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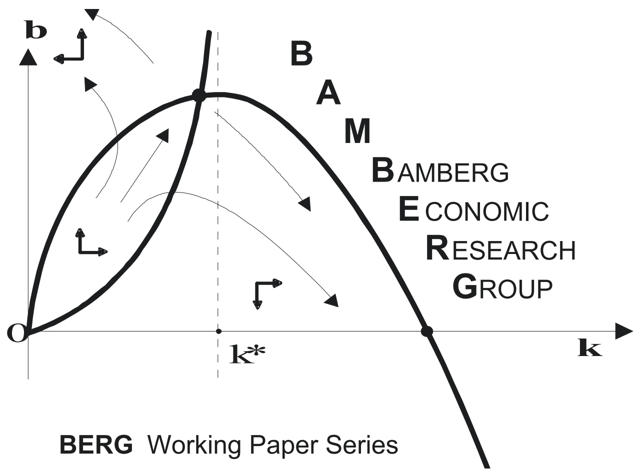

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Input specificity and labor's bargaining power: A production tree approach to functional income distribution[*]

Lasare Samartzidis[†] Philipp Mundt[‡] Jan Schulz[§]

Abstract

This article examines how input relationships in fragmented production systems shape functional income inequality. We argue that input specificity — reflecting the degree of specialization in intermediate goods production — affects workers' bargaining power and, consequently, the labor share through skill premia and the disruptive potential of strikes. Using regional input-output data for European economies and a novel methodology for constructing sectoral production trees, we measure input specificity and analyze its impact on the functional income distribution. Our results suggest significant regional and sectoral differences in input specificity and reveal a robust positive association between input specificity and labor share, offering new insights into regional economic inequality.

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1 Introduction

Economic inequality is one of the major challenges in the 21st century (Atkinson, 2013). Increasing 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 aspect of inequality is the functional income distribution, which describes who reaps the benefits of value-added created in the production process. Over the past forty years, the organization of production and global trade patterns have undergone a significant transformation. Driven by major advancements in information and communication technology, along with a steady trend toward trade liberalization, production has become increasingly vertically fragmented and geographically dispersed. This "rise of global value chains" (Antràs, 2020) shifted trade from final to intermediate goods and specialized tasks. However, the implications of this transformation on the functional income distribution remain elusive.

One key factor influencing functional inequality is the relative bargaining power of workers and firms. When labor markets are imperfectly competitive, higher bargaining power of labor leads to higher wages and, under the assumption of inelastic labor demand, an increase in the labor share (McDonald and Solow, 1981). In this paper, we highlight a channel that links labor's bargaining power to input specificity and relational structures in fragmented production. Our understanding of input specificity builds on the definition by Barrot and Sauvagnat (2016), where it denotes the importance and, consequently, the degree of specialization of intermediate goods in the production process.

Input specificity is theoretically linked to wages and labor share through two channels. First, the production or use of specific inputs in the production process likely requires 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 calls "structural power" (Perrone, Wright, and Griffin, 1984; Wallace, Griffin, and Rubin, 1989; Wright, 2000; Selwyn, 2012; Schmalz, Ludwig, and Webster, 2018; Nowak, 2022). Therefore, a strike in a sector producing essential intermediate goods has more disruptive potential than in a sector with easily substitutable inputs, which increases workers' bargaining power and wages. Both channels lead us to hypothesize that higher specificity is associated with higher labor shares.[1] However, to the best of our knowledge, no empirical studies have yet examined whether producing more specific output leads to higher labor shares. This raises the question: can relational structures within the production network predict the labor share?

To measure input specificity, we apply a methodology recently proposed by Zhu et al. (2015). This approach simplifies the complexity of the entire production network by constructing production trees for individual root nodes, representing economic sectors in geographical regions. These production trees capture the essential input relationships between nodes and exhibit two extreme configurations: a chain structure, where each node is directly linked to only one other node, and a hub-and-spoke or star configuration, where a single hub is connected to many other nodes. This methodology enables us to analyze production linkages from the perspective of an individual region-sector, rather than taking a bird's-eye view of the entire network.

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 likely 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 in 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.

An important innovation of our paper is the examination 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 prosperity, and the functional distribution of income. We argue that a regional level of aggregation is more appropriate to study the role of input specificity, as

[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.

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 obtain the following main results. First, our measurement of production structure suggests that theoretical models of disaggregated production activities assuming value 'chains' or hub-and-spoke networks are overly simplistic. Instead, more realistic models should conceptualize input relationships as more complex topological structures in between these two extremes, aligning with the concept of global production networks outlined in 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 the functioning of the economy. In contrast, manufacturing sectors undergo numerous consecutive stages of industrial processing that increase the degree of specificity before final products are sold in end consumer markets, making production trees in these sectors more chain-like.

Third, our analysis uncovers significant regional heterogeneity in input specificity. The European periphery relies on inputs with above-average specificity while supplying more ubiquitous intermediates. In contrast, core regions exhibit the opposite pattern, receiving inputs with below-average specificity but producing more specialized inputs. This observation aligns with previous findings on the relatively lower complexity of peripheral production, a related but distinct concept (Gräbner et al., 2020). Distinguishing between regions in Central and Eastern Europe as well as Western Europe, we find that heterogeneity in production structure largely disappears. Therefore, it seems that bargaining institutions in Western Europe enable workers to leverage their favorable positions within the production network more effectively, thereby increasing their labor share compared to Eastern Europe.

Fourth, we conduct panel regressions to investigate the relationship between input specificity and labor share. Consistent with our hypothesized effect, we find a significantly positive relationship across various model specifications, implying that the production of more specific inputs is associated with higher labor shares. Given the slowly varying nature of both variables, however, the relationship seems structural and thus better explains cross-sectional differences in the labor share than time trends therein.

The remainder of this paper is organized as follows: Section 2 reviews related literature. Section 3 introduces our regional data, while we explain our methodology in more detail in Section 4. Section 5 presents descriptive findings on regional and sectoral differences regarding the structure of production trees and employs regression analysis to obtain inferential results on the nexus between production structure and the labor share. Section 6 concludes, discusses our study's limitations and posits avenues for further research.

2 Related literature

Our study relates to other research analyzing the distribution of factor incomes. After being famously constant for most of recorded history (Kaldor, 1961), the recent secular decline in the US 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). One view in this literature highlights the role of capital accumulation in explaining shifts in the functional income distribution. Piketty (2014) spotlights the increase in aggregate savings, while Karabarbounis and Neiman (2014) argue that a drop in the price of investment goods might have led to a rise in the capital-output ratio that depresses the labor share.

