# Growing Together and Apart: Scale Economies and Labor Specialization in Global Value Chains*

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**Abstract**

This paper analyzes how division of labor along global value chains generates scale economies and productivity growth. We construct a novel dataset linking the universe of cross-border transactions between Danish and Swedish firms to administrative worker-firm data from both countries, providing detailed occupation information on every buyer and supplier. This allows us to construct a novel measure of occupational similarity between firms in global value chains. Exploiting exogenous shifts in demand, we show that positive demand shocks lead to higher measured productivity while occupational similarity with foreign suppliers declines, consistent with greater specialization. We then propose and structurally estimate a parsimonious model with task specialization and outsourcing using our novel data. Our quantification and counterfactual show that scale and labor specialization with foreign suppliers are a quantitatively important economic mechanisms for generating higher labor productivity and lower input costs.

JEL: F10, F12, F16, D24, L11, L25
Keywords: international supply chain, outsourcing, scale economies, labor specialization, labor productivity, production networks, relationship specificity.

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# 1 Introduction

> "The greatest improvement in the productive powers of labour [...] seem to have been the effects of the division of labour." (Wealth of Nations, Chapter 1, 1776)

The division of labor - breaking down work into tasks so that workers can specialize in a subset of tasks - is believed by many economists to be key to economic progress, by providing efficiency gains when producing goods and services. In today's economy, this division occurs increasingly between firms as production is fragmented across borders in global value chains (GVC). Yet, the empirical evidence on the magnitude of these gains remains limited. In particular, we lack evidence on how the division of labor across firms in GVCs affect scale economies, labor productivity and input prices.

In this paper we address these gaps in the literature and make three main contributions. *First*, we assemble a new comprehensive dataset linking transactions between Danish and Swedish firms with matched employer-employee data. This dataset enables us to construct a novel measure of the division of labor across firms, the occupational similarity between buyers and suppliers, a dimension previously unobserved in GVC data. *Second*, we provide novel empirical evidence that positive exogenous demand shocks increase the buyers' scale and measured productivity while reducing the occupational similarity with suppliers, consistent with greater specialization in the GVC. *Third*, we propose a parsimonious task-trade model and structurally estimate it using simulated method of moments. This allows us to quantify the importance of labor specialization for scale economies, measured productivity and input prices. In the rest of this section we elaborate on each of these contributions.

One of the reasons for the lack of progress is that the division of labor is typically unobserved in standard data on firms and GVCs. In this paper, we make progress by building a comprehensive register-based dataset covering both Denmark and Sweden. Our key data source is VAT records with all goods and services transactions between Danish and Swedish firms. Because each transaction includes VAT identifiers of the buyer and supplier firms, we can merge the VAT data with other register data on firms and workers. The final dataset spans 2012-2018 and combines: (1) the universe of firm-to-firm trade flows between Denmark and Sweden, (2) detailed employer-employee data from both Denmark and Sweden on all workers and their characteristics, including narrowly defined occupations, and (3) detailed firm level data for both countries on firm characteristics, such as sales, costs, and employment.[1] This novel merged *and* linked data enables us to measure for the first time, occupation similarity between buyers and their (foreign) suppliers, providing a direct measure of specialization across firms in the GVC. Specifically, for each buyer firm and its foreign suppliers, we measure occupation similarity by computing a cosine similarity index ranging from 0 (completely different occupational structure) to 1 (identical occupational structure).

[1] Relative to the previous studies that have used employer-employee and firm-level data from a single country (e.g., Hummels et al., 2014) our data covers the workers and firms on both sides of international trade. Relative to those that have matched customs data from importing and exporting countries (e.g., Blum et al., 2010), our data provides detailed information on all the workers that buyer and seller firms employ.

The second contribution of this paper is to provide new evidence on how demand shocks shape the division of labor between buyers and suppliers in the value chain. We adopt a long-differences specification and examine the change from the base period of 2012-13 to the end period of 2017-18. An empirical challenge is to find an exogenous demand shifter. Here, we turn to the world import demand (WID) shocks commonly used in the trade literature (Hummels et al., 2014). Specifically, in the base period, we observe the portfolio of products that buyer firm $i$ exports to third countries, outside of Denmark and Sweden, as well as the shares of these products in $i$'s third-country export. The demand shock for $i$ is then the weighted average of the change in global imports of these products, from all other sources than Sweden and Denmark, where the weights are the base-period export shares.

Our empirical analysis shows that a positive demand shock raises the buyer's sales, employment and labor productivity, while reducing the value added to sales ratio and the labor share. As buyers expand, they also increase imports from their foreign suppliers in Denmark and Sweden. Importantly, using our unique data, we find that occupation similarity *declines* between the Swedish (Danish) buyers and their Danish (Swedish) suppliers. Therefore, buyers and their foreign suppliers grow together, in the sense that they trade more, but also grow apart - in the sense that they increasingly specialize in different tasks along the value chain.

