Table 1: Dimensions of Worker Power and Empirical Strategy

	Structural Power		Associational Power	Institutional Power
	Workplace Bargaining Power	Marketplace Bargaining Power		
Concept	Disruptive potential	Specialized skills	Collective representation Coordinated wage demands	Coordinated wage-setting Legal protections
Operationalization	*Input specificity* Sectoral size	*Input specificity* Human capital	Union density Unemployment rate	Regional split (difference in bargaining regimes)

arrangements - such as centralized wage-setting or legally mandated worker representation - reinforce labor's position in negotiations. Evidence from Western Europe suggests that long-standing, coordinated bargaining systems constrain inequality and stabilize labor's share. In contrast, more fragmented institutions in Eastern Europe, often tied to post-transition economic structures, provide weaker support (Bernaciak, 2015; Astrov et al., 2019; Grodzicki and Geodecki, 2016; Kónya, Krekó, and Oblath, 2020; Bellocchi, Marin, and Travaglini, 2023). This concerns, in particular, the decentralized and single-employer wage-bargaining prevalent in Eastern Europe.

Table 1 summarizes how the three dimensions of power are conceptualized and how we operationalize them in our empirical analysis. The main variable of interest in our subsequent analysis is input specificity, which we interpret as the extent to which workers in a sector produce inputs that are difficult for downstream sectors to substitute. This focus differs from most studies of structural power, which typically emphasize the scale or concentration of inputs supplied, rather than their substitutability (cf., e.g., Perrone, Wright, and Griffin, 1984; Wallace, Griffin, and Rubin, 1989). Accordingly, our measure is conceptually distinct from supplier concentration or monopoly power, which may generate bargaining power even when the inputs supplied are relatively generic.

Our hypothesis is that the labor share increases with input specificity. This is due to the fact that workers producing more specific intermediate inputs possess greater "structural power," which refers to the power that workers derive "simply from their location [...] in the economic system" (Wright, 2000, p. 962). In particular, the literature differentiates between "marketplace bargaining power" resulting from scarce skills and "workplace bargaining power," which stems from workers' strategic position within the production network (Silver, 2003). We expect that both forms of power are positively correlated with supply specificity: educated workers with scarce skills are likely essential for producing specific inputs for other sectors, and the ripple effects of a work stoppage increase in proportion to the criticality of an input for other producers.[1]

Our main empirical result is that workers involved in producing critical inputs receive a larger share of value added, even after controlling for heterogeneity in unionization and unemployment rates. To our knowledge, the only study that points in this direction is Bloesch, Larsen, and Taska (2022). However, their argument, grounded in traditional O-ring theory, does not consider the topology of the input network as a determinant of workers' bargaining power.[2] Our paper complements their approach by focusing on the impact of production structure on workers' bargaining power, holding other determinants constant, whereas they focus on position-specific skills and their effect on bargaining power within a production structure featuring strong complementarities. Our work thus responds to the call by Selwyn (2012) and Selwyn (2015) to incorporate power dynamics and class analysis into the study of global production networks.

Our empirical analysis of spatial variations in production structure and inequality within the European Union also connects with the broader literature on regional heterogeneity across Europe. Despite the European Union's high level of integration and interconnectedness, substantial spatial asymmetries remain in terms of functional income distribution and value-added generation. Notably, countries in the European periphery consistently display lower labor shares across various sectors compared to Western European countries, with little consensus in the literature on the underlying reasons for this disparity (Grodzicki and Geodecki, 2016; Kónya, Krekó, and Oblath, 2020; Bellocchi, Marin, and Travaglini, 2023). In terms of integration into production networks, the periphery itself is heterogeneous: while Central and Eastern European

[1]Note that this channel does not require that strikes actually materialize; the mere potential for disruption is sufficient. As illustrated in the famous metaphor by Müller-Jentsch (1997), strikes can be seen as a 'sword on the wall,' and simply pointing to this sword may be enough to secure higher wages in negotiations.

[2]Traditional O-ring theory highlights the effect of strong complementarities of inputs, where small mistakes might impact aggregate output multiplicatively. The case of sequential production in the foundational papers by Kremer (1993) and Costinot, Vogel, and Wang (2013) implicitly assumes a chain-like production structure, which is overly simplistic as our empirical analysis demonstrates.

states are catching up to North-Western Europe, the gap for Southern European countries remains significant (Grodzicki and Geodecki, 2016). This is puzzling from the perspective of the Power Resources approach, as a similar position within the production network would be expected to lead to similar bargaining outcomes (Wright, 2000). Our analysis confirms this result using a more granular dataset and offers an explanation based on the interplay between historical differences in bargaining institutions and structural power (Bernaciak, 2015; Astrov et al., 2019).

3 Data

To analyze the relationship between production linkages and the functional income distribution, our study employs input-output and labor income data from the EUREGIO database (Thissen et al., 2018), a multi-country input-output table for European economies. The dataset covers the period 2000-2010, capturing a key phase of European economic integration. It distinguishes fourteen NACE-2 sectors and includes 24 countries, as detailed in Tables 4 and 5 in the appendix. Overall, the sample accounts for approximately 94% of European production and 80% of employment during the sample period, thereby covering a substantial share of Europe's economic activity.

As an empirical innovation of our study, we use 248 NUTS-2 regions as the primary unit of analysis. The use of detailed regional rather than country-level data enables us to address the "challenge of granularity" (Weber and Schulz, 2025), which refers to the problem that country-level data often obscure significant regional variation in economic performance and the labor share. For example, while Northern Italy belongs to the European core, the southern *Mezzogiorno* is classified as peripheral. Moreover, input linkages between European regions are strongly influenced by spatial proximity (Bolea et al., 2022). By distinguishing between such structurally different regions, our dataset enables us to exploit spatial heterogeneity in the empirical analysis.

Based on these data, we construct annual production networks in which each region-sector combination represents a node and trade relationships in intermediate goods or supporting services create weighted edges between these region-sectors. These networks serve as the foundation for deriving our measure of input specificity, which we will discuss in more detail in Section 4.

The key variable for the subsequent empirical analysis of the functional income distribution is the labor share. We calculate it as the ratio of compensation of employees to value added. This excludes the income of the self-employed as it should be irrelevant for our proposed channel, which builds on the bargaining power of workers in wage negotiations (Gutiérrez and Piton, 2020). Excluding the self-employed yields a labor share that falls below the well-known two-thirds rule described by Johnson (1954), which implies that approximately 66% of national income is distributed to the workforce. Consequently, the average labor share across years and regions in our data is merely 0.49, with a standard deviation of 0.08.

Consistent with previous work documenting significant cross-sectional variation in the functional income distribution (see, for example, Kónya, Krekó, and Oblath, 2020; Arif, 2021; Schiavone, 2023), Figure 1 reports substantial heterogeneity of labor shares across regions and sectors. Labor shares are higher, on average, in sectors related to industrial production compared to services and primary sectors (raw materials). Moreover, more developed core regions exhibit higher labor shares than regions in the periphery.[3] Cross-sectional differences are even more pronounced between East and West, with the Eastern regions belonging to countries that joined the European Union during the 2004 enlargement. It therefore seems worthwhile to explore whether these differences can be attributed to power relationships in fragmented production.

Compared to the cross-sectional heterogeneity, the variation of the labor share over time is considerably smaller, as the evolution of the average labor share in Figure 1 illustrates. The latter remains relatively stable throughout the sample period, aside from a moderate decline during the 2007 financial and banking crisis. To validate this graphical impression, we calculate the ratio of (i) each region's labor share to the average labor share across all regions (between mean), and (ii) each region's labor share to its own time-series average (within mean) and plot the distribution of these relative deviations in the bottom panel of Figure 1. The distributions confirm that labor shares are more dispersed in the cross-sectional than in the time domain. We will discuss the implications of this finding on our regression design in Section 5.2.

[3] In our definition, core regions generate value added above the cross-sectional average.