Another prominent view in the extant literature holds that technological change is a major determinant of income shares. Building on a theoretical task-based model in the spirit of Acemoglu and Autor (2011), Acemoglu and Restrepo (2018) argue that automation contributes to lower labor shares. 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) provide insights into the micro origins of the income distribution. While the former attribute the declining labor share to the rise of superstar firms, which have high profit margins and a low labor share in value added, the latter present evidence that the reallocation of value added towards the lower end of the labor share distribution is primarily driven by firms whose labor share decreases as they grow in size.

More closely related to the argument of this paper are studies that explore the role of bargaining power in explaining functional income distribution. Pertinent research underscores the importance of labor market regulations (Blanchard and Giavazzi, 2003; Ciminelli, Duval, and Furceri, 2022) and the strength of institutions like trade unions (Fichtenbaum, 2011; Henley, 1987) as key determinants of bargaining power. In a seminal study, Stansbury and Summers (2020) show that the decline in worker power statistically accounts for nearly the entire decrease in the labor share of the US economy. While the authors employ various proxies for workers' bargaining power to construct a compelling argument, they do not account for power disparities arising from workers' positions within the production network. This oversight is notable, given that power asymmetries in global value chains (e.g., seller-driven vs. buyer-driven structures) are well documented in the extant literature (Dallas, Ponte, and Sturgeon, 2019), partly using methodologies similar to ours (Iliopoulos, 2022). However, previous studies have not explored power relationships derived from the production structure (Selwyn, 2012), especially not as a determinant of the functional income distribution.

This paper seeks to address this gap by showing that workers involved in the production of critical inputs enjoy a higher labor share in value added, even after controlling for heterogeneity in unionization and unemployment rates. To our knowledge, the only study that hints at 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.

[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.

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, degrees of integration into the production network, 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 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).

Last but not least, the present article connects to the growing body of literature that highlights the role of production networks in explaining economic outcomes. Recent contributions in macroeconomics demonstrate how input linkages facilitate the transmission of idiosyncratic shocks and contribute to aggregate fluctuations (for example, Acemoglu et al., 2012; Baqaee, 2018; Giovanni, Levchenko, and Mejean, 2014). Production networks help explain business cycle comovement (Shea, 2002; Di Giovanni, Levchenko, and Mejean, 2017) and have been shown to amplify the effects of technological improvements (McNerney et al., 2021), with implications for economic development and growth. In related work, Savin and Mundt (2022) and Mundt et al. (2023) show how countries' productivity adjusted for global value chain participation affects growth in individual industries, finding that productive upstream suppliers are an important driver of growth in end-consumer markets. Moreover, recent developments during the COVID-19 pandemic and the Ukraine war highlight how input-output relationships contribute to inflation spillovers. In this context, the study by Weber et al. (2024) identifies sectors that are systemically important for maintaining aggregate price stability. Ipsen, Aminian, and Schulz (2023) and Ipsen and Schulz (2024) apply this methodology to the European Union, confirming the existence of systemically significant prices for Europe and structural differences between Europe's core and periphery that we also document in our study.

Despite this recent surge of interest in the economic implications of production networks, the nexus between input linkages and functional income distribution remains largely unexplored in the existing literature, with the exception of studies that focus specifically on offshoring (Guschanski and Onaran, 2022; Guschanski and Onaran, 2023). Against this background, our work adds to this literature by illustrating how production networks contribute to a better understanding of economic inequality.

3 Data

To analyze the relationship between production relationships and the functional income distribution, our study employs regional 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, offering insights into a key phase of Eastern European economic integration. It classifies the economy into fourteen NACE-2 sectors and includes 248 NUTS-2 regions in 24 European countries, as detailed in Tables 3 and 4 in the appendix. These regions account for approximately 94% of European production and 80% of employment during the sample period, therefore capturing a significant share of Europe's economic activity.

As one empirical innovation of our study, we use NUTS-2 regions as the primary unit of our analysis. The use of detailed regional rather than the usual country-level data enables us to address the "challenge of granularity" (Weber and Schulz, 2024), 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. Similarly, input linkages between European regions empirically depend on the spatial proximity between them (Bolea et al., 2022). Our dataset distinguishes between these structurally distinct regions and allows us to leverage spatial heterogeneity in the analysis.

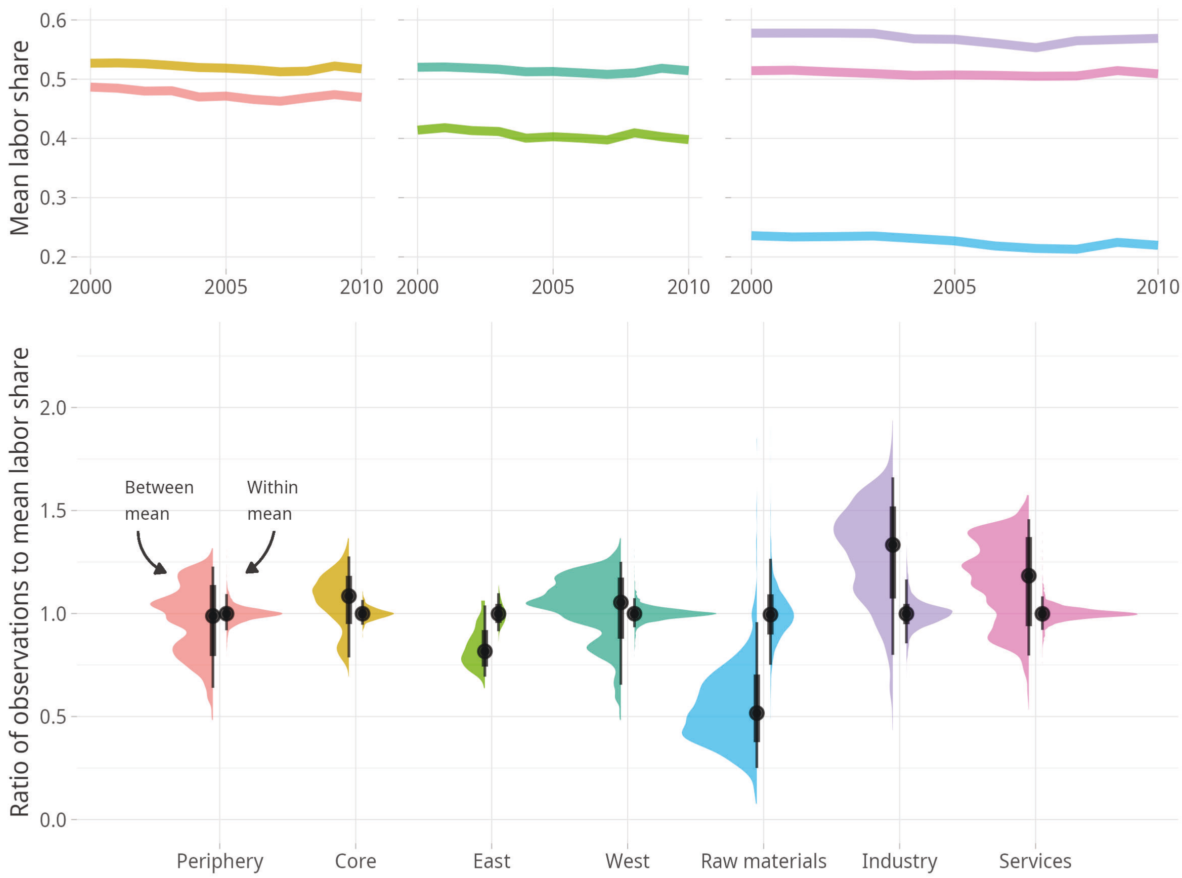


Figure 1: Mean and dispersion of labor shares.