The third contribution of the paper is to propose and estimate a parsimonious model of labor specialization and outsourcing (following e.g. Grossman and Rossi-Hansberg, 2008; Costinot, 2009). The buyer firm produces output by combining a unit continuum of tasks, each of which can either be produced in-house using labor or outsourced to a foreign supplier. Task productivity varies across tasks and firms, creating potential gains from specialization when in-house production is relatively inefficient (high unit costs). But outsourcing a task is also costly, due to e.g. transaction costs, monitoring costs or costs associated with reorganizing production. We model this as a task-specific fixed cost. The buyer firms will then optimally outsource tasks where the efficiency gains from doing so are relatively large. In this environment, a positive demand shock will lead to: (i) more specialization, i.e., more tasks being outsourced, and less task similarity between the buyer and its suppliers; (ii) a lower value added to sales ratio and labor share; and (iii) higher labor productivity (value added per worker). The economic intuition is straightforward: more sales and profits imply that the marginal gain from specialization increases, while the marginal transaction cost remains fixed. Importantly, the model predictions of (i)-(iii) are in line with the empirical results described above.

For the quantitative analysis, we estimate the parameters of the model using simulated method of moments (SMM). The quantification allows us to assess the importance of labor specialization along the supply chain in generating productivity growth and scale economies.

The estimation results show that costs related to outsourcing are economically important; total fixed costs of outsourcing is about 31,400 USD, or 1.1 percent of the average firm's total labor cost. Furthermore, scale economies due to specialization along the supply chain are substantial. Specifically, the elasticity of output quantity to labor, or the returns to scale coefficient, is 1.05, implying that doubling employment yields 5% higher output per worker.

We also find that labor productivity for the 90th percentile firm is 30 percent higher than for the 10th percentile firm, confirming that specialization gives rise to substantial dispersion in labor productivity (in the model, labor productivity is equalized across firms in the absence of outsourcing).

Next, we ask whether the estimated model can explain our reduced-form findings. We simulate the WID shocks in the model and estimate the same regressions described above on simulated data. We find that all the simulated coefficient estimates have the same signs as the data coefficient estimates, and their magnitudes are 1/10th to 1/5th relative to the actual coefficient estimates.[2]

Finally, as a counterfactual, we simulate the scenario of prohibitively expensive outsourcing, in which the buyer firm would produce all tasks in-house and there would be no labor specialization across firms. We find that for the average buyer firm, labor productivity would be 0.29 log points or 34% lower in the counterfactual, and the input price index 0.096 log points or 10% higher. These results suggest that outsourcing and labor specialization significantly boost firms' labor productivity and reduce their input costs, complementing previous work on the economic significance of supplier links in the GVC literature.[3]

This paper relates to the following distinct bodies of work. The first is the literature on global value chains (e.g., Antràs and Chor, 2013; Antràs et al., 2017; Baldwin and Venables, 2010; Blaum et al., 2018; Costinot et al., 2013; Grossman et al., 2023), which emphasizes the mechanism of supplier links.[4] In comparison, our model and quantification highlight the reorganization of tasks between buyer firms and their foreign suppliers and how this interacts with buyer firm scale.

Our stylized model draws from the (mostly) theoretical work on offshoring and task trade (e.g., Feenstra and Hanson, 1996; Grossman and Rossi-Hansberg, 2008), as well as labor specialization and trade (e.g., Becker et al., 2025; Chaney and Ossa, 2013; Costinot, 2009). We parameterize the distributions of task productivity, estimate these parameters using our unique data, and quantify the economic significance of the mechanism of labor specialization across firms linked in the GVC.

The third is the literature that shows that foreign sourcing affects measured productivity and marginal costs (e.g., Amiti and Konings, 2007; De Loecker et al., 2016; Goldberg et al., 2010; Gopinath and Neiman, 2014; Halpern et al., 2015), which emphasizes the mechanism through the number of imported products. Relative to this literature, we focus on task reorganization in GVCs.

More broadly, our study also relates to the empirical literature on the division of labor (e.g., Atalay et al., 2024; Baumgardner, 1988; Becker et al., 2025; Boehm and Oberfield, 2022; Duranton and Jayet, 2011; Garicano and Hubbard, 2009; Tian, 2021),[5] the literature on domestic

[2] In the data, there are likely other sources of scale economies operating at the same time, e.g. division of labor within the firm itself or learning-by-doing.

[3] For example, Antràs et al. (2017) shows that if all foreign supplier links were lost, the average U.S. buyer firm would experience a 9% increase in marginal cost.

[4] Antràs and Chor (2022) provide a recent survey.

[5] For example, Boehm and Oberfield (2022) uses data on plants' input and output mix to explore the relationship

production networks (e.g., Bernard et al., 2018, 2019, 2022; Demir et al., 2024; Dhyne et al., 2021, 2025; Lim, 2018),[6] and the literature on search and matching in international trade (e.g., Benguria, 2021; Blum et al., 2010; Eaton et al., 2025).

The rest of the paper is organized as follows. Section 2 presents the data, key data patterns and our measures of labor specialization between buyer firms and their foreign suppliers. Section 3 constructs the WID variables and shows how the buyer firm responds to exogenous demand shocks. Section 4 introduces the quantitative model, Section 5 estimates the model, and Section 6 provides model validation. Section 7 concludes.

# 2 Data

In this section, we describe the data and the construction of our main sample. We leave additional details to the Data Appendix. We also highlight the main data patterns and clarify our measures for labor specialization.