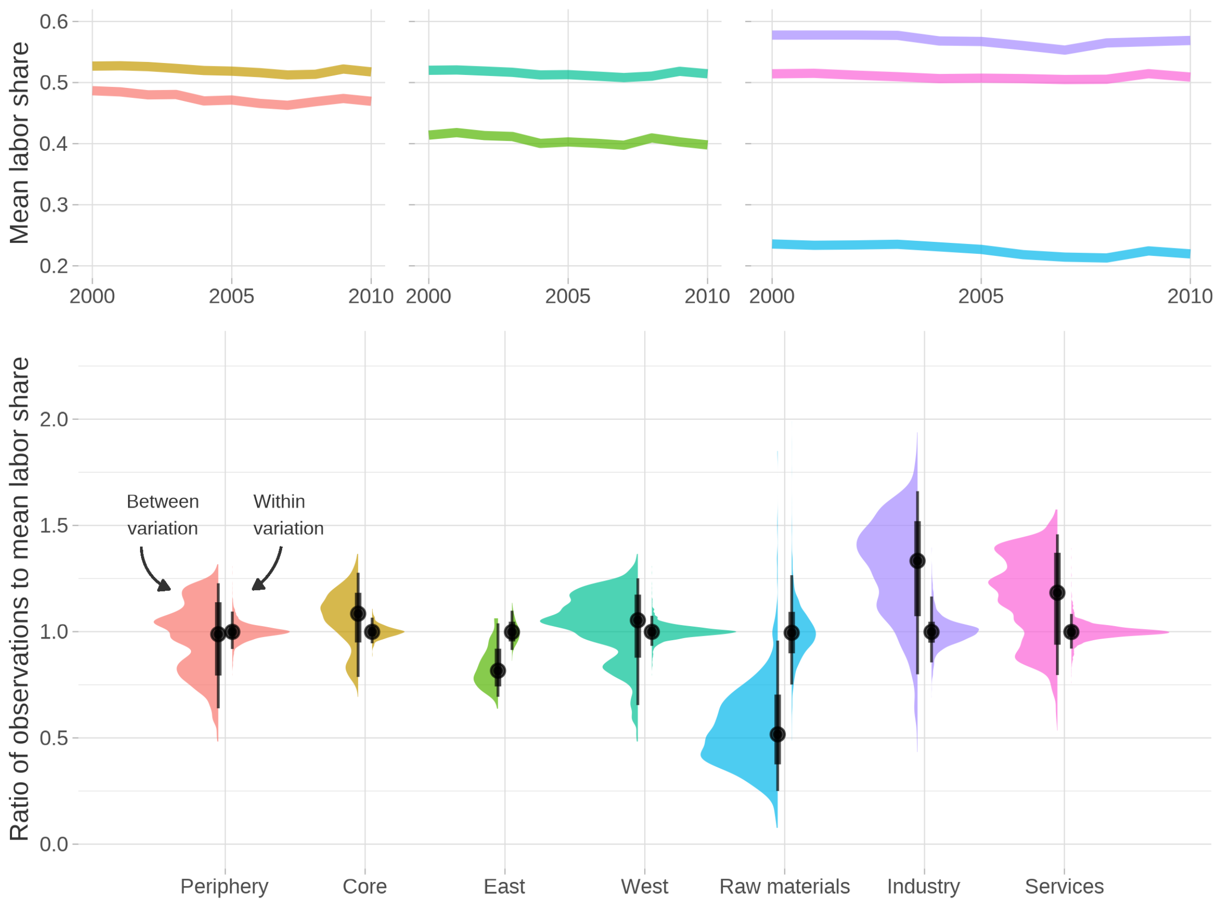

Figure 1: Mean and dispersion of labor shares. The top panel shows the evolution of the average labor share over the sample period. The bottom panel compares cross-sectional and time-series dispersion of labor shares across peripheral and core regions, East and West, and economic sectors. Left-hand violins show the distribution of labor shares relative to the cross-sectional average (between variation), while right-hand violins show the distribution relative to each region's time-series average (within variation).

4 Methodology

Production networks are typically studied from an aggregate, system-wide perspective. Here, we adopt a complementary approach by examining the network from the vantage point of individual nodes. Specifically, we reconstruct the input–output network as an ensemble of production trees rooted in individual region–sectors, following Zhu et al. (2015). Observing input relationships from the perspective of a given region–sector allows us to approximate the information available to workers about their position and integration within the production network, and to derive our measure of input specificity.

To operationalize this perspective, we proceed in three steps. First, we construct annual production networks using regional input–output data from EUREGIO. Second, after filtering out economically negligible transactional links, we derive production trees for each region–sector using a breadth-first search algorithm. Third, we characterize the topology of these trees by estimating an allometric scaling relationship between tree size and cumulative tree size. The resulting scaling exponent summarizes the narrowness of production structures and serves as our measure of input specificity. Figure 2 provides a visual overview of the procedure.

4.1 Network Construction

The subsequent analysis builds on regional input–output data from EUREGIO, which record inter-industry transactions between European regions. These data can be represented as an input–output network in which nodes correspond to region–sectors and weighted directed edges capture intermediate deliveries of goods and services between them. The resulting transactions matrix describes the flow of intermediate inputs across industries and regions and thus maps the structure of production interdependencies within and across the economies.

The input-output network can be examined from both a demand-side and a supply-side perspective. The demand perspective traces how changes in final demand propagate through the economy via backward linkages (Leontief, 1951). By contrast, the supply perspective focuses on forward linkages and identifies the region–sectors that absorb the output of a given sector (Ghosh, 1958). Because many manufacturing processes rely on raw materials that are rarely linked backward to other inputs (Cahen-Fourot et al., 2020; Daly, 1995), the

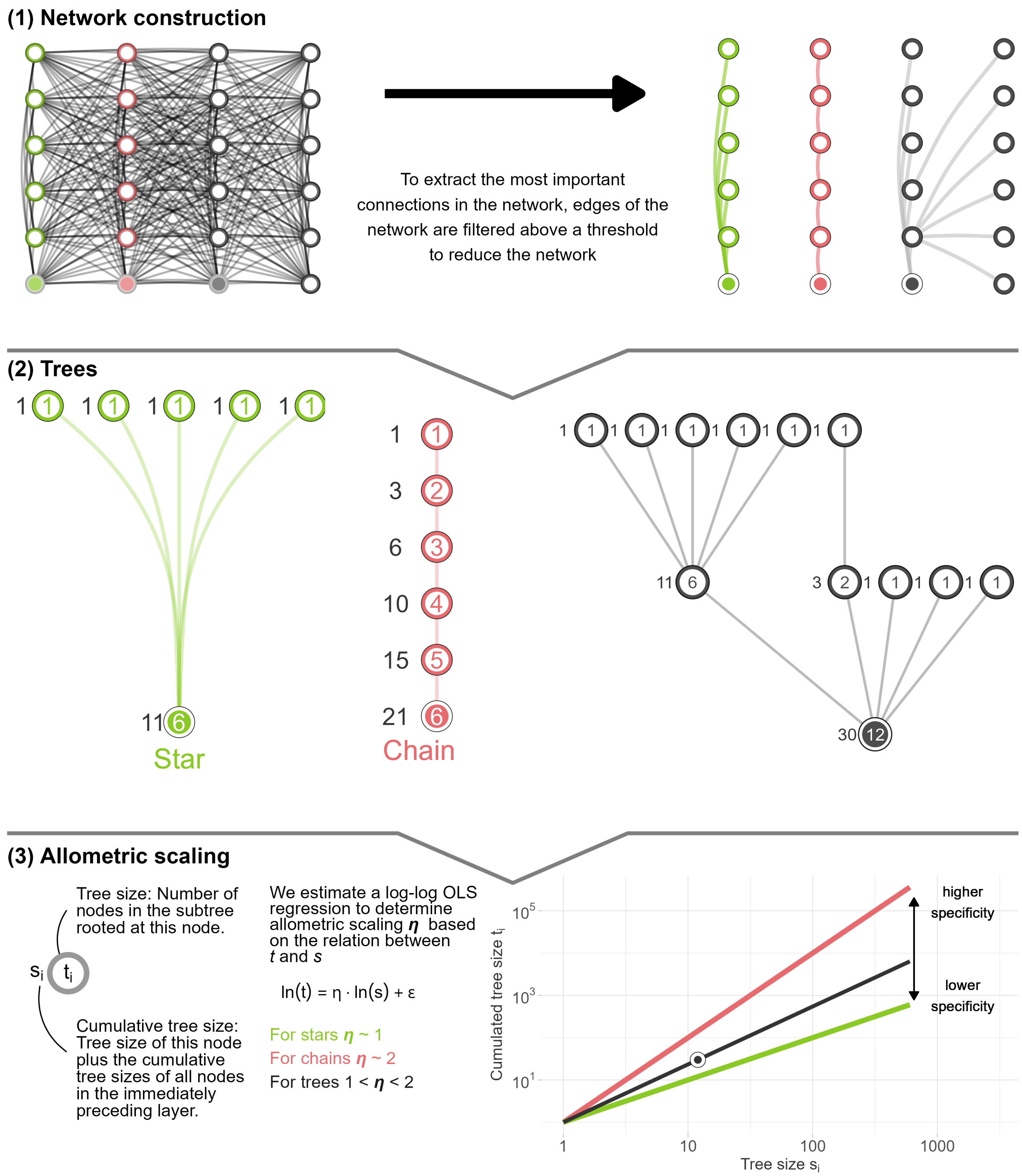

Figure 2: From production networks to production trees and their allometric scaling properties. **(1):** The production network (left) is reduced by thresholding edge weights to retain key connections (right). **(2):** A breadth-first search algorithm generates production trees for each node. The trees shown are rooted at the filled nodes highlighted in green, red, and black in panel (1). Star (green) and chain (red) structures represent limiting cases of tree topologies, while empirical realizations may lie between these extremes. **(3):** Each tree is characterized by its size and cumulative size at the root node. The allometric scaling exponent (ASE) summarizes their relationship across an ensemble of trees. Higher exponents indicate structures closer to a chain topology.

supply perspective more accurately captures the role of raw materials in production.

Formally, the demand view relates to the technical coefficient matrix $\mathbf{A}$, computed as

$$\mathbf{A} = \mathbf{Z}\hat{\mathbf{x}}^{-1}, \tag{1}$$

where $\mathbf{Z}$ is the intermediate transactions matrix and $\hat{\mathbf{x}}$ is a diagonal matrix of total outputs. Entries $a_{i,j}$ are technical coefficients representing the intermediate input from region-sector i required per unit of output of region-sector j. We compare this perspective with the supply view, which builds on the allocation coefficient matrix

$$\mathbf{B} = \hat{\mathbf{x}}^{-1}\mathbf{Z}. \tag{2}$$

In this matrix, entries $b_{i,j}$ represent the share of region-sector i's output that is sold to region-sector j (Miller and Blair, 2012, p. 543).[4]

Equipped with the technical and allocation coefficient matrices for each year, we filter the baseline input–output network by applying a threshold to link weights. This step determines which inter-sectoral linkages are retained for the tree construction in the next step. As the threshold increases, weaker links are removed and the network becomes sparser, eventually reducing the number of production trees. At the same time, the distribution of tree sizes is important, as greater variation facilitates the analysis of differences in tree topology. Following Zhu et al. (2015), we select the threshold that maximizes the coefficient of variation in tree size while still retaining a sufficiently large number of trees. As shown in Figure 6 in the appendix, a minimum threshold of 0.015 is close to this optimum for both the demand and supply perspectives. We therefore use this threshold in the subsequent empirical analysis.