Notes: The top panel shows the time evolution of the average labor share, while the bottom panel illustrates time series and cross-sectional dispersion of labor shares for peripheral and core regions, East and West, and economic sectors. Left violins refer to the ratio of labor share observations to the cross-sectional average (between mean), while violins on the right refer to the ratio of observations to the time series average (within mean).

The key variable for the subsequent empirical analysis of the functional income distribution is the labor share. We calculate it as the ratio of employee compensation 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 clearly 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.

To describe the input relationships between regions, we use input-output matrices from the EUREGIO dataset. 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. A typical annual network consists of 3,724 nodes and approximately twelve million edges. These networks serve as the foundation for building production trees and deriving our measure of input specificity, which we will discuss next.

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

4 Methodology

For the subsequent empirical analysis, we transform the entire production network into an ensemble of production trees, with each region-sector represented by its own tree. We then analyze the structure of these trees by examining the scaling relationship between tree size and cumulative tree size. A detailed explanation of our methodology is provided below, accompanied by a visual guide in Figure 2 to illustrate our approach.

4.1 Construction of production trees

To reduce the overall complexity of the production network and isolate the production tree for a specific industry in a given region, we follow Zhu et al. (2015) and model input relationships as production trees. Each production tree starts from a different region-sector as root node. The trees are then constructed layer by layer, beginning with nodes directly connected to the root, followed by nodes connected to the first-layer nodes, and so on.

However, we diverge from Zhu et al. (2015) in three main aspects. First, we focus on direct output contributions to assess the quantitative importance of links between nodes on two adjacent layers of the tree. This contrasts with the approach of Zhu et al. (2015), which employs the Leontief inverse to capture first and all higher-order linkages, including direct and indirect output 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.

Second, we complement the demand perspective in Zhu et al. (2015) with a supply perspective. The demand perspective relates to seminal work by Leontief and measures the impact of output changes on input requirements along backward linkages. The supply perspective, by contrast, follows Ghosh (1958) and reveals which region-sectors receive output through forward linkages. Since many manufacturing processes rely on raw materials that are rarely linked backward to other inputs (Cahen-Fourot et al., 2020; Daly, 1995), the supply perspective provides a more accurate representation of the role of raw materials in production, which is often overlooked in the literature. Formally, the demand view relates to the technical

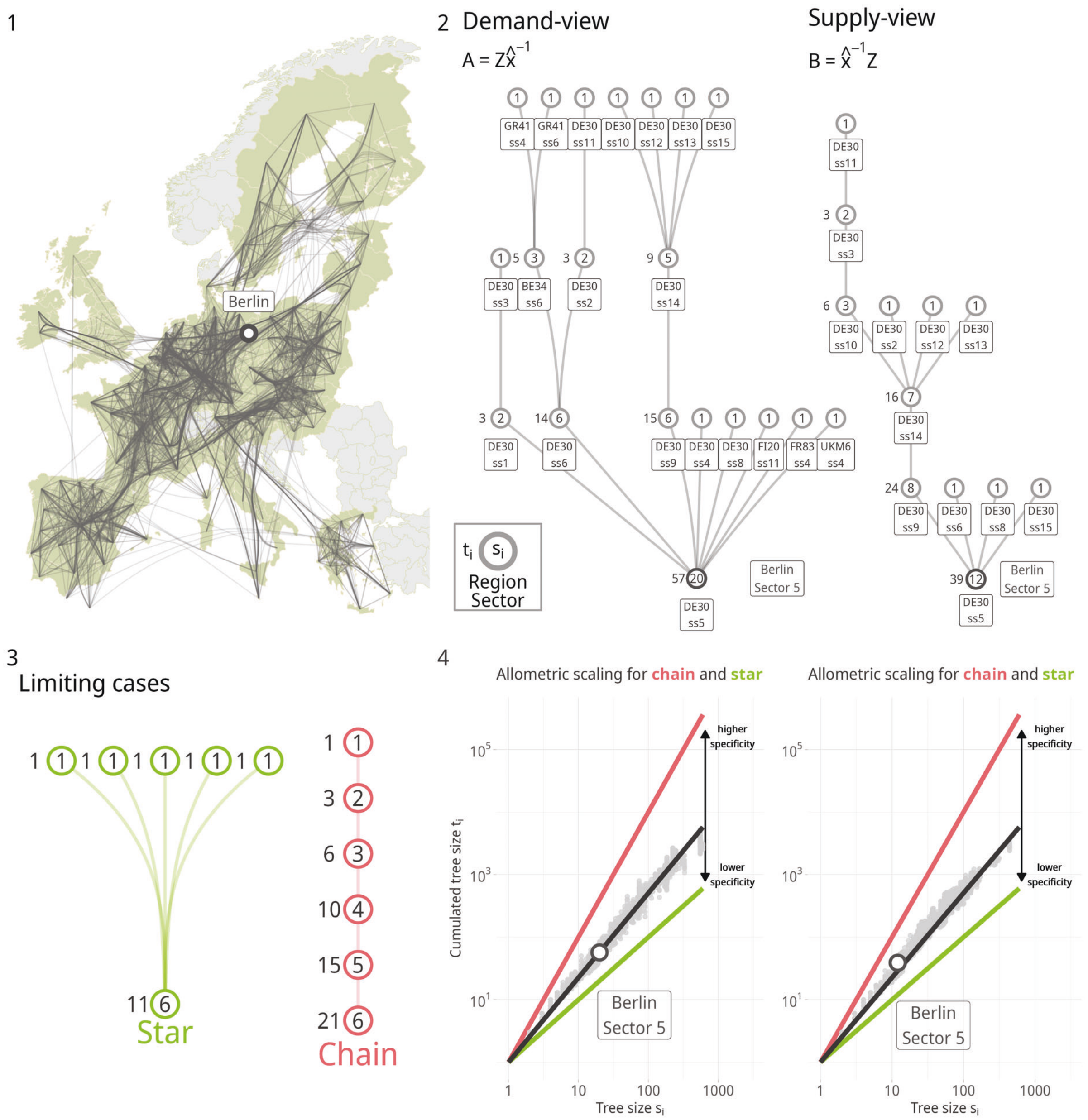


Figure 2: From production networks to production trees.