## 2.1 Data Sources

The cornerstone of our data is the universe of cross-border firm-to-firm trade relationships. All exporters in Denmark and Sweden are required to submit an EU sales form every month (for goods or joint export of goods and services) or quarter (for services) for exports to firms in other EU countries.[7] On that form, the exporter reports its own VAT registration number, its customer's VAT registration number, and the total value of exported goods, services or triangulated trade.[8] If the exporter sells to multiple customers in a month or quarter, it submits the VAT numbers of the various customers as different lines, one per customer. Before submitting the form, the exporter should verify the validity of the VAT numbers by using a VIES VAT number validation service. When the form is submitted, the format of the VAT numbers is checked to ensure it matches the structure in the destination. If the format of the VAT number is incorrect, an error will be shown asking for additional information. The validity of the numbers are, in addition, later checked separately in the country of the customer. If the number is invalid (e.g. the customer is not registered for VAT) this information is reported back to the local tax authorities in Denmark and Sweden that contacts the exporters.

We obtain data from these monthly or quarterly sales forms from both Danish and Swedish tax authorities for 2012-2018. The key for us in constructing the firm-to-firm match is that the data from Denmark (Sweden) will include Swedish (Danish) VAT numbers. We first combine these data on a server in Statistics Denmark. Next, having ensured that all VAT numbers are anonymized with the same key, we can link Swedish VAT numbers reported in Denmark to firm identifiers in other Swedish register data (see below). Likewise, we can link Danish VAT numbers

between fragmentation of production and growth, by focusing on plants' vertical spans of production.

[6] Bernard and Moxnes (2018) provide an early review of the literature.

[7] Small goods exporters may apply to file the sales list at the quarterly level.

[8] Triangulated trade refers to transactions when a firm sells goods as an intermediary between a supplier and the final customer. In these triangulated transactions, the goods are shipped directly from the supplier to the customer without entering the intermediaries country of origin.

reported in Sweden to other Danish registers. We use annual aggregates of the sales-form data where each observation shows the export value by year, by (Swedish or Danish) supplier, by (Swedish or Danish) customer.

We merge the VAT register data with the multiple administrative registers from Denmark and Sweden covering the period 2012-2018. First, we obtain data on firm characteristics from The Firm Statistics Register and the Firm Account Statistics from Denmark, and the Structural Business Activity (Swedish: Företagens ekonomi, FEK) and the VAT Register (MOMS) from Sweden. These data sources cover the universe of private-sector firms, and provide data on variables such as revenue, value added, employment, and industry affiliation. Second, we match workers to firms using The Employment Statistics for Employees and the Education Attainment Register from Denmark, and the Longitudinal Integrated Database (LISA) from Sweden. These data cover the population of private-sector workers, and provide data on worker characteristics such as salary, occupation, and education. Third, the Statistics for International Trade in Goods from Denmark and the Foreign Trade Register from Sweden provide data on firm imports (exports) by origin (destination) country by 8-digit Combined Nomenclature (CN) products. Across all these administrative data, both firms and workers are associated with unique identifiers, which allow for consistent matching across datasets.

While previous studies have used data comparable to *subsets* of our data, we are in the unique position to observe detailed characteristics of firms and their employees on *both* sides of cross-border transactions.[9] Such level of detail is essential for our analyses, as we show below.

In our data, the variable definitions and classification codes are largely comparable between Denmark and Sweden with one important exception: employees' occupation codes. Whereas Denmark has adopted the International Standard Classification of Occupation (ISCO08), prepared by the International Labor Organization, the Swedish classification system, SSYK12, is based on, but different from, ISCO08. As we will see, comparing occupation structure between a firm and its suppliers is crucial for our empirical analysis. We tackle this by aggregating 4-digit ISCO08 enough to ensure comparability and label this grouping 'ISCO+'.[10]

## 2.2 Sample Construction and Coverage

The aim of the reduced-form empirical analysis in Section 3 is to examine the effect of an exogenous demand shock (defined below) on the focal firm. As described below, we adopt a long-difference approach and use years 2012-13 as the initial period and 2017-18 as the end period. We trim our data in the following ways. First, we require that the focal firm reports positive total revenue and employment in both periods. This is necessary for studying changes

[9] For example, with Danish matched worker-firm data and customs data, Hummels et al. (2014) observe one side of international trade. Eaton et al. (2022) use firm-to-firm customs data from France but do not observe firm or labor market data for foreign customers.

[10] Statistics Sweden provides a many-to-many concordance file between SSYK12 and ISCO08. We construct ISCO+ as the most disaggregated grouping that ensures (a) there exists a many-to-one key between ISCO08 and ISCO+, and (b) there exists a many-to-one key between SSYK12 and ISCO+. This is akin to the so-called CN8+ product classification, suggested by Van Beveren et al. (2012), which ensures a many-to-one key between all year-specific CN classifications and CN8+. See Appendix B for further details.

Table 1: Sample coverage, 2012–2013 (%)

| | All | Denmark | Sweden | Manufacturing | Wholesale/Retail |
|---|---|---|---|---|---|
| # Firms | 6.45 | 8.54 | 5.45 | 25.8 | 13.9 |
| Employment | 43.4 | 48.4 | 41.7 | 80.3 | 51.3 |
| Revenue | 60.8 | 61.8 | 60.2 | 89.7 | 63.9 |
| Imports from DK/SE | 73.2 | 72.5 | 74.2 | 88.8 | 71.5 |
| Exports to third countries | 94.7 | 94.1 | 95.1 | 97.3 | 86.1 |

within the focal firm. Second, the focal firm must have at least one Swedish/Danish supplier in both periods.[11] This is required in order to study how the focal firm has changed relative to its foreign suppliers. Third, to construct exogenous demand shocks the focal firm must, according to the customs data, be an exporter to other countries than Sweden and Denmark (a 'third-country exporter') in the initial period. As for the focal firm's foreign suppliers, we only impose the first restriction, but not the latter two.