[4]While we focus on direct input contributions to assess the quantitative importance of links between nodes on two adjacent layers of the tree, Zhu et al. (2015) employ the Leontief inverse and thus capture direct and indirect input contributions. Since this method can lead to the repeated enumeration of links, and given that we seek to delineate the actual monetary flow of goods and supporting services between region-sectors, we concentrate exclusively on first-order linkages.

4.2 Deriving Production Trees from the Network

In the next step, we employ a breadth-first search algorithm to generate supply and demand trees for each sector in a given region (for a detailed description of the algorithm, see e.g. Cormen et al., 2022, chapter 22). The algorithm is applied to the reduced production network obtained after filtering links, represented by either the technical coefficients matrix (demand perspective) or the allocation coefficients matrix (supply perspective) from the previous step.

The intuition behind the algorithm is as follows. First, we initialize a region–sector as the root node, which forms the bottom layer of the production tree. The tree is then expanded iteratively layer by layer: starting with nodes directly connected to the root, followed by nodes connected to the first-layer nodes, and so on. In each step, we identify all nodes directly connected to those in the previous layer and add them to the tree, provided that the corresponding links do not represent self-loops and that the nodes are not already present in the tree. The procedure continues until no additional nodes can be added.

4.3 Estimating Input Specificity via Allometric Scaling

To quantify the structure of production trees, we follow the methodology proposed by Zhu et al. (2015) and examine the relationship between tree size, s_i, and cumulative tree size, t_i, for each production tree i. Tree size refers to the total number of nodes in the subtree rooted at node i, while cumulative tree size is defined as the sum of the tree sizes of all nodes contained in that subtree.

For illustration, consider the production tree shown on the right in Figure 2-2. All nodes in the top layer have a tree size of one because they are terminal nodes. In the second layer from the top, the first node on the left has a tree size of six, as it forms the root of a subtree containing five additional nodes. The cumulative tree size of this subtree, obtained by summing the tree sizes of its six nodes, equals eleven. We apply this procedure to compute s_i and t_i for the bottom layer of each production tree.

For various combinations of tree size and cumulative tree size derived from pooling observations across an ensemble of trees, t scales with s according to a power law

$$t \sim s^{\eta}, \tag{3}$$

where η is the allometric scaling exponent (ASE). This exponent serves as a summary statistic of production structure that measures the narrowness of a tree. It has two limit cases. When $\eta = 1$, it represents a star (or hub-and-spoke) configuration, where a single hub region-sector is directly connected to all its suppliers (demand view) or customers (supply view). For $\eta = 2$, it represents a hierarchical chain structure, where each region-sector on a given layer is directly linked to only one other region-sector. When the scaling exponent falls within the range $\{\eta \in \mathbb{R} \mid 1 < \eta < 2\}$, the production structure is a hybrid between a chain and a star. We therefore use the allometric scaling exponent as a continuous measure of input specificity. A higher scaling exponent suggests more chain-like, narrow production structures, and greater input specificity. Conversely, a lower exponent implies that the trees are wider, implying lower input specificity. Figure 2-3 illustrates the scaling law for the two theoretical limiting cases (red line for chains and green line for stars), as well as for trees in between (black line).

To determine the allometric scaling exponent based on empirical data, we estimate the following log-log regression using ordinary least squares

$$\ln(t) = \eta \cdot \ln(s) + \epsilon. \tag{4}$$

We perform this estimation from both the supply and demand perspectives, yielding measures for the supply degree of specificity (SDS) and the demand degree of specificity (DDS), such that $\eta \in \{SDS, DDS\}$. It is important to note that the scaling law holds asymptotically for a large number of observations, which precludes estimating the allometric scaling exponent for individual region-sectors in isolation. Instead, we estimate the exponents by pooling observations within regions or sectors.

Measuring substitutability or input specificity is conceptually difficult as it relates to the counterfactual question of how easily a given input could be replaced if it became unavailable or prohibitively expensive. We argue that one can plausibly interpret the chain-likeness of a tree as a measure of input specificity. An input used widely across sectors in a hub-and-spoke configuration is not tailored to the needs of any single production process, making it easier to replace in the event of failure. In contrast, a more chain-like structure suggests that an input is closely adapted to production across specific sectors and thus more difficult to substitute. In this sense, our proposed measure of chain-likeness serves as a proxy for the substitutability of a given input used in the production of final goods or inputs of another sector.

For intuition, consider two stylized cases. Generic but scarce inputs such as rare earth minerals may be purchased by many downstream users. In our topology, this typically corresponds to a broad (star-like) supply tree and thus low topological specificity - even though market power may arise from supplier concentration or geopolitical scarcity. By contrast, customized intermediate goods (e.g., specialized automotive components produced for a narrow set of downstream processes) tend to generate narrow, chain-like supply trees, capturing low substitutability. In such settings, production often relies on firm- and task-specific know-how, so workers are harder to replace quickly, and temporary disruptions are less easily mitigated by switching suppliers or reallocating labor. This makes the disruptive potential of labor disputes more salient. Our measure is designed to proxy substitutability/topology rather than physical scarcity or seller concentration.[5] Naturally, this argument only applies to supply specificity, i.e., SDS, not to demand specificity measured by DDS. We therefore do not necessarily expect a positive relationship between DDS and the labor share but do so for SDS, as the ripple effects in case of failure should be higher here.

5 Results

We begin by outlining several general observations regarding the fitted allometric scaling exponents, drawing on the descriptive statistics in Table 2 and the empirical counterpart to the visual abstract in Figure 3. An immediate finding is that all exponents lie clearly within the

[5] We thank an anonymous referee for suggesting this example. Note that our specificity measure captures topological substitutability in production networks (how tailored an intermediate input is to downstream production), not seller concentration, geological scarcity, or geopolitical supply risk. Hence, inputs such as rare earth minerals can generate substantial market power through concentrated supply even if they are topologically non-specific in our sense. Conversely, customized intermediates may be topologically specific and difficult to substitute even when upstream markets are not highly concentrated.