Notes: **1:** Network representation of the EUREGIO multinational input-output data. Nodes are the centers of NUTS-2 regions and weighted edges represent the share of trade between two regions in total production. To enhance visual clarity, only the top one per cent of all connections in terms of trade value are plotted. **2:** Using the technical coefficient ($\mathbf{A}$) and allocation coefficient matrix ($\mathbf{B}$), we construct production trees for backward and forward linkages by applying a breadth-first search algorithm, using the assumptions stated in the main text. Here, we show an example of a demand and supply tree for the sector *Coke, refined petroleum, nuclear fuel and chemical* ($SS5$) for the German region *Berlin* ($DE30$). The number inside the circle represents tree size, while the number next to the circle is cumulative tree size. **3:** Topology of the two limiting cases, star and chain. **4:** The allometric scaling exponent (ASE) for the relationship between tree size and cumulative tree size is estimated from an ensemble of trees. In this example, all regions are pooled together.

coefficient matrix $\mathbf{A} = (a_{i,j})$ computed from

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

where $\mathbf{Z}$ is the interindustry sales matrix and $\hat{\mathbf{x}}$ is a diagonal matrix of total output. Entries $a_{i,j}$ are technical coefficients that represent the proportion of intermediate input of region-sector i in the total output of region-sector j. We compare this perspective to 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 distribution of region-sector i's output across region-sectors j that purchase inputs from i (Miller and Blair, 2012, p. 543).

Third, we use regional rather than country-level input-output data, which allows for a more detailed understanding of the spatial patterns in production structure by capturing regional economic heterogeneity within countries. Such nuances would be obscured in more aggregated data.

Equipped with the technical and allocation coefficient matrices for each year, we use a breadth-first-search algorithm to construct supply and demand trees for each sector in a given region (Cormen et al., 2022). The intuition of the algorithm can be summarized as follows: In the first step, we initialize one region-sector as the root node, which constitutes the bottom layer of the production tree. Then, to form a new layer of the tree, we determine all nodes that are directly connected to the previous layer. We add them as new leaf nodes if their links do not represent self-loops and have weights above an endogenous threshold, disregarding nodes which are already present in the tree. These steps are repeated until no new leaves can be added.

The threshold for link weights determines the number of production trees that emerge. Specifically, as the threshold increases, the number of available trees decreases because the algorithm identifies fewer quantitatively significant relationships and eventually disregards all linkages to other region-sectors. Additionally, the variation in tree sizes is of interest, as greater variation enhances the potential for analyzing differences in tree topology. Following Zhu et al. (2015), we determine the threshold that maximizes the coefficient of variation while still retaining a relatively large number of trees. As illustrated in Figure 5 in the appendix, we find that a minimum threshold of 0.015 is reasonably close to the optimum for both the demand and supply perspective. Hence, we use this threshold in the subsequent empirical analysis.

4.2 Assessing input specificity using allometric scaling

To assess the structure of production trees with a quantitative summary measure, we adopt the methodology established by Zhu et al. (2015) and analyze the relationship between tree size and cumulative tree size at the bottom layer of each production tree. Tree size, s_i, represents the total number of nodes in the subtree rooted in node i, while cumulative tree size, t_i, is the sum of all s_i values in the subtree rooted in node i. For instance, in the production tree for demand links in Figure 1-2, all nodes on the top layer have a tree size of one because they are terminal nodes. On the second layer from the top, node $DE30 - SS14$ has tree size five, as it is the root of a subtree containing four additional nodes. The cumulative tree size for this subtree, calculated by summing the tree sizes of all five nodes, is nine. We use this approach to determine s_i and t_i at 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, Zhu et al. (2015) find that T scales with S according to a power law

$$T \sim S^{\eta}, \tag{3}$$

where η is the allometric scaling exponent. This exponent serves as a summary statistic of production structure that has two limit cases. When $\eta = 1$, it represents a hub-and-spoke or star configuration, where a single hub region-sector is directly connected to all its suppliers (in the demand view) or customers (in the supply view). When $\eta = 2$, it represents a hierarchical chain structure, where each region-sector on a given layer is directly linked to only one other region-sector (see Fig 2-3). When the scaling exponent falls within the range $\{\eta \in \mathbb{R} | 1 < \eta < 2\}$, the production structure is a hybrid between a chain and a star. We therefore use the allometric scaling exponent as a measure of input specificity. A higher scaling exponent suggests more

Table 1: 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

chain-like structures and greater input specificity. Conversely, a lower exponent implies that the trees are more star-like, implying lower input specificity. Figure 2-4 illustrates the scaling law for the two theoretical limiting cases (red line for chains and green line for stars), as well as for our intermediate empirical scenarios (black line).

To determine the allometric scaling exponent based on empirical data, we apply ordinary least squares to the log-log regression

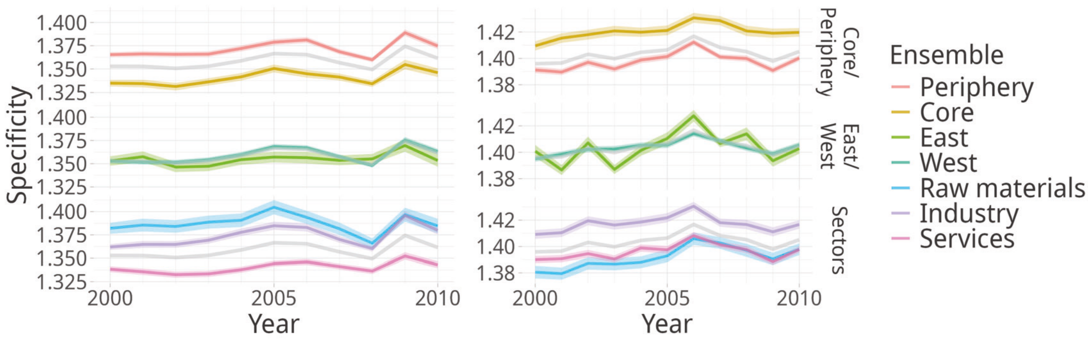
$$ln(t) = \eta \cdot ln(s) + \epsilon. \tag{4}$$

We estimate this regression for both the supply and demand views, referring to the allometric scaling exponent for the demand view as $ASEA$ and for the supply view as $ASEB$, i.e., $\eta \in \{ASEA; ASEB\}$.

5 Results

We start by discussing some general observations on the fitted allometric scaling exponents, referring to the descriptive statistics in Table 1. Notice that all values in the table are calculated for pooled estimates over all years and observational units, i.e., allometric scaling exponents estimated at the level of regions or sectors.