Table 1 shows the coverage of our estimation sample. Although the sample contains a small fraction of Danish and Swedish firms (6.5%), it comprises 43% of employment, 61% of revenue, and 95% of third-country exports, and these shares are even larger among manufacturing firms.

Table 2 provides a further comparison of the population and our estimation sample. It shows that relative to the VAT-data population (in the initial period, 2012-13), the focal firms in our sample are larger in size, have higher labor productivity, and engage in larger volumes of international trade. For example, the average Swedish firm in the full population has 14 employees, while the average Swedish firm in the estimation sample has 103 employees.

### 2.3 Key Data Patterns

The firms in our sample vary substantially in size and labor productivity. Figure 1 shows a binned scatter plot, with log sales on the horizontal axis and log value added per worker on the vertical axis. Two-digit industry (NACE) and country (Denmark/Sweden) fixed effects are included, so that cross-industry and cross-country variation is excluded from the analysis. The figure shows a strong positive correlation between size and labor productivity. The slope coefficient is 0.103 and the $R^2$ is 0.23. A firm at the 90th percentile of the sales distribution has 50 percent higher value added per worker than the one at the 10th percentile.

Figure 2 shows a binned scatter plot with log sales on the horizontal axis and the labor share, defined as the wage bill relative to total costs, on the vertical axis. Total costs are constructed as purchases by the firm (goods and services, foreign and domestic) plus the wage bill. Importantly, capital is not included, so that the labor share is unaffected by spending on capital. Again, two-digit industry and country fixed effects are included. The figure shows that large firms have a substantially lower labor share compared to small firms. A firm at the 90th percentile of the sales distribution has a 12 percentage points lower labor share compared to a firm at the 10th

[11] E.g., a Swedish focal firm must have a least one Danish supplier in both periods (but not necessarily the same one).

Table 2: Firm characteristics, 2012–2013. Population vs. estimation sample.

| | Population | | | Estimation sample | | |
|---|---|---|---|---|---|---|
| | All | Denmark | Sweden | All | Denmark | Sweden |
| *Employment* | | | | | | |
| Mean | 13.7 | 13.8 | 13.6 | 92.1 | 77.6 | 103.0 |
| Median | 3.0 | 3.0 | 3.0 | 17.5 | 16.5 | 18.5 |
| *Sales* | | | | | | |
| Mean | 4.5 | 5.0 | 4.3 | 42.6 | 36.5 | 47.1 |
| Median | 0.5 | 0.6 | 0.4 | 5.5 | 5.3 | 5.8 |
| *Value added per worker* | | | | | | |
| Mean | 79.4 | 95.7 | 73.0 | 144.0 | 207.7 | 95.9 |
| Median | 62.6 | 68.8 | 59.8 | 80.5 | 82.8 | 78.4 |
| *Imports from DK/SE* | | | | | | |
| Share $> 0$ | 0.25 | 0.32 | 0.21 | 1.00 | 1.00 | 1.00 |
| Mean (cond. on $> 0$) | 0.24 | 0.31 | 0.18 | 0.67 | 0.85 | 0.52 |
| Median (cond. on $> 0$) | $< 0.01$ | $< 0.01$ | $< 0.01$ | 0.02 | 0.03 | 0.02 |
| *#Suppliers in DK/SE* | | | | | | |
| Share $> 0$ | 0.25 | 0.32 | 0.21 | 1.00 | 1.00 | 1.00 |
| Mean (cond. on $> 0$) | 3.3 | 3.7 | 3.0 | 5.5 | 6.3 | 4.3 |
| Median (cond. on $> 0$) | 2 | 2 | 2 | 3 | 4 | 2 |
| *Exports to third countries* | | | | | | |
| Share $> 0$ | 0.13 | 0.14 | 0.13 | 1.00 | 1.00 | 1.00 |
| Mean (cond. on $> 0$) | 4.7 | 4.9 | 4.6 | 9.2 | 7.5 | 10.5 |
| Median (cond. on $> 0$) | 0.04 | 0.10 | 0.02 | 0.20 | 0.28 | 0.15 |

*Notes:* Value added per worker is measured in thousands of euros, while the remaining nominal variables are measured in million euros.

percentile.

While these empirical patterns are merely correlations, they are nevertheless consistent with the central hypotheses we investigate in this paper. First, large firms may be able to reorganize production vis-à-vis their suppliers in a way that gives labor productivity improvements compared to small firms. Second, large firms may be able to outsource more tasks, which lowers their labor share compared to small firms.

Next, we explore the importance of relationship-specificity in our sample by adapting Nunn (2007)'s measure to our firms. For each focal firm, $i$, that is engaged in goods imports according to the customs data, we compute $rs_i$ as the share of goods imports that are differentiated according to the Rauch (1999) classification.[12] $rs_i$ ranges from 0 to 1. High values of $rs_i$ indicate high relationship specificity, because it is more difficult to find alternatives for differentiated goods than for homogeneous goods, which are either traded on organized exchanges or have reference prices. For the focal firms in our sample, the mean value of $rs_i$ is 0.82. Likewise, we calculate the relationship specificity measure for each foreign supplier $j$, $rs_j$ based on their goods exports. For the foreign suppliers, the mean $rs_j$ is also 0.82. These results suggest that relationship-specificity is high among Danish-Swedish firm-to-firm links.