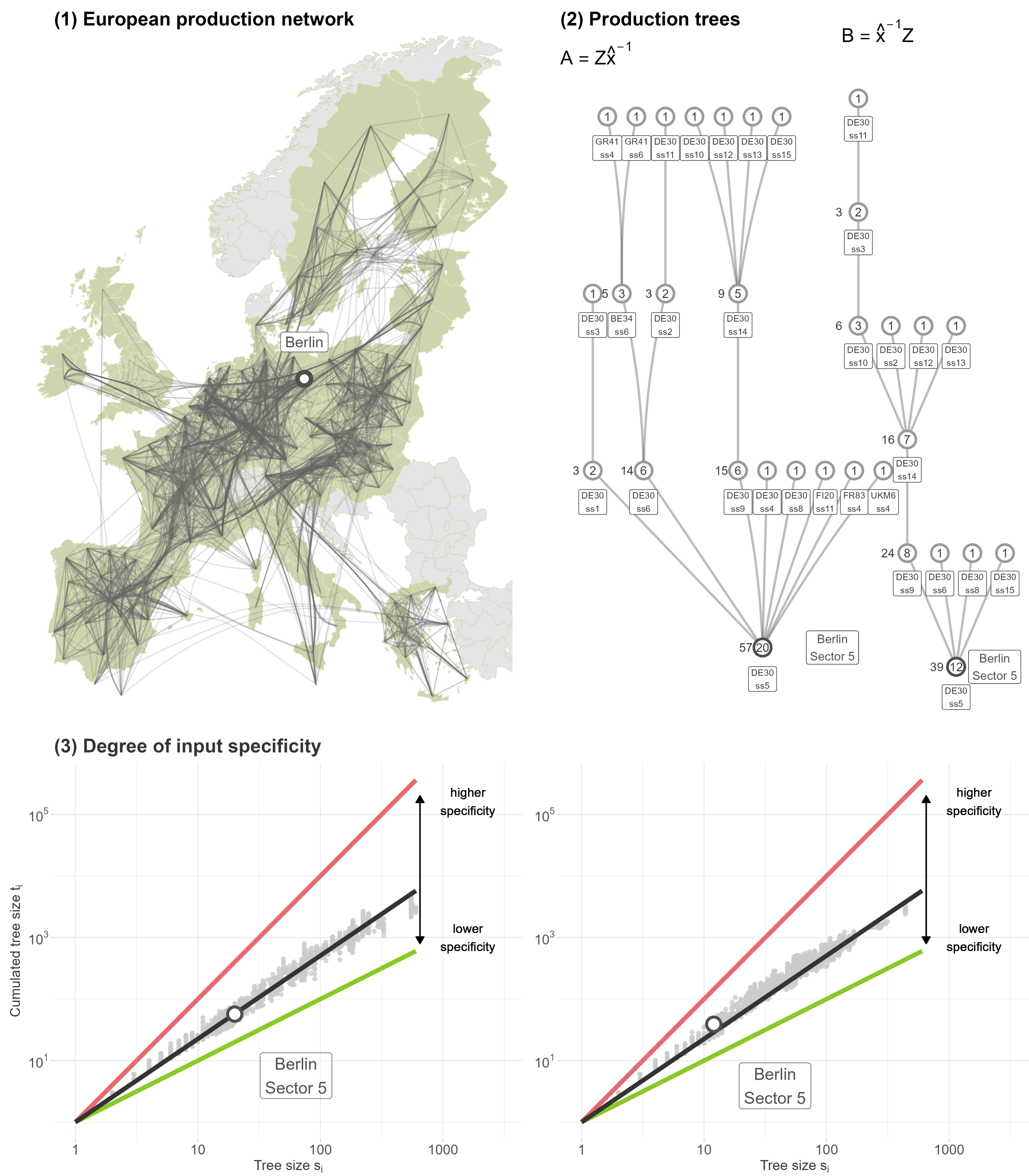

Figure 3: **(1)**: Network representation of the EUREGIO data. Nodes represent NUTS-2 regions, and weighted edges capture bilateral trade flows measured as a share of the sending region's total outgoing trade. For visual clarity, only the top one percent of these shares are displayed. **(2)**: Exemplary demand-side (left) and supply-side (right) production trees, shown for the sector Coke, refined petroleum, nuclear fuel and chemical ($SS5$) in Berlin ($DE30$). **(3)**: Allometric scaling relationship between s_i and t_i for demand-side (left) and supply-side (right) production trees. Grey dots represent all trees, while the two specific trees illustrated in panel (2) are highlighted by white circles.

Table 2: Summary statistics for the estimated allometric scaling exponents.

	Min	Mean	Max	SD
Demand View				
Regions ($N = 248$)	1.23	1.37	1.55	0.04
Sectors ($N = 14$)	1.30	1.38	1.53	0.04
Supply View				
Regions ($N = 248$)	1.30	1.41	1.61	0.04
Sectors ($N = 14$)	1.37	1.41	1.45	0.02

range of one to two, suggesting that empirical production structure differs markedly from both chain and star configurations. Our analysis therefore supports the findings of Zhu et al. (2015) using more regionally disaggregated data, indicating that theoretical models of fragmented production based on these topologies are overly simplistic (for a recent example of models based on these topologies, see e.g., Bloesch, Larsen, and Taska, 2022).

Moreover, our comparison of supply and demand trees reveals systematic differences between upstream and downstream production structures, a pattern illustrated by the two exemplary trees in Figure 3-2. The estimated exponents are consistently higher from the supply perspective, implying structures closer to the chain topology than those of demand trees. This pattern suggests greater diversification in demanded inputs and a higher degree of specificity in supplied inputs within the production process.

Although we estimate the scaling exponent using an ensemble of trees, there remains sufficient variation to be exploited in the regression of the labor share on the degree of specificity in Section 5.2. Given the limited number of observations available in the sectoral classification, we conduct these regressions at the regional level, which also exhibits greater variation (see Table 2).

5.1 Patterns of Input Specificity Across Industries and Regions

Figure 4 presents year-by-year estimates of input specificity for different ensembles of production trees, disaggregated by regions in the core and periphery, East and West, and economic sectors. Throughout all years, core regions exhibit lower specificity in demand links but higher specificity in supply links compared to peripheral regions. In line with previous research on the core-periphery divide in Europe (Gräbner et al., 2020), this implies that peripheral regions

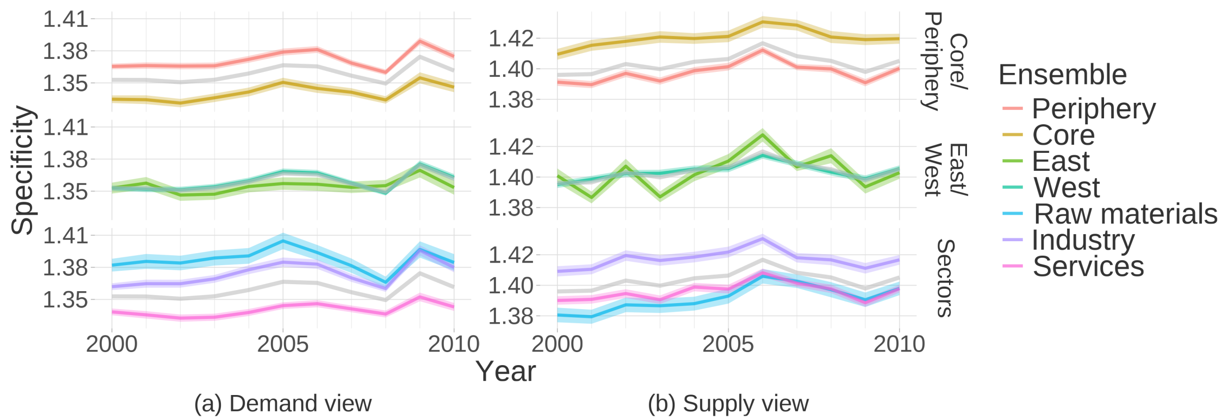

Figure 4: Ordinary least squares estimates of the allometric scaling exponent (input specificity) for regions located in the core and periphery, East and West and for different economic sectors. 95% confidence intervals are computed as ± 1.96 standard errors. Grey lines represent the average allometric scaling exponent.

depend on more specific inputs in their upstream relationships, while supplying comparatively more ubiquitous inputs downstream. In this way, the central asymmetry of dependency theory, which gave rise to the core-periphery distinction, lives on in a modified form. Peripheral regions focus not only on producing primary, rather than refined, intermediate goods, but the average intermediate good they produce is also less specific than that produced in core regions (Kvangraven, 2021). Moreover, due to the lower specificity of inputs produced in peripheral regions, these regions rely on specific imports, as reflected in their relatively higher scaling exponent for demand links.

Perhaps unexpectedly, yet consistent with the findings of Grodzicki and Geodecki (2016), we do not find a similar pattern between Eastern and Western regions, for which the estimated coefficients are relatively similar. Importantly, this does not necessarily imply that Eastern regions produce inputs that are equally “sophisticated” as those produced in Western regions. Our measure of supply specificity captures the extent to which intermediate inputs are tailored to downstream production processes - rather than product complexity or quality. During 2000–2010, Central and Eastern European regions became deeply integrated into European value chains (“Factory Europe”), which plausibly led to convergence in production-network topology even if upgrading trajectories differed. Consistent with this interpretation, the East–West gap in our data emerges less in average levels of specificity than in how specificity translates into labor shares (see also Section 3).[6]

For the sectoral disaggregation, we find similarly plausible results. Raw material sectors rely on relatively specific inputs for their production while supplying their output to a wide range of other sectors. This result is consistent with an "inverted pyramid" structure of production (Cahen-Fourot et al., 2020), where raw materials rely on specific inputs (narrow demand trees) but serve as rather universal inputs for other sectors (broad supply trees). The most striking difference between economic sectors is observed in supply trees, where industrial sectors provide more specialized inputs to the rest of the economy compared to the service and raw materials sectors.

Another notable observation is that the proposed measure of input specificity evolves only gradually over time and remains within a relatively narrow range across all ensembles, at least over the sample period 2000–2010. This suggests that the scaling relationship reflects rather persistent features of the organization of production. At the same time, the data exhibit modest but systematic fluctuations that are broadly shared across regions and sectors. In particular, the exponents rise gradually in the mid-2000s, decline during the global financial crisis, and partially recover thereafter. These dynamics are consistent with a deepening of production relationships in the years following the Eastern European enlargement, followed by a temporary disruption during the crisis. The relatively modest crisis effect is in line with evidence from the international trade literature showing that the collapse in trade during the crisis occurred primarily along the intensive margin - that is, through reductions in trade volumes along existing links rather than the widespread disappearance of trade relationships (see, e.g., Bricongne et al., 2012; Bems, Johnson, and Yi, 2013).

Overall, the systematic heterogeneity we document lends support to the plausibility of the proposed measure of input specificity. Moreover, the ranking of input specificity broadly aligns with the ranking of labor shares across sectors and regions. For example, input specificity is higher in the industrial sector than in services, mirroring the corresponding pattern in labor shares. However, the difference in labor shares between Eastern and Western regions

[6] We also compared input specificity within each sector to assess whether similar aggregate specificity levels between Eastern and Western Europe could be driven by sectoral composition. This comparison does not reveal a clear within-sector gap, and the remaining differences are small and not consistently in one direction. These results suggest that the similarity in aggregate specificity is unlikely to be driven by sectoral composition effects.

documented in Section 3 cannot be explained by differences in input specificity alone. This suggests that additional mechanisms are required to account for the East–West gap in labor shares, an issue we revisit in Section 5.3.

Taken together, these observations suggest that supply-oriented input specificity is a promising candidate for explaining heterogeneity in labor shares. To examine this channel more systematically, we next estimate panel regressions relating input specificity to the labor share.

5.2 Input Specificity and its Relation to the Labor Share

This section presents the regression framework and empirical results. Among the different methods of estimating such a relationship in the context of panel data, the fixed effects within estimator is likely the most widely used. However, since both input specificity and labor share exhibit limited variation over time, and the within transformation removes the time-invariant component of input specificity, the fixed-effects within estimator will likely underestimate the association between production structure and income distribution. To address this issue, we employ correlated random effects estimation, which accounts for both within variation and the structural, time-invariant component of input specificity that we documented in Section 5.1.