An immediate finding is that all exponents fall clearly within the range of one to two, suggesting that empirical production trees differ significantly from both chain and star configurations. Our analysis, therefore, supports the findings of Zhu et al. (2015) for regionally more disaggregated data, demonstrating that theoretical models based on these topologies (for example, Bloesch, Larsen, and Taska, 2022) are overly simplistic.



(a) Demand view

(b) Supply view

Figure 3: 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.

Notes: The 95% confidence intervals are computed as $\pm$ 1.96 standard errors. Grey lines represent the average allometric scaling exponent.

Moreover, the construction of production trees based on both technical and allocation coefficients reveals systematic differences in production structure upstream and downstream. The estimated coefficients are consistently higher from the supply perspective, indicating that supply trees more closely resemble a chain structure than demand trees. This indicates greater diversification in demand links and a higher degree of specificity in supply links. Further, although we estimate the scaling exponent from an ensemble of trees sampled across regions, we still observe sufficient variation that can be exploited in the subsequent regression of the labor share on the degree of specificity. Due to the limited number of observations in the sectoral classification, we will conduct our subsequent regression analyses on the regional level, which also exhibits greater variation.

5.1 Patterns of input specificity across industries and regions

Figure 3 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 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 for Eastern and Western regions, for which the estimated coefficients are relatively similar.

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 aligns with our implicit prior of an “inverted pyramid” of production (Cahen-Fourot et al., 2020), where raw materials rely on specific inputs (narrow demand trees) but serve as nearly 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. This is consistent with previous research documenting that industrial sectors produce the most complex products (Felipe et al., 2012).

The systematic heterogeneity we document underscores the plausibility of the proposed measure of input specificity. Moreover, it seems worth noting that the ranking of input specificity aligns with the ranking of labor shares across sectors and regions. For example, input specificity in the industrial sector is higher than in the service sector, as is its labor share. However, the difference in labor shares between Eastern and Western regions documented in Section 3 cannot be explained by different degrees of input specificity alone. Therefore, an additional mechanism is needed to explain the differences in labor shares between East and West. We will revisit this issue in Section 5.3.

Overall, supply-oriented input specificity appears to be a strong candidate for explaining heterogeneity in labor shares. To explore this channel more systematically, we study the nexus between input specificity and the labor share within a panel regression framework.

5.2 Input specificity and its relation to labor share

In this section, we seek to assess whether the labor share systematically varies with the degree of input specificity. Among the different methods of estimating such relationships 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 model 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 specifity that we documented in Section 5.1.

Specifically, we apply Mundlak's (1978) version of the correlated random effects estimator

$$LS_{i,t} = a + b_t + c_i + \alpha_0 ASEA_{i,t} + \alpha_1 ASEB_{i,t} + \alpha_2 \overline{ASEA}_i + \alpha_3 \overline{ASEB}_i + \alpha_4 \mathbf{X}_{i,t} + \alpha_5 \bar{\mathbf{X}}_i + \ {}_{i,t}, \tag{5}$$

where LS denotes the labor share, $ASEA$ ($ASEB$) is the degree of specificity for the demand (supply) view, and $\mathbf{X}_{i,t}$ is a vector of controls.[4] A bar over a variable stands for the time series average. b_t are year dummies. c_i is a region-specific heterogeneity term (random effect). 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 if the degree of specificity correlates with the labor share across regions, capturing structural, time-invariant heterogeneity.

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

[4] $ASEA$, $ASEB$ and $\mathbf{X}$ are mean-centered.

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.

Since our analysis focuses on "structural power" as opposed to "associational power" - which refers to bargaining power derived from the formation of collective organizations (Wright, 2000) - we include three controls to isolate the effect of structural power: (i) country-level data on trade union density, defined as the percentage of workers organized in trade unions relative to the total workforce, sourced from the OECD/AIAS database on Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts (ICTWSS), (ii) regional unemployment rates, and (iii) on-the-job training rates from Eurostat. The latter variable describes the share of people aged 25 to 64 who received formal or non-formal training or both in the four weeks preceding the quarterly EU Labour Force Survey (Eurostat, 2023). This metric serves as a proxy for human capital investments and the skills required for producing specific inputs (Backman, 2014). While union density is the most evident direct proxy for associational power, it is unfortunately not available at the regional level. Therefore, we use country-level union density rates for each region in a specific country.

Moreover, to isolate the effect of input specificity on structural power from the influence of a region's size or economic importance, we introduce a size variable as additional control. This variable is defined as the ratio of value added to the total value added across all regions. By using this variable, we control for structural power workers gain by being employed in a region with a high share of value added and, therefore, a greater potential for disruption.

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 as well as country fixed effects to account for unobserved country heterogeneity.[5] These country fixed effects

[5]As Eq. (5) illustrates, the baseline specification includes year fixed effects.

are primarily motivated by differences in bargaining regimes that are typically based in national legislature and might directly affect labor shares.

Table 2 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 increasing the average specificity of their supplied inputs experience an increase in the labor share over time (within effect). Simultaneously, regions producing more specific inputs exhibit a higher average 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 investment 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 stronger 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.[6] 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 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.[7] We take this to imply that supply specificity represents

[6]We checked whether this 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.

[7]The only exception is the unemployment rate, which shows a weakly positive correlation with the labor share. As we demonstrate in Table 5 in the appendix, the within effect turns positive once we exclude the global financial and banking crisis during which value added declined faster than labor income, causing the labor share to rise as unemployment increased.

Table 2: Correlated random effects estimates of Eq. (5).

	Model 1	Model 2	Model 3	Model 4
Constant	-0.5899**	0.3884***	0.4189***	-0.0672
	(0.2782)	(0.1201)	(0.1270)	(0.1309)
Within				
Degree of specificity (demand)	0.0367**	0.0367**	0.0448***	0.0400**
	(0.0147)	(0.0147)	(0.0152)	(0.0172)
Degree of specificity (supply)	0.0640***	0.0640***	0.0600***	0.0620***
	(0.0137)	(0.0137)	(0.0138)	(0.0160)
Unemployment rate			0.0004***	0.0003**
			(0.0001)	(0.0002)
Union density				-0.0003
				(0.0002)
Job training				0.0001
				(0.0003)
Size			3.4392***	2.0829*
			(0.9896)	(1.2311)
Between				
Degree of specificity (demand)	-0.0029	-0.1211**	-0.1818***	-0.1572**
	(0.1430)	(0.0529)	(0.0666)	(0.0718)
Degree of specificity (supply)	0.7693***	0.1920***	0.2241***	0.1856***
	(0.1486)	(0.0640)	(0.0639)	(0.0677)
Unemployment rate			0.0018***	0.0015**
			(0.0006)	(0.0006)
Union density				0.0145***
				(0.0020)
Job training				0.0027**
				(0.0014)
Size			0.0693	-0.0136
			(0.4435)	(0.4741)
Country FE		X	X	X
Num.Obs.	2728	2728	2507	1897
Marginal R^2	0.096	0.860	0.872	0.858
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 considers only the variance of the fixed effects, while the conditional R^2 takes both fixed and random effects into account.

structural power as a distinct channel, separate from the conventional channels relating to human capital, associational power and size.