### 2.4 Measures of Labor Specialization

Our first set of measures of labor specialization focuses on the focal firm's *top occupation*. Intuitively, if the top occupation has an increasing wage-bill share, the focal firm relies more heavily on that occupation and so becomes more specialized. To be specific, define firm $i$'s wage bill share of occupation $o$ as$\theta_{io} = W_{io}L_{io}/\sum_{o'} W_{io'}L_{io'}$ where $L_{io}$ is the number of employees and $W_{io}$ is the average wage for occupation $o$ in firm $i$.

We employ two definitions of *top occupation*. The first definition is based on the level of $\theta_{io}$; i.e.

$$o_i^{*1} = \arg\max_o \{\theta_{io}\}. \tag{1}$$

Equation (1) says that the top occupation is simply the occupation with the highest wage bill share among the firm's own employees, and it gives us the first measure of labor specialization, $\theta(o_i^{*1})$.

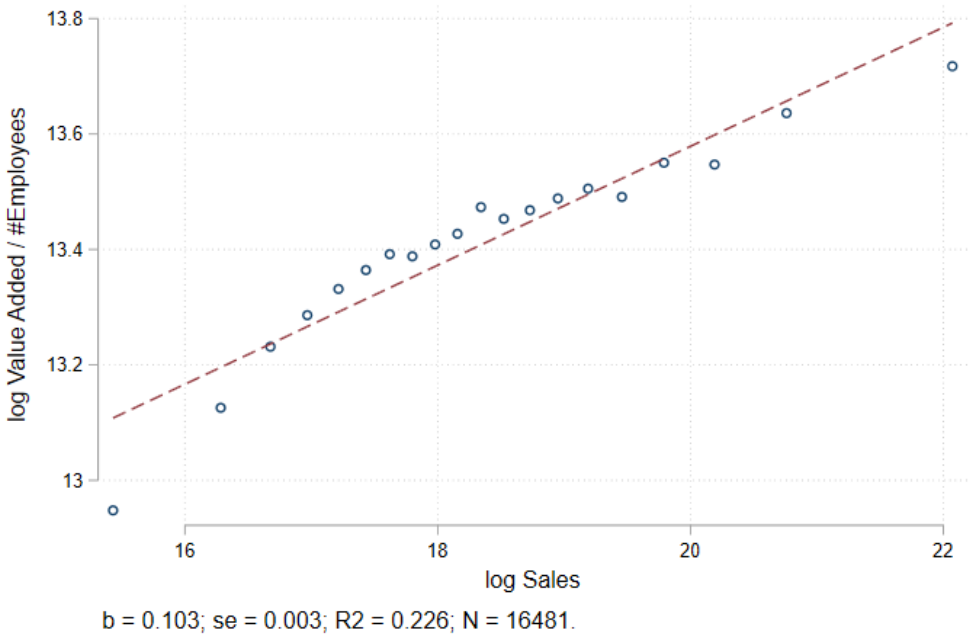
The second definition is based on the value of $\theta_{io}$ relative to $i$'s foreign suppliers. Let $\Theta_{io} = \sum_{i'} W_{i'o}L_{i'o}/\sum_{i',o'} W_{i'o'}L_{i'o'}$ be the wage bill share of occupation $o$ of firm $i$ and firm $i$'s suppliers combined. The alternative definition of $i$'s top occupation is then

$$o_i^{*2} = \arg\max_o \left\{\frac{\theta_{io}}{\Theta_{io}}\right\}. \tag{2}$$

In equation (2), $o_i^{*2}$ is conceptually identical to revealed comparative advantage (RCA): If

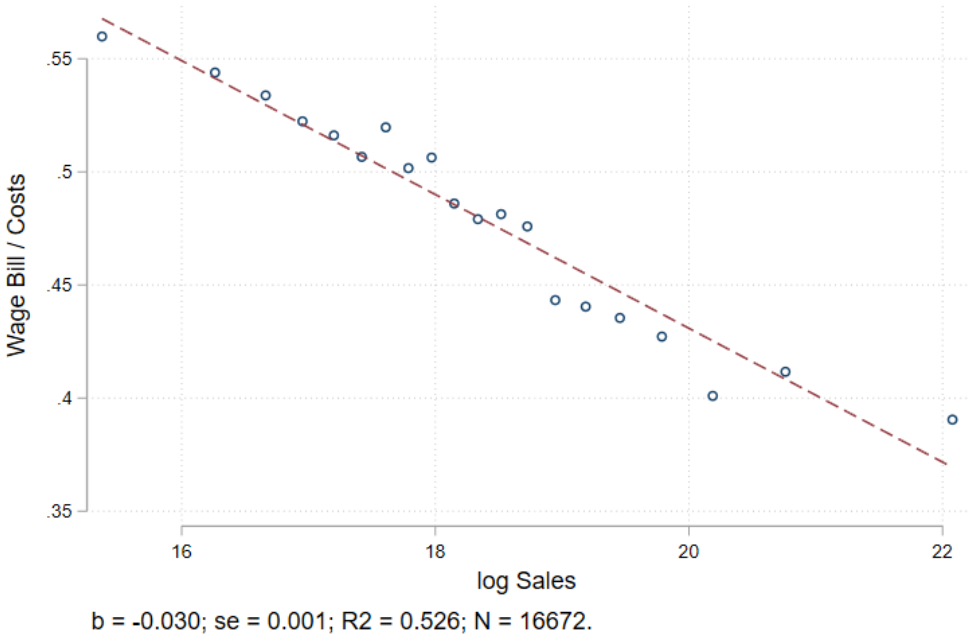
[12]For this exercise, we condition on firms being goods importers according to the customs data in 2012-2013. In recent work, Cajal-Grossi et al. (2023)'s measure is based on the number of suppliers, while Martin et al. (2026) measures "relationship stickiness" using the average duration of buyer-supplier relationships.