Specifically, we estimate

$$LS_{i,t} = a + b_t + c_i + \alpha_0 DDS_{i,t} + \alpha_1 SDS_{i,t} + \alpha_2 \overline{DDS}_i + \alpha_3 \overline{SDS}_i + \alpha_4 \mathbf{X}_{i,t} + \alpha_5 \bar{\mathbf{X}}_i + \epsilon_{i,t} \tag{5}$$

via correlated random effects (Mundlak, 1978), where LS denotes the labor share observed within a region. DDS (SDS) is the degree of specificity for the demand (supply) view, obtained by estimating the scaling law between tree size and cumulative tree size across all sectoral production trees within a region, and $\mathbf{X}_{i,t}$ is a vector of controls. A bar over a variable stands for the time series average. b_t are year dummies and c_i is a region-specific heterogeneity term. The coefficients α_0, and α_1 represent the within effects, indicating whether and how the degree of specificity for backward and forward linkages is associated with the labor share within a region over time. As demonstrated by Wooldridge (2019), estimates of these coefficients are identical to those obtained from the standard fixed effects specification, implying that correlated random effects provides the same information as the standard fixed effects model. However, the former offers additional insights through the between effects, represented by the coefficients α_2 and α_3. These measure whether the degree of specificity correlates with the labor share across regions, capturing structural, time-invariant heterogeneity.[7]

Since our analysis focuses on structural power rather than associational power - which refers to bargaining power derived from the formation of collective organizations (Wright, 2000) - we include three control variables to isolate the effect of structural power. First, we use data on trade union density, defined as the percentage of workers organized in trade unions relative to the total workforce. These data are sourced from the OECD/AIAS database on Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts (ICTWSS). While union density is the most direct proxy for associational power, it is unfortunately not available at the regional level. We therefore assign each region the union density rate of its corresponding country. Second, we incorporate (region-specific) unemployment rates. Third, we capture human capital as the share of employed persons with tertiary education, using data from Eurostat (Eurostat, 2026). This variable proxies the skills required for producing specific inputs (Backman, 2014).

Moreover, to disentangle the qualitative effect of input specificity on structural power from quantitative differences in regional scale or economic importance, we include a size variable as an additional control. This variable is defined as the ratio of a region's value added to total value added across all regions. Its inclusion allows us to account for the structural power workers derive from being employed in a region that contributes a large share of aggregate value added and therefore has greater potential to generate disruptions.[8] Controlling for value added thus accounts for the fact that disruptions originating in economically more important regions are likely to generate larger spillover effects than disruptions originating in smaller

[7] Based on the suggestion of an anoynmous reviewer, we also experimented with a two-stage procedure where, in the first stage, we estimate a standard fixed-effects model including only the time-varying regressors. In the second stage, we regress the estimated region fixed effects on the cross-sectional means of input specificity and the remaining time-invariant controls. The resulting coefficients are identical to those obtained from the Mundlak, 1978 correlated random effects specification in equation (5), consistent with the close relationship between the two approaches.

[8] Importantly, this variable is not intended to proxy for population size, but rather to capture a region's economic weight within production networks. Although population and value added may be correlated, regions with similar population sizes can differ substantially in value added due to differences in industrial structure, productivity, and capital intensity.

regions, even when their positions within the production network are otherwise similar.

We estimate Eq. (5) for regional observations, where cross-sectional units are the 248 NUTS-2 regions. To check the robustness of our findings, we consider different econometric models that vary in the number and composition of explanatory variables and the inclusion of country fixed effects to account for unobserved country heterogeneity.[9] These country fixed effects are primarily motivated by differences in bargaining regimes that are typically based in national legislature and might directly affect labor shares.

Table 3 below summarizes the results. Consistent with our theoretical predictions, the estimated coefficients for both the within and between effect are positive for supply trees. This implies that regions in which the specificity of supplied inputs increases tend to exhibit higher labor shares over time (within effect). At the same time, regions producing more specific inputs exhibit a higher labor share than regions producing more ubiquitous inputs. These effects are highly significant across all model specifications, even after controlling for associational power, human capital and size effects, which hints at the robustness of our findings. Yet a quantitative comparison of the fitted coefficients suggests that the structural between effect is substantially larger than the dynamic within effect, a likely consequence of the relatively strong persistence of the labor share over the sample period. We also find that the effect size for supply trees is typically larger than for demand trees, consistent with the idea that producing rather than sourcing specific inputs leads to a higher labor share through specialized skills and higher bargaining power.

The fourth specification should, in principle, display the most accurate estimate of effect size, as it includes all discussed controls. However, incorporating these controls reduces the sample size by about 30 percent compared to the more parsimonious Models 1 and 2.[10] Therefore, we present both types of model specifications: one that maximizes the number of observations (Model 3) and one that includes additional controls (Model 4).

The highly significant coefficient estimates across all specifications are in line with the hypothesized positive association between supply specificity and labor share in the data. As

[9]As Eq. (5) illustrates, the baseline specification includes region-specific random effects and year fixed effects.

[10]We checked whether the drop in the number of observations may have introduced a systematic bias in our analysis and confirm that missing observations do not cluster systematically in specific regions. In Model 4, the only country with missing data across all regions and all years is the United Kingdom.

Table 3: Correlated random effects estimates of Eq. (5).

	Model 1	Model 2	Model 3	Model 4
Constant	-0.5899**	0.3884***	0.4189***	-0.1152
	(0.2782)	(0.1201)	(0.1270)	(0.1334)
Within				
Supply Degree of specificity	0.0640***	0.0640***	0.0600***	0.0636***
	(0.0137)	(0.0137)	(0.0138)	(0.0160)
Demand degree of specificity	0.0367**	0.0367**	0.0448***	0.0380**
	(0.0147)	(0.0147)	(0.0152)	(0.0171)
Unemployment rate			0.0004***	0.0005***
			(0.0001)	(0.0002)
Union density				-0.0003
				(0.0002)
Human capital				0.0264
				(0.0236)
Size			3.4392***	2.5154**
			(0.9896)	(1.2395)
Between				
Supply degree of specificity	0.7693***	0.1920***	0.2241***	0.2070***
	(0.1486)	(0.0640)	(0.0639)	(0.0671)
Demand degree of specificity	-0.0029	-0.1211**	-0.1818***	-0.1617**
	(0.1430)	(0.0529)	(0.0666)	(0.0727)
Unemployment rate			0.0018***	0.0015***
			(0.0006)	(0.0006)
Union density				0.0159***
				(0.0018)
Human capital				0.0662
				(0.0444)
Size			0.0693	-0.1947
			(0.4435)	(0.4803)
Country fixed effects	No	Yes	Yes	Yes
Number of observations	2728	2728	2507	1974
Marginal R^2	0.096	0.860	0.872	0.862
Conditional R^2	0.954	0.954	0.958	0.955

Notes: Standard errors are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Marginal R^2 reflects the proportion of variance explained by the fixed effects alone, whereas conditional R^2 reflects the proportion of variance explained by both fixed and random effects.

expected, including the country fixed effects considerably reduces cross-sectional variability and, consequently, the between effect. Yet, the latter remains highly significant. In the fourth specification, the significant coefficients of the controls exhibit the expected signs, but do not materially affect the coefficient for supply specificity. We take this to imply that supply specificity represents structural power as a distinct channel, separate from the conventional channels relating to human capital, associational power and size.

The only variable exhibiting an unexpected sign is the unemployment rate. Yet, as we demonstrate in Table 6 in the appendix, its positive coefficient does not represent a stable relationship, but is driven by the period after the global financial and banking crisis. Restricting the sample to the pre-crisis period 2000–2007, the coefficient on unemployment turns negative, consistent with the idea that a deterioration in labor-market conditions reduces bargaining power and, in turn, the labor share. The positive coefficient pertaining to the post-crisis period can be rationalized by nominal wage rigidities in the face of sharp declines in output in times of crisis.[11] If wages adjust sluggishly, while value added is plummeting the labor share increases when unemployment rises (see, e.g., McLaughlin, 1994; Kahn, 1997, for empirical evidence).[12]

To put the estimated coefficients into perspective, consider an increase in supply specificity by its standard deviation of 0.04 (see Table 2). A back-of-the-envelope calculation for the estimated between effect of 0.7693 shows that this corresponds to an increase in the labor share of 3 percentage points, i.e., $\Delta LS = 0.769 \times 0.04 = 0.031$. The resulting increase corresponds to a sizeable share of the variation in regional labor shares (about 38 % of their standard deviation of 0.08). This approximation suggests that the identified channel is not only statistically but also economically significant.

We conducted several additional checks to assess the robustness of our findings. First, we repeat the empirical analysis using alternative thresholds for link selection in the range 0.01–0.02, rather than the baseline value of 0.015 used in the main specification. The results, reported in Figure 7 in the appendix, show that our findings remain qualitatively unchanged.

Second, in Table 7 in the appendix, we report results from a specification that includes the

[11] For theoretical explanations of nominal wage rigidity see, for example, Erceg, Henderson, and Levin (2000), Shapiro and Stiglitz (1984) and Lindbeck and Snower (1986).

[12] In fact, between 2008 and 2010 average value added declined by 1.77 percentage points and total nominal wages by merely 1.07 percentage points across regions in our sample.

capital–output ratio as an additional control variable. The ratio is computed using data from the ARDECO database (Auteri et al., 2024). The inclusion of this control does not qualitatively affect our main results, suggesting that differences in capital intensity cannot account for the variation in labor shares across sectors documented in Figure 4.

Third, we examine whether using gross value added - which includes income accruing to both employees and the self-employed - in the denominator of the labor share biases our results, especially in regions with a high share of self-employment. To address this concern, we include the share of self-employed individuals as an additional control variable. As reported in Table 8 in the appendix, the results remain robust to this modification, indicating that our findings are not materially driven by regional differences in self-employment.