To put the estimated coefficients into perspective, consider an increase in supply specificity by its standard deviation of 0.04 (see Table 1). 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. Yet, the average estimates for the full sample might mask important sectoral and geographical heterogeneity to which we will turn in the next section.

5.3 Geographical and sectoral variation in effect sizes

The descriptive analysis in Section 3 highlighted sectoral and geographical heterogeneity in the functional distribution of income. While our regression results point to a positive association between input specificity and the labor share in the full sample, the aim of our analysis here is to assess whether the observed heterogeneity translates into differences in the estimated effect sizes. To investigate this, we extend Model 2 by adding interaction terms based on the geographical and sectoral groupings discussed in Section 5.1: core vs. peripheral regions, Eastern vs. Western regions as well as regions with an above-average share of value added from the service sector vs. the remaining regions.[8] The pertinent regression coefficients of the between effect are presented in Figure 4.[9]

In the geographical disaggregation, we find no significant differences in effect sizes between core and peripheral regions. We take this to imply that the disparity in labor shares between these regions reflects differences in average input specificity between core and periphery, as documented in Section 5.1, rather than regional differences in workers' ability to leverage favorable positions within the production system to secure higher wages. If the latter were true, we would expect a larger coefficient for input specificity in core regions, which our

[8] As Figure 6 in the appendix illustrates, we do not observe significant differences in effect sizes for the remaining two sectors and thus focus on services.

[9] Results for the model without country fixed effects are qualitatively similar (see Figure 8 in the appendix).

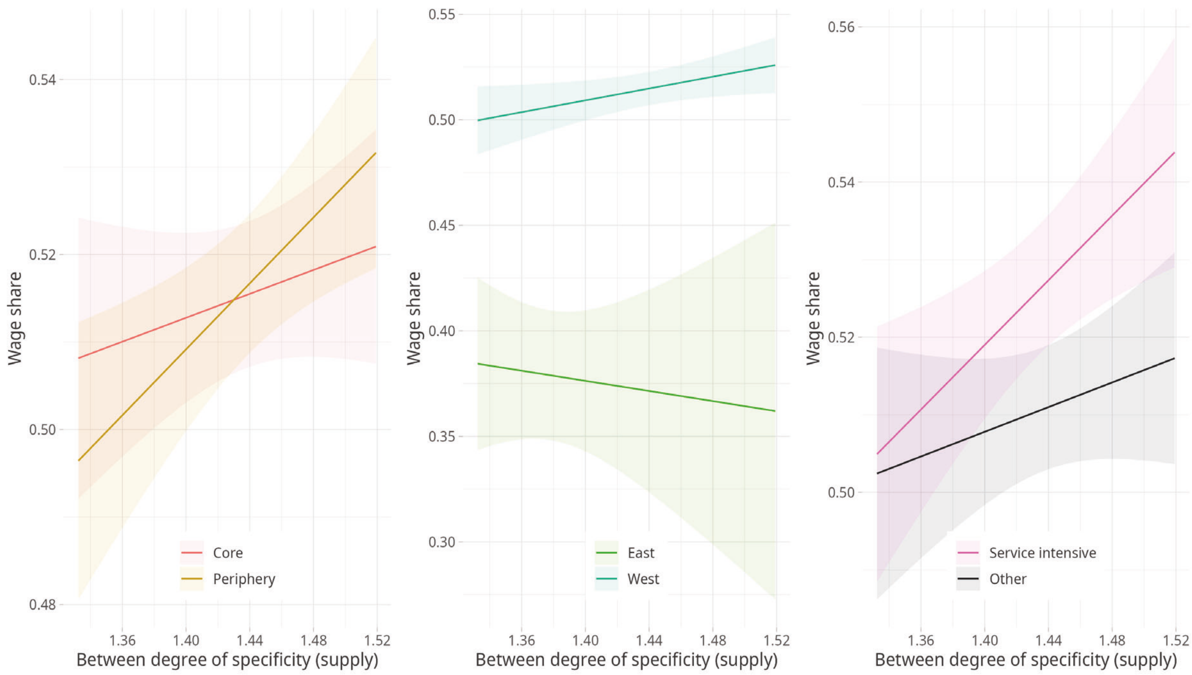


Figure 4: Effect size by regions and sectors.

Notes: The figure displays the estimated coefficient of the between effect. Each sub-figure presents a distinct extension of Model 2 with country fixed effects, incorporating an interaction term between the degree of supply specificity and a dummy variable reflecting a regional or industrial grouping.

regressions do not support.

In contrast, Figure 4 reveals significant differences in effect sizes between Eastern and Western regions. While the estimated coefficient is significantly positive for Western regions, it is insignificant for the East. This suggests that only workers in the West are able to leverage their advantageous positions within the production system, which might explain why Western regions have higher wage shares, despite similar levels of input specificity in East and West (see Figure 3). This would imply that higher input specificity is a necessary, but not sufficient, condition for higher labor shares. We interpret this finding as evidence of institutional differences between Eastern and Western regions that cannot be solely explained by variation in value-added production that distinguishes core from peripheral regions. As Bernaciak (2015) and Astrov et al. (2019) document, decentralized single-employer bargaining predominates in post-Soviet countries, with economic development largely driven by foreign capital that is more susceptible to cost pressure. In a similar vein, Smith et al. (2014) show that high competitive pressure in the clothing industry, resulting from the Eastern European clothing sector's reliance on key orders from the West, might also contribute to a less favorable bargaining position in the East. Consequently, workers in Eastern regions may find themselves in a structurally disadvantaged position, unable to leverage the disruptive potential of strikes or their specific skills to secure higher wages.

Our results also indicate a higher effect size for regions with service-intensive value added generation, though the difference is small and partially insignificant. We conjecture that this results from the growing skill intensity of services compared to the other two sectors (Buera and Kaboski, 2012). Since firm-specific skills, knowledge and specific production are likely complementary, specialized workers become harder to replace, which strengthens their bargaining position.[10] Similarly to the case of Eastern and Western regions, this comparatively greater ability to leverage specific input production might also explain why workers in services secure a higher labor share than those in raw materials, although their average level of specificity does not differ substantially and even overlaps in some years, as Figure 3 illustrates. Overall, both types of disaggregation suggest that sectoral and institutional differences influence whether and how a favorable bargaining position from input specificity 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 shape the functional income distribution, as producing more specific inputs implies higher labor shares. It offers several contributions. First and foremost, we propose a methodology to empirically assess and 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.