Figure 1: Sales and Labor Productivity




*Notes:* The figure shows a binned scatter plot with log sales on the horizontal axis and log value added per worker on the vertical axis, both residualized by 2-digit industry (NACE) and country (Denmark/Sweden) fixed effects.

Figure 2: Sales and Labor Share




*Notes:* The figure shows a binned scatter plot with log sales on the horizontal axis and the wage bill-cost ratio on the vertical axis, both residualized by 2-digit industry (NACE) and country (Denmark/Sweden) fixed effects. Costs are constructed as the purchases by the firm (goods and services, foreign and domestic) plus the wage bill.

$\theta_{io} > \Theta_{io}$, firm $i$ is said to have RCA in occupation $o$ because it relies relatively more on occupation $o$ than its suppliers, and $o_i^{*2}$ is simply the occupation with the highest degree of RCA. Equation (2) gives us the second measure of labor specialization, $\theta(o_i^{*2})$.

Summarizing equations (1) and (2), large values of $\theta(o_i^{*1})$ and $\theta(o_i^{*2})$ indicate a high degree of labor specialization for the focal firm $i$. Note that both $o_i^{*1}$ and $o_i^{*2}$ are calculated in the initial period and so are not time-varying.

The second set of measures of specialization focuses on the similarity in occupational structure between the focal firm $i$ and its foreign suppliers $j$, by comparing the set of wage bill shares across occupations. Specifically, we construct a similarity index $sim_{ij}$ between the focal firm $i$ and a single supplier $j$ as the cosine similarity between their wage bill shares:

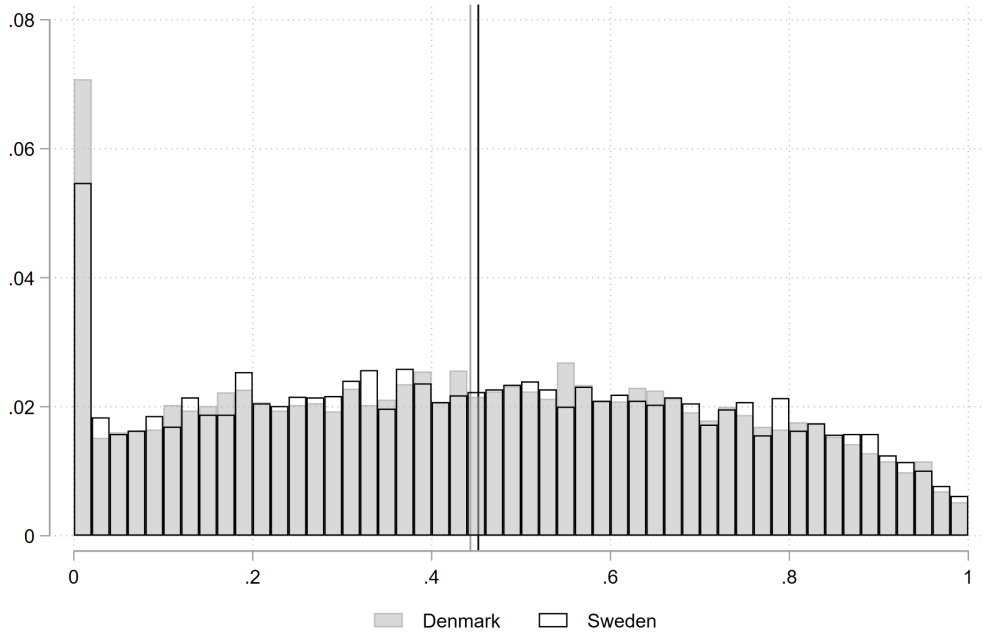
$$sim_{ij} = \frac{\sum_o \theta_{io}\theta_{jo}}{\left(\sum_o \theta_{io}^2 \sum_o \theta_{jo}^2\right)^{1/2}}, \tag{3}$$

which takes value zero if $i$ and $j$ have no occupations in common (i.e. no similarity), and one if they have identical wage bill shares for all occupations $o$ (i.e. max similarity).[13] We obtain the third measure of labor specialization, $sim_i$, by averaging $sim_{ij}$ across suppliers; i.e. $sim_i = \sum_j w_{ij} sim_{ij}$, where $w_{ij}$ is the share of $i$'s purchases from supplier $j$.

Figure 3 shows a histogram of $sim_i$ for the initial period, 2012-13. The white bars with black frames are for firms in Sweden and the gray bars are for firms in Denmark. The bar heights sum to 1 for each country by construction. Figure 3 shows that $sim_i$ varies substantially across focal firms.

[13] In the same way, Jaffe (1988) and Bloom et al. (2013) use cosine similarity of research effort across fields to measure technology proximity between firms.

Figure 3: Occupation Similarity, $sim_i$




*Notes:* The histogram presents the distribution of the occupation similarity index for the initial period: $sim_i = \sum_j w_{ij} sim_{ij}$ where $w_ij$ is the share of $i$'s purchases from supplier $j$ and $sim_{ij}$ is defined in equation (3). The vertical axis indicates the share of firms in each bar in Denmark (gray bars) and Sweden (white bars), respectively. Vertical lines indicate means for Danish (gray line) and Swedish (black line) firms, respectively.