5.3 Geographical Variation in Effect Sizes: East vs. West

The descriptive analysis in Section 3 revealed substantial geographical heterogeneity in the functional distribution of income. In particular, labor shares are markedly higher in the West than in the East (Figure 1), although average levels of input specificity are nearly identical across the two macro-regions (Figure 4). From the perspective of our argument, this pattern poses a puzzle. If input specificity is an important determinant of bargaining power in the context of production networks, differences in structural position alone appear insufficient to account for the pronounced East–West gap in labor shares.

A possible explanation is that institutional arrangements shape distributive outcomes alongside structural positions. Existing work documents systematic institutional differences between Eastern and Western Europe. In many post-socialist economies, wage bargaining is predominantly decentralized at the firm level and often embedded in development strategies characterized by strong cost competition and reliance on foreign capital (Bernaciak, 2015; Astrov et al., 2019). Sectoral evidence further suggests that intense competitive pressure - such as that faced by Eastern European suppliers in buyer-driven value chains - can weaken workers' bargaining positions even when production structures are comparable (Smith et al., 2014). These accounts point to institutional environments in which workers may capture a smaller share of value added despite similar degrees of input specificity.

Conceptually, institutions can affect the functional income distribution in two distinct ways. First, they may exert a *level effect*, shifting labor shares upward or downward independently of workers' structural positions. Second, they may act as *slope shifters*, conditioning the extent to which higher input specificity translates into higher labor shares by amplifying or dampening the returns to structural bargaining power. If institutional arrangements differ systematically between Eastern and Western regions, both mechanisms could in principle contribute to the observed East–West gap in labor shares.

As a first diagnostic step, we examine whether the relationship between supply specificity and labor shares differs across macro-regions. Specifically, we extend Model 1 by interacting the between component of supply specificity with a dummy variable for Eastern regions. The latter serves as a coarse proxy for a bundle of institutional and historical differences that are known to vary systematically across these regions.

Estimates from this specification (see Table 9 in the appendix) indicate differences in marginal effects across macro-regions, but also substantial differences in estimation precision. The average marginal effect of supply specificity on labor shares is 0.66 (SE $= 0.14$, $p < 0.001$) for Western regions. In contrast, the corresponding effect for Eastern regions amounts to 0.04 (SE $= 0.61$) and is statistically indistinguishable from zero ($p = 0.95$). Despite these differences in point estimates, a Wald test fails to reject the null hypothesis that the coefficient on the interaction between supply specificity and the Eastern-region indicator equals zero at conventional significance levels, likely reflecting the relatively small number of observations in Eastern regions.

Figure 5 illustrates these results by translating the estimated coefficients into predicted labor shares over the observed range of supply specificity, holding all remaining covariates constant. For comparable levels of supply specificity, predicted labor shares are systematically higher in Western than in Eastern regions, reinforcing the conclusion that differences in average input specificity alone cannot explain the East–West labor-share gap. At the same time, the wide confidence band around the East-specific relationship highlights considerable estimation uncertainty and underscores the limitations of using a coarse geographical proxy to assess slope heterogeneity.

To directly assess whether bargaining institutions act as slope shifters in the specificity-

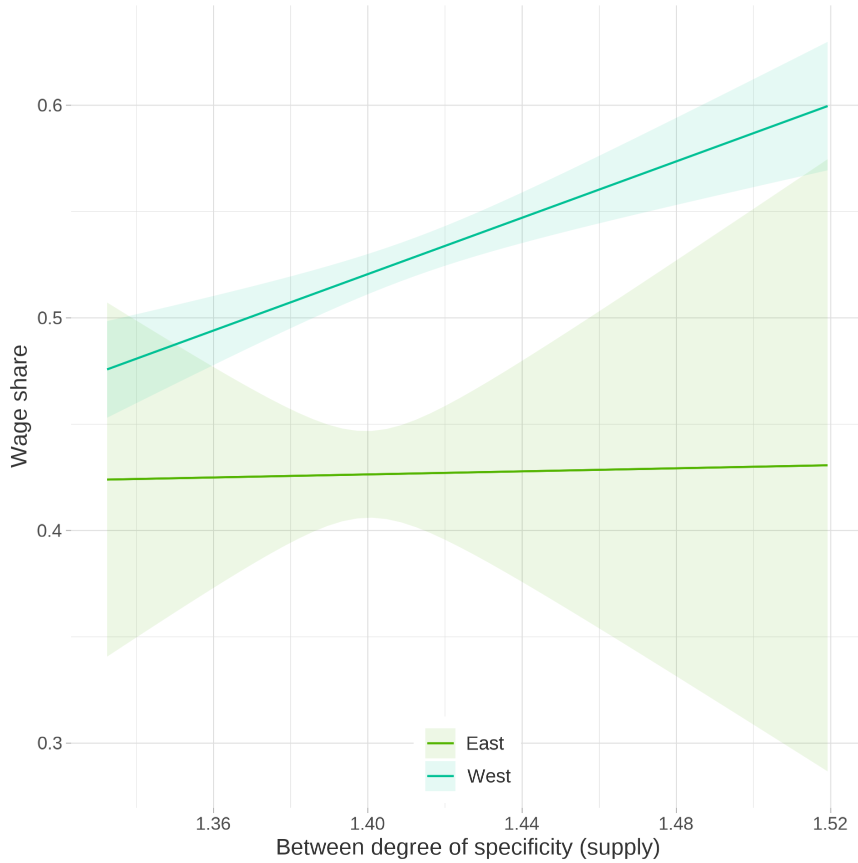

Figure 5: Effect size by macro-regions (East vs. West). The figure illustrates the model-implied relationship between input specificity and the labor share across macro-regions. It is based on an extension of Model 1 that includes an interaction between supply specificity and an Eastern-region indicator. Predicted labor shares are evaluated over the observed range of supply specificity and averaged over the observed values of the remaining covariates.

labor-share relationship, we therefore move beyond the coarse East–West distinction and turn to explicit measures of wage-setting institutions. Specifically, we exploit cross-country variation in bargaining regimes – distinguishing between centralized (coordinated) and decentralized (non-coordinated) systems. Institutional coordination is measured using the coordination index from the OECD ICTWSS database, which ranges from 1 ("no coordination") to 5 ("binding norms"). We collapse this ordinal scale into a binary indicator that equals 1 when no wage coordination is present and 0 otherwise. This transformation reflects our focus on the presence versus absence of coordination rather than differences in its intensity. As expected, this institutional divide overlaps strongly with the East–West split in our sample: the vast majority of Western observations fall under coordinated bargaining (1,877 coordinated vs. 4 non-coordinated), whereas Eastern observations are predominantly characterized by non-coordinated regimes (405 non-coordinated vs. 35 coordinated). Importantly, however, this overlap is not perfect. The presence of a non-trivial number of coordinated observations in the East and few non-coordinated observations in the West provides slightly more identifying variation beyond geography, allowing us to more directly test whether bargaining institutions condition the extent to which structural power translates into higher labor shares.

As Table 10 in the appendix shows, the average marginal effect of supply specificity on labor shares is 0.62 (SE $= 0.16$) and highly statistically significant in coordinated wage bargaining regimes ($p < 0.001$). In contrast, the corresponding effect in non-coordinated regimes is 0.13 (SE $= 0.31$) and statistically indistinguishable from zero ($p = 0.69$). A Wald test of the interaction between supply specificity and the coordinated bargaining indicator points to heterogeneous effects across bargaining regimes ($p = 0.075$), suggesting that the relationship between supply specificity and labor shares differs across institutional settings.[13]

Taken together with the East–West comparison, these findings suggest that large geographical differences in labor shares are primarily reflected in level differences in predicted labor shares at comparable degrees of supply specificity. At the same time, the institutional results indicate that bargaining regimes may also condition the returns to structural power, shaping the slope of the specificity-labor-share relationship under certain institutional arrangements. This pattern is consistent with a view in which institutions influence bargaining outcomes both independently of firms' structural positions and, more tentatively, by augmenting the extent to which structural power translates into higher labor shares.

6 Discussion

Adding to the literature on the nature and causes of inter-regional inequality, this study shows that production networks are systematically related to the functional income distribution, as regions producing more specific inputs tend to exhibit higher labor shares. It offers several contributions. First and foremost, we propose a methodology to empirically assess and

[13] In the coordination–specificity interaction model, we omit country fixed effects because the bargaining-regime indicator is measured at the national level and exhibits very limited within-country variation over time. As a result, it is nearly collinear with country fixed effects, leaving insufficient within-country variation for reliable identification.

compare the level of input specificity in fragmented production systems. Building on the pioneering work of Zhu et al. (2015), this methodology disaggregates the input-output network into production trees for individual region-sectors, interpreting the structure of these trees as a phenomenological measure of input specificity.

Furthermore, we test the structural power hypothesis of wage determination, which posits that workers' position in the production system influences the labor share. Supporting this hypothesis, our regression analysis indicates a positive relationship between supply specificity and the labor share, thus helping to explain why labor shares tend to be higher in core regions and in industrial sectors. Our study is thus an important step to integrate power considerations and class analysis into the study of global production networks.