[10]Notably, the hypothesis that primarily logistic workers provide essential services to downstreams producers (Nowak, 2022) does not hold in our sample, as effect sizes are statistically indistinguishable for regions with intensive value added generation in logistics sectors ($S10$ and $S12$) and other regions (see Figure 7 in the appendix).

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 workers in core regions and in industrial sectors secure a larger share of total value added. 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 nuanced picture. Despite notable differences in average labor shares, Eastern and Western regions show little variation in terms of input specificity. However, our analysis suggests that workers in Western regions are better able to translate higher levels of specificity into higher labor shares compared to their Eastern counterparts. We hypothesize that this effect originates in less-established bargaining institutions in post-Soviet states. 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 imply that they operate on different levels: while skill, human capital investment, and structural power shape workers' bargaining potential, institutional disparities across countries determine the extent to which this potential can be realized. 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 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 structure to the functional income distribution.

Conflict of interest statement

All authors declare that they have no conflicts of interest.

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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 Zenodo repository at https://doi.org/10.5281/zenodo.14134659.

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A Appendix

A.1 Sample

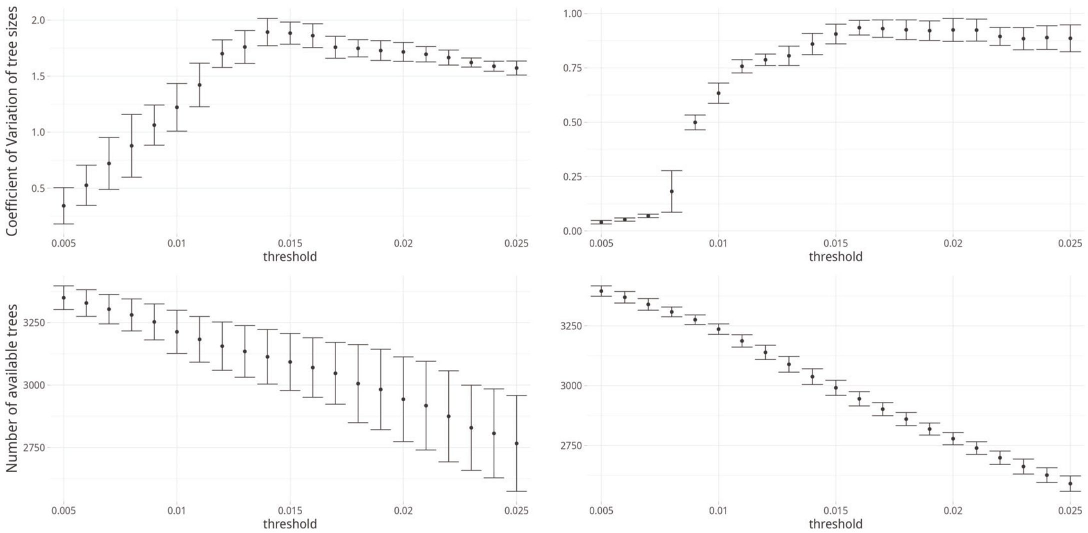
Table 3: Countries in the EUREGIO database.

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*
Luxemburg	*LU*
Latvia	*LV*
Malta	*MT*
Netherlands	*NL*
Poland	*PL*
Portugal	*PT*
Sweden	*SE*
Slovenia	*SI*
Slovakia	*SK*
United Kingdom	*UK*

Table 4: 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 5: Average coefficient of variation of tree sizes (top) and average number of available trees (bottom) as a function of the threshold for link weights.

Notes: 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 Additional experiments on effect size

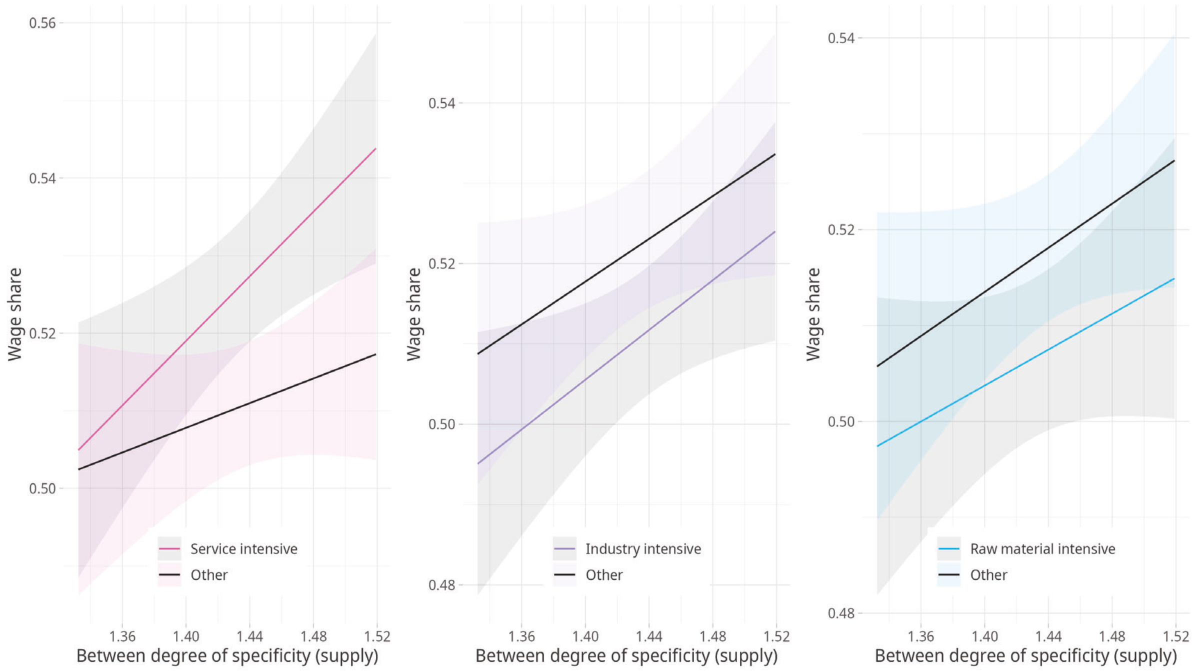


Figure 6: Effect size for services, industry, and raw materials compared to other sectors.

Notes: The figure displays the estimated coefficient of the between effect. Each sub-figure presents a distinct extension of Model 2 with country fixed effects, incorporating an interaction term between the degree of supply specificity and a dummy variable for regions with an above-average value added share in services, industry and raw materials, respectively.