We supplement $sim_{ij}$ with a similarity index where wage bill shares $\theta_{io}$ are replaced by dummy variables that take value one if firm $i$ has at least one employee in occupation $o$:

$$bisim_{ij} = \frac{\sum_o \mathbf{1}\{\theta_{io} > 0\}\mathbf{1}\{\theta_{jo} > 0\}}{\left(\sum_o \mathbf{1}\{\theta_{io} > 0\}\sum_o \mathbf{1}\{\theta_{jo} > 0\}\right)^{1/2}} \tag{4}$$

Equation (4) gives us the fourth, and final, measure of labor specialization, $bisim_i = \sum_j w_{ij} bisim_{ij}$, where $w_{ij}$ is, again, the share of $i$'s purchases from supplier $j$. Summarizing equations (3) and (4), high values of $sim_i$ and $bisim_i$ indicate high similarity between focal firm $i$'s occupational structure relative to its foreign suppliers and so a *low* degree of labor specialization.

Table 3 provides summary statistics for all four measures of labor specialization for Danish and Swedish firms separately. The distributions of all four measures of labor specialization are virtually identical among Danish and Swedish firms. The mean of $\theta(o_i^{*1})$ is 0.54, which means that the largest occupation takes up 54% of the wage bill in the average firm. This measure of specialization varies substantially across firms, spanning from 39% at the 25th percentile to 66% at the 75th percentile. $\theta(o_i^{*2})$ is smaller than $\theta(o_i^{*1})$ by construction, but it varies more across firms. This indicates that the occupation with the highest degree of RCA relative to suppliers is not always the largest occupation within the firm itself, indeed it may be rather small. Relative to $sim_i$, the variation in $bisim_i$ is smaller, yet sizable: the measure increases by two-thirds when

moving from the 25th to the 75th percentile.

Table 3: Measures of Labor Specialization

| | Denmark | | | | | Sweden | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | SD | P25 | P50 | P75 | Mean | SD | P25 | P50 | P75 |
| $\theta(o_i^{*1})$ | .54 | .21 | .39 | .51 | .66 | .54 | .20 | .39 | .50 | .66 |
| $\theta(o_i^{*2})$ | .27 | .28 | .05 | .16 | .41 | .27 | .28 | .05 | .17 | .41 |
| $sim_i$ | .44 | .27 | .21 | .44 | .66 | .45 | .27 | .22 | .45 | .67 |
| $bisim_i$ | .32 | .14 | .24 | .32 | .40 | .32 | .13 | .24 | .32 | .40 |

*Notes:* The table presents means, standard deviations (SD), and percentiles of four measures of labor specialization in the initial period (2012-13). $\theta(o_i^{*1})$ is the wage-bill share of the occupation with the highest wage-bill share among the firm's own employees, see equation (1). $\theta(o_i^{*2})$ is the wage-bill share of the occupation with the highest degree of revealed comparative advantage among the firm itself and its suppliers combined, see equation (2). $sim_i$ is the occupation similarity index: $sim_i = \sum_j w_{ij} sim_{ij}$ where $w_i j$ is the share of $i$'s purchases from supplier $j$ and $sim_{ij}$ is defined in equation (3). $bisim_i$ is an alternative occupation index based on dummy variables instead of wage-bill shares: $bisim_i = \sum_j w_{ij} bisim_{ij}$, where $bisim_{ij}$ is defined in equation (4).

# 3 Reduced-Form Model and Results

In this section, we explore how the focal firm responds to exogenous demand shocks, in terms of size, labor productivity, and labor specialization.

## 3.1 Specification and Identification Strategy

We start by spelling out our empirical specification, which is in long-differences:

$$\Delta \ln y_i = \alpha_{s(i)} + \gamma_{r(i)} + \beta z_i + \epsilon_i. \tag{5}$$

In equation (5), $\Delta$ is the change from period 0 (2012-13) to period 1 (2017-18), $i$ indexes the focal firm, $\alpha_{s(i)}$ represents 2-digit industry fixed effects, and $\gamma_{r(i)}$ represents country fixed effect (Sweden or Denmark). The dependent variable, $y_i$, denotes various outcomes related to firm $i$. Some are readily available from the data sources, such as sales, employment, and value added, while others are constructed from the raw data, such as the labor specialization measures based on equations (1)-(4).

The main explanatory variable, $z_i$, is a measure of demand which is orthogonal to the error term, $\epsilon_i$. We follow the trade literature and employ a so-called world import demand (WID) shock from (Hummels et al., 2014). Specifically, $z_i$ is defined as:

$$z_i = \sum_{c,p} \omega_{icp} \Delta \ln imports_{cp}. \tag{6}$$

Table 4: Firm-level Outcomes.

| | (1) $\Delta \ln Sales$ | (2) $\Delta \ln L$ | (3) $\Delta \ln$ DK/SE Imp | (4) $\Delta \ln \frac{ValueAdded}{Sales}$ | (5) $\Delta \ln LaborShare$ | (6) $\Delta \ln \frac{ValueAdded}{L}$ | (7) $\Delta \ln TFP$ |
|---|---|---|---|---|---|---|---|
| $z$ | 0.121*** | 0.059*** | 0.137** | -0.028** | -0.045*** | 0.037*** | 0.029** |
| | (0.020) | (0.015) | (0.056) | (0.013) | (0.013) | (0.014) | (0.012) |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 16,788 | 16,788 | 16,788 | 16,297 | 16,628 | 16,297 | 13,074 |