While the concept of 'disruptive potential' seems closely related to the structural power argument in Perrone, Wright, and Griffin (1984), previous research assessed this potential primarily by the quantitative weight of inputs in the production process, without considering their substitutability. Our approach may therefore also help to explain a recent puzzle raised by Nowak (2022), namely that logistics workers occupying 'choke points' struggle to leverage this structural power to secure higher wages. Nowak (2022) attributes this partially to the political orientation of trade unions in his case study of Brazilian truck drivers. Our complementary, yet more quantitative, explanation emphasizes the limited substitutability of inputs as another necessary condition for realizing disruptive potential.

Comparing Eastern and Western regions in the European Union, our findings reveal a more nuanced picture. Despite notable differences in average labor shares, Eastern and Western regions show little variation in average input specificity. At the same time, our interaction analysis yields suggestive evidence that the positive association between supply specificity and the labor share is stronger under coordinated bargaining regimes. Taken together, these results indicate that the East–West gap in labor shares cannot be explained by input specificity alone. Rather, they are consistent with the view that institutional settings shape how structural positions in production networks translate into income for workers, primarily through affecting labor shares independently of structural power and thus generating level shifts and, more tentatively, through differences in the returns to structural power, i.e., by acting as a slope shifter. In this respect, our findings seem consistent with prior research indicating that institutional, skill, and bargaining power disparities are important determinants of regional inequality (Bathelt, Buchholz, and Storper, 2024). However, our results suggest that they operate on different levels: while skill, human capital investment, and structural power shape workers' bargaining potential, institutions condition how far this potential is realized in observed labor shares. As a result, policies aimed at strengthening workers' bargaining positions may disproportionately benefit those already in favorable positions within the production network.

Despite these positive findings, our study has several limitations as well. First, the availability of regional data is, unfortunately, limited, restricting the number of control variables that we can reasonably include into the regression models. Second, the coverage of our dataset is limited to the relatively short period 2000—2010 for which the labor share in Europe is relatively stable. This hinders the application of empirical methods exploiting time variation in the data, which would be appropriate to study the fall of the labor share as a long-term phenomenon with its onset already in the mid-1970s for most European economies (Gutiérrez and Piton, 2020).

Our study suggests several avenues for further research. First, as input specificity should also pertain to production processes at the firm level, testing our hypothesis within firm-level production networks could reveal insights that may be obscured by the sectoral aggregation in our dataset. Second, while we attempt to control for potential confounders, the limitations of our dataset allow us to document only a robust correlation, without inferring causality. Apart from standard methods of causal inference, a possible approach to address this limitation could involve directly examining how supply chain topology impacts perceptions of disruptive potential among workers and management. An investigation of this kind would certainly strengthen the credibility of our proposed mechanism by showing that network topology directly influences bargaining behavior. Despite these limitations, we believe that our empirical study provides new insights into the determinants of the functional income distribution, linking the topology of production networks to regional labor shares.

Conflict of interest statement

All authors declare that they have no conflicts of interest.

Funding statement

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Data access statement

The data analysed in this study, along with the R code to reproduce all results, figures, and tables, are available in a Mendeley repository at https://doi.org/10.17632/d422yfrr8r.1.

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A Appendix

A.1 Sample

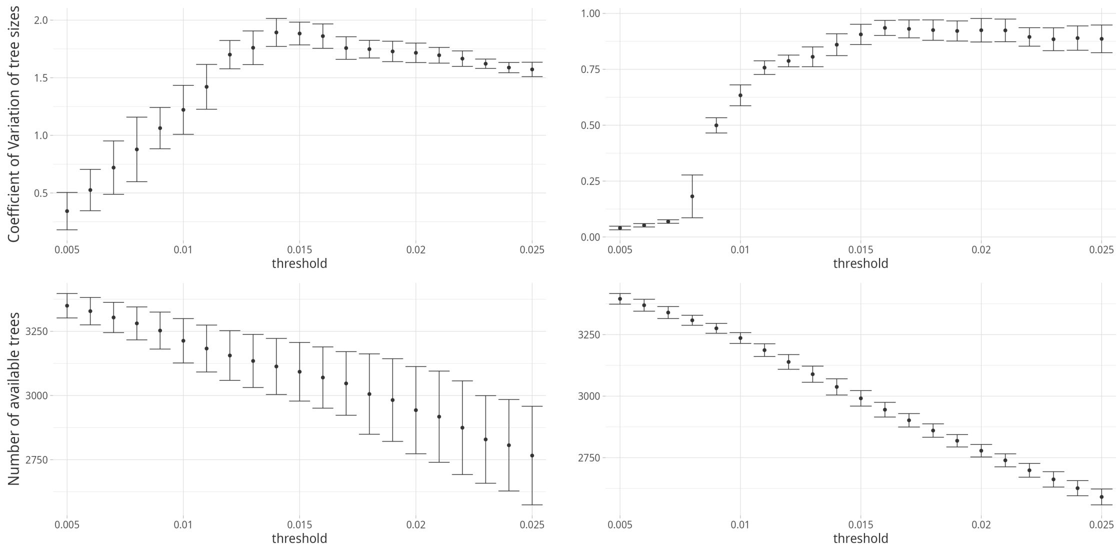
Table 4: Countries in the EUREGIO database.

Country	ISO-code
Austria	*AT*
Belgium	*BE*
Czech Republic	*CZ*
Germany	*DE*
Denmark	*DK*
Estonia	*EE*
Spain	*ES*
Finland	*FI*
France	*FR*
Greece	*GR*
Hungary	*HU*
Ireland	*IE*
Italy	*IT*
Lithuania	*LT*
Luxembourg	*LU*
Latvia	*LV*
Malta	*MT*
Netherlands	*NL*
Poland	*PL*
Portugal	*PT*
Sweden	*SE*
Slovenia	*SI*
Slovakia	*SK*
United Kingdom	*UK*

Table 5: Sectors in the EUREGIO database.

Category	Sector	Sector Code
Raw materials	Agriculture	$S1$
	Mining, quarrying and energy supply	$S2$
Industry	Food, beverages and tobacco	$S3$
	Textiles and leather	$S4$
	Coke, refined petroleum, nuclear fuel and chemicals	$S5$
	Electrical, optical and transport equipment	$S6$-$S7$
	Other manufacturing	$S8$
	Construction	$S9$
Services	Distribution	$S10$
	Hotels and restaurants	$S11$
	Transport, storage and communications	$S12$
	Financial intermediation	$S13$
	Real estate, renting and business activities	$S14$
	Non-market services	$S15$

A.2 Determination of the threshold for link weights



(a) Demand view

(b) Supply view

Figure 6: Average coefficient of variation of tree sizes (top) and average number of available trees (bottom) as a function of the threshold for link weights. The mean is computed over $T = 11$ years from 2000 to 2010. 95% confidence intervals are computed as $t_{1-0.05/2,\,T-1} \approx 2.23$ standard errors, where $t_{1-0.05/2,\,T-1}$ denotes the 97.5th percentile of Student's t distribution with 10 degrees of freedom, and the standard error is the sample standard deviation divided by $\sqrt{T}$.

A.3 Robustness checks

Table 6: Correlated random-effects estimates of Eq. (5) for the period 2000–2007.

	Model 1	Model 2	Model 3	Model 4
Constant	-0.6290**	0.3973***	0.4190***	-0.1363
	(0.2834)	(0.1244)	(0.1313)	(0.1397)
Within				
Supply degree of specificity	0.0535***	0.0542***	0.0461***	0.0352**
	(0.0144)	(0.0144)	(0.0146)	(0.0166)
Demand degree of specificity	0.0568***	0.0550***	0.0618***	0.0592***
	(0.0168)	(0.0167)	(0.0173)	(0.0196)
Unemployment rate			-0.0001	-0.0005**
			(0.0002)	(0.0002)
Union density				0.0007***
				(0.0003)
Human capital				-0.0234
				(0.0257)
Size			6.2980***	7.3328***
			(1.4401)	(1.6314)
Between				
Supply degree of specificity	0.7999***	0.1808***	0.2207***	0.2072***
	(0.1514)	(0.0663)	(0.0660)	(0.0702)
Demand degree of specificity	-0.0057	-0.1156**	-0.1786***	-0.1561**
	(0.1457)	(0.0548)	(0.0689)	(0.0762)
Unemployment rate			0.0021***	0.0018***
			(0.0006)	(0.0006)
Union density				0.0161***
				(0.0019)
Human capital				0.0794*
				(0.0466)
Size			0.1445	-0.1354
			(0.4584)	(0.5033)
Country fixed effects	No	Yes	Yes	Yes
Number of observations	1984	1984	1811	1421
Marginal R^2	0.102	0.869	0.881	0.869
Conditional R^2	0.968	0.968	0.971	0.969

Notes: Standard errors are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Marginal R^2 considers only the variance of the fixed effects, while the conditional R^2 takes both fixed and random effects into account.

Table 7: Correlated random effects estimates of Eq. (5), including capital intensity as additional control variable.