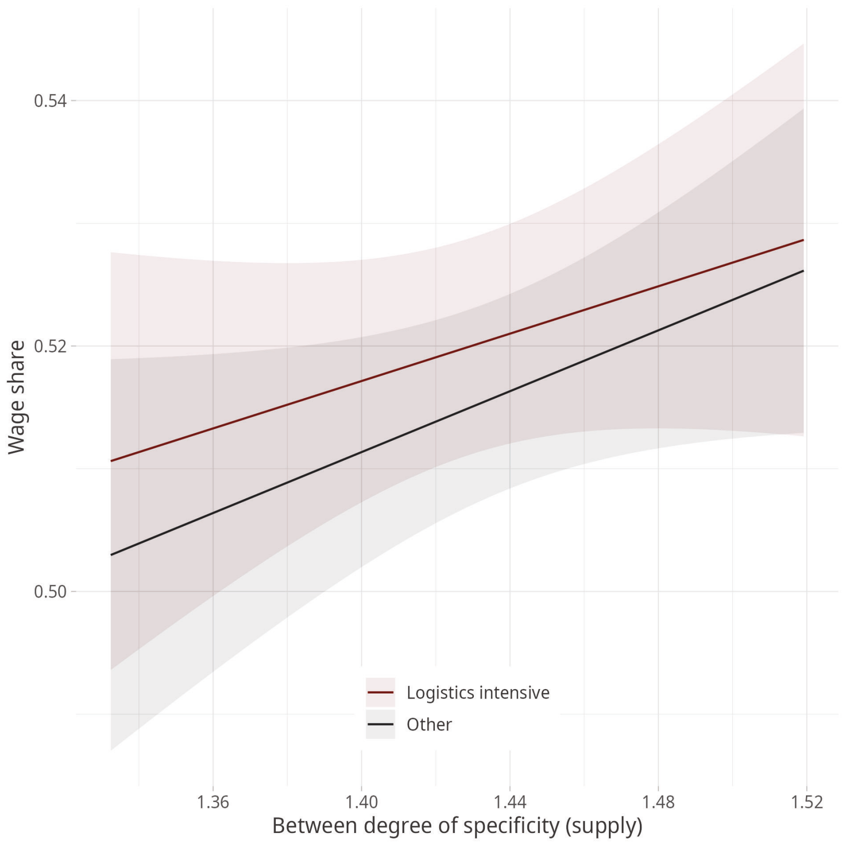


Figure 7: Effect size for the logistics industry compared to other industries.

Notes: The figure displays the estimated coefficient of the between effect in an extension of Model 2 with country fixed effects. This model incorporates an interaction term between the degree of supply specificity and a dummy variable for regions with an above-average value added share in the logistics sector.

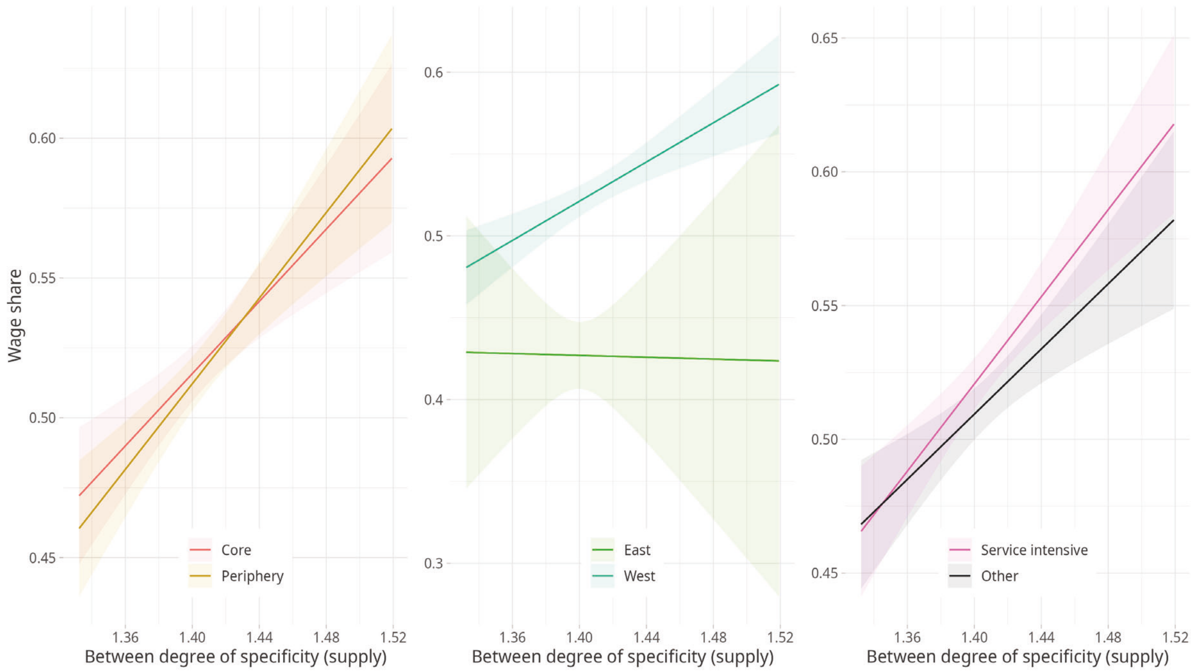


Figure 8: Effect size by regions and sectors without country fixed effects.

Notes: The figure displays the estimated coefficient of the between effect. Each sub-figure presents a distinct extension of Model 1 without country fixed effects, incorporating an interaction term between the degree of supply specificity and a dummy variable reflecting a regional or industrial grouping.

A.4 Robustness check

Table 5: Correlated random effects estimates of Eq. (5) using data from 2000 to 2007.

	Model 1	Model 2	Model 3	Model 4
Constant	−0.6290**	0.3973***	0.4190***	−0.0735
	(0.2834)	(0.1244)	(0.1313)	(0.1367)
Within				
Degree of specificity (demand)	0.0568***	0.0550***	0.0618***	0.0617***
	(0.0168)	(0.0167)	(0.0173)	(0.0199)
Degree of specificity (supply)	0.0535***	0.0542***	0.0461***	0.0367**
	(0.0144)	(0.0144)	(0.0146)	(0.0168)
Unemployment rate			−0.0001	−0.0004*
			(0.0002)	(0.0002)
Union density				0.0010***
				(0.0003)
Job training				−0.0002
				(0.0003)
Size			6.2980***	6.5868***
			(1.4401)	(1.6712)
Between				
Degree of specificity (demand)	−0.0057	−0.1156**	−0.1786***	−0.1685**
	(0.1457)	(0.0548)	(0.0689)	(0.0751)
Degree of specificity (supply)	0.7999***	0.1808***	0.2207***	0.1912***
	(0.1514)	(0.0663)	(0.0660)	(0.0707)
Unemployment rate			0.0021***	0.0018***
			(0.0006)	(0.0006)
Union density				0.0148***
				(0.0021)
Job training				0.0027*
				(0.0015)
Size			0.1445	0.0418
			(0.4584)	(0.4955)
CountryFE		X	X	X
Num.Obs.	1984	1984	1811	1346
Marginal R^2	0.102	0.869	0.881	0.863
Conditional R^2	0.968	0.968	0.971	0.968

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.

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