	Model 1	Model 2	Model 3	Model 4
Constant	-0.5899**	0.4005***	0.4401***	-0.1094
	(0.2782)	(0.1245)	(0.1297)	(0.1348)
Within				
Supply degree of specificity	0.0640***	0.0466***	0.0443***	0.0398**
	(0.0137)	(0.0139)	(0.0138)	(0.0157)
Demand degree of specificity	0.0367**	0.0378**	0.0469***	0.0400**
	(0.0147)	(0.0148)	(0.0151)	(0.0168)
Unemployment rate			0.0001	0.0001
			(0.0002)	(0.0002)
Union density				-0.0010***
				(0.0002)
Human capital				-0.0297
				(0.0238)
Size			1.5494	2.1223*
			(1.0343)	(1.2357)
Capital intensity		0.0228***	0.0238***	0.0264***
		(0.0023)	(0.0024)	(0.0029)
Between				
Supply degree of specificity	0.7693***	0.1966***	0.2188***	0.2029***
	(0.1486)	(0.0649)	(0.0644)	(0.0673)
Demand degree of specificity	-0.0029	-0.1304**	-0.1869***	-0.1647**
	(0.1430)	(0.0568)	(0.0686)	(0.0738)
Unemployment rate			0.0019***	0.0016***
			(0.0006)	(0.0006)
Union density				0.0162***
				(0.0018)
Human capital				0.0702
				(0.0449)
Size			0.0082	-0.1893
			(0.4626)	(0.4848)
Capital intensity		-0.0016	-0.0016	-0.0015
		(0.0019)	(0.0020)	(0.0020)
Country fixed effects	No	Yes	Yes	Yes
Number of observations	2728	2486	2421	1928
Marginal R^2	0.096	0.868	0.874	0.867
Conditional R^2	0.954	0.959	0.961	0.958

Notes: Standard errors are shown in parentheses. ***, **, and * indicate statistical significance at the 1%,5%, and 10% level, respectively. Marginal R^2 reflects the proportion of variance explained by the fixed effects alone, whereas conditional R^2 reflects the proportion of variance explained by both fixed and random effects.

Table 8: Correlated random effects estimates of Eq. (5), including the share of self-employed as additional control variable.

	Model 1	Model 2	Model 3	Model 4
Constant	0.2810	0.4297***	0.4705***	-0.0814
	(0.2390)	(0.1203)	(0.1266)	(0.1330)
Within				
Supply degree of specificity	0.0613***	0.0452***	0.0441***	0.0390**
	(0.0140)	(0.0139)	(0.0138)	(0.0157)
Demand degree of specificity	0.0289*	0.0338**	0.0470***	0.0377**
	(0.0150)	(0.0149)	(0.0151)	(0.0169)
Unemployment rate			0.0001	0.0001
			(0.0002)	(0.0002)
Union density				-0.0010***
				(0.0002)
Human capital				-0.0253
				(0.0240)
Size			1.5596	2.2046*
			(1.0395)	(1.2368)
Capital intensity		0.0224***	0.0238***	0.0272***
		(0.0024)	(0.0024)	(0.0030)
Share self-employed	-0.0823***	-0.0050	0.0025	0.0445
	(0.0253)	(0.0256)	(0.0265)	(0.0299)
Between				
Supply degree of specificity	0.2194*	0.1462**	0.1737***	0.1726**
	(0.1285)	(0.0637)	(0.0641)	(0.0672)
Demand degree of specificity	0.0047	-0.0822	-0.1469**	-0.1271*
	(0.1168)	(0.0560)	(0.0679)	(0.0741)
Unemployment rate			0.0014**	0.0013**
			(0.0006)	(0.0006)
Union density				0.0156***
				(0.0018)
Human capital				0.0788*
				(0.0443)
Size			-0.0543	-0.2498
			(0.4511)	(0.4774)
Capital intensity		-0.0015	-0.0013	-0.0013
		(0.0019)	(0.0020)	(0.0020)
Share self-employed	-0.6867***	-0.2334***	-0.1961***	-0.1538**
	(0.0558)	(0.0565)	(0.0574)	(0.0608)
Country fixed effects	No	Yes	Yes	Yes
Number of observations	2538	2452	2420	1927
Marginal R^2	0.436	0.876	0.879	0.870
Conditional R^2	0.957	0.959	0.961	0.958

Notes: Standard errors are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Marginal R^2 considers only the variance of the fixed effects, while the conditional R^2 takes both fixed and random effects into account.

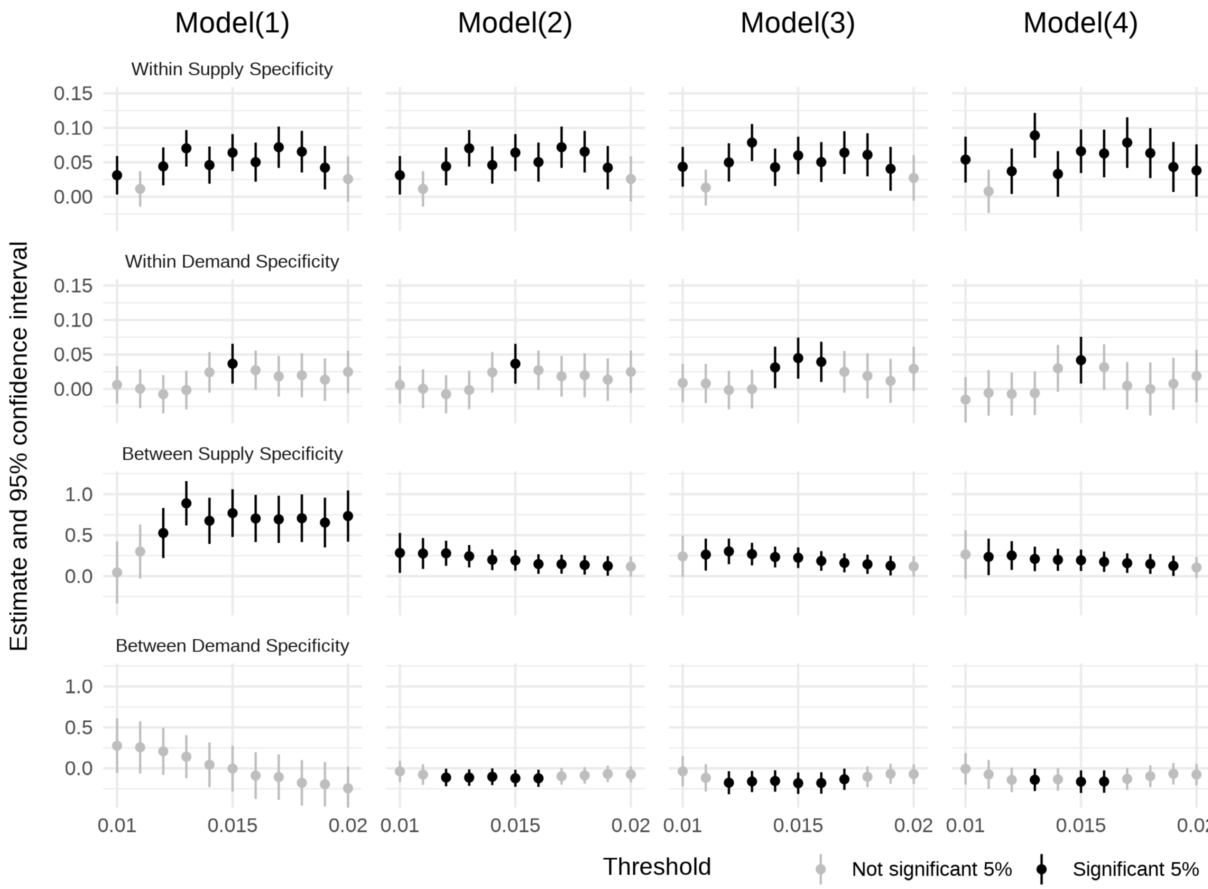


Figure 7: Estimates of the within and between effects across alternative thresholds for link weights and model specifications reported in Table 3. Error bars indicate 95% confidence intervals. Black estimates are statistically significant at the 5% level.

A.4 Interactions

Table 9: Correlated random effects estimates of Eq. (5), including an additional interaction between supply specificity and a dummy for regions in Eastern Europe.

	Model 1	Model 2
Constant	-0.1745	0.3633***
	(0.2588)	(0.1239)
Within		
Supply Degree of specificity	0.0640***	0.0640***
	(0.0137)	(0.0137)
Demand degree of specificity	0.0367**	0.0367**
	(0.0147)	(0.0147)
Between		
Supply degree of specificity	0.6630***	0.2042***
	(0.1357)	(0.0657)
Demand degree of specificity	-0.1860	-0.1154**
	(0.1291)	(0.0534)
East	0.7837	0.2313
	(0.8748)	(0.4280)
Supply degree of specificity x East	-0.6271	-0.2602
	(0.6246)	(0.3100)
Country fixed effects	No	Yes
Number of observations	2728	2728
Marginal R^2	0.285	0.860
Conditional R^2	0.954	0.954

Notes: Standard errors are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Marginal R^2 considers only the variance of the fixed effects, while the conditional R^2 takes both fixed and random effects into account.

Table 10: Correlated random effects estimates of Eq. (5), including an interaction of between supply degree of specificity and a dummy for uncoordinated wage bargaining.

	Model 1	Model 2
Constant	-0.3827	0.3900***
	(0.2931)	(0.1311)
Within		
Supply Degree of specificity	0.0806***	0.0792***
	(0.0160)	(0.0159)
Demand degree of specificity	0.0387**	0.0390**
	(0.0166)	(0.0166)
Between		
Supply degree of specificity	0.6188***	0.1869***
	(0.1578)	(0.0691)
Demand degree of specificity	-0.0048	-0.1171**
	(0.1485)	(0.0567)
No coordination	0.6801*	0.0545
	(0.3851)	(0.3098)
Supply degree of specificity x No coordination	-0.4938*	-0.0362
	(0.2775)	(0.2235)
Country fixed effects	No	Yes
Number of observations	2321	2321
Marginal R^2	0.071	0.854
Conditional R^2	0.948	0.950

Notes: Standard errors are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. Marginal R^2 considers only the variance of the fixed effects, while the conditional R^2 takes both fixed and random effects into account.