Note: Labor share is defined as the wage bill relative to total costs. TFP is computed using the Ackerberg et al. (2015) method ('acfest' in Stata), using deflated revenue, labor, capital and materials. Industry FE refers to NACE 2-digit fixed effects. Country FE is a dummy for whether the firm is Swedish or Danish. Robust standard errors in parentheses. Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

In equation (6), $imports_{cp}$ is country $c$'s total purchases of (4-digit HS) product $p$ from the world market, except from Sweden and Denmark, and $\omega_{icp}$ is the share of firm $i$'s exports in period 0 allocated to country-product pair $cp$. Note that, when constructing this instrument, the weights are calculated from the Swedish/Danish customs data, i.e. the sample is limited to firms that are third-country exporters (to other countries than Sweden/Denmark) of goods in period 0.

We estimate equation (5) with OLS and interpret the coefficient estimate, $\beta$, as a causal effect. The underlying identification assumption is that the change in country $c$'s imports of product $p$ from the world, minus Denmark and Sweden, is uncorrelated with the error term, $\epsilon_i$. Intuitively, this assumption says that firm $i$, being part of the small open economies of Denmark or Sweden, does not have a significant influence over aggregate trade of Denmark or Sweden's trade partners.

### 3.2 Results: Firm-Level Outcomes

Table 4 presents the results and clarifies the ways in which the focal firm changes in response to exogenous demand shocks. Columns (1) and (2) show that the focal firm increases both sales and employment, but that sales grow at a faster rate. Column (3) shows that the focal firm also increases purchases from its Danish/Swedish suppliers, at a rate comparable to the increase in sales.

Next, we present results for firms' sourcing of intermediates. Column (4) shows the impact on the value added to sales ratio while column (5) shows the impact on the labor share, defined as wage costs relative to total costs. Both these measures decline, suggesting that firms increase their reliance on intermediates when they grow.

Finally, column (6) shows that a positive demand shock raises labor productivity, as measured by value added per worker. As a robustness, we compute the focal firm's TFP by two-digit industry and report the results in column (7). These results are suggestive of economies of scale in production.

In summary, Table 4 shows that, in response to positive demand shocks to the focal firm, sales, employment and labor productivity of the focal firm and its purchases from foreign suppliers grow together, while the value added to sales ratio and the labor share decline. Section 4 will interpret these responses through the lens of a parsimonious quantitative model.

Table 5: New Links

| | (1) $\Delta \ln \#Suppliers$ | (2) $\Delta \#Suppliers$ | (3) $1\{\Delta \#Suppliers > 0\}$ | (4) $1\{NewSupplier\}$ |
|---|---|---|---|---|
| $z$ | 0.001 | 0.026 | 0.001 | 0.013 |
| | (0.017) | (0.095) | (0.013) | (0.011) |
| Industry FE | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes |
| N | 16,788 | 16,788 | 16,788 | 16,788 |

Note: This table presents OLS estimates of regression equation (5) across different outcome variables. In column (3), the outcome is a dummy that takes value one if the focal firms had more suppliers in period 1 (2017-18) than in period 0 (2012-13) and zero otherwise. In column (4), the outcome is a dummy that takes value one if the focal firm served at least one supplier in period 1 that it did not serve in period 0 and zero otherwise. Industry FE refers to NACE 2-digit fixed effects. Country FE is a dummy for whether the firm is Swedish or Danish. Robust standard errors in parentheses. Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6: Between-Firm Outcomes.

| | (1) $\Delta\theta\left(o^{*1}\right)$ | (2) $\Delta\theta\left(o^{*2}\right)$ | (3) $\Delta sim$ | (4) $\Delta bisim$ | (5) $\Delta sim$ fix $w_{ij}$ | (6) $\Delta sim$ fix $\theta_{jo}$ | (7) $\Delta sim$ fix $\theta_{io}$ |
|---|---|---|---|---|---|---|---|
| $z$ | 0.014* | 0.019*** | -0.016** | -0.010** | -0.017*** | -0.010* | -0.009** |
| | (0.008) | (0.007) | (0.007) | (0.004) | (0.006) | (0.005) | (0.004) |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $N$ | 16,788 | 16,788 | 16,788 | 16,788 | 16,788 | 16,788 | 16,788 |

Note: This table presents OLS estimates of regression equation (5) across different outcome variables. Columns (5), (6), and (7) present versions of column (3), but where $w_{ij}$ (import weights), $\theta_{jo}$ (the suppliers' wage bill shares), and $\theta_{io}$ (the focal firm's wage bill shares) are fixed in period 0, respectively (see equation (3)). Robust standard errors in parentheses. Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

### 3.3 Results: Between-Firm Outcomes

We now examine whether focal firms establish new foreign (Danish/Swedish) supplier links and report our results in Table 5. In columns (1) and (2), the dependent variable is the change in the (log of the) number of foreign suppliers. In column (3), the dependent variable is a dummy variable for whether the number of foreign suppliers increases from period 0 to period 1. In column (4), it is a dummy for whether the focal firm has new foreign suppliers in period 1. While the coefficient estimates for all four measures are positive, they lack statistical significance. These results suggest that new foreign-supplier links are unlikely to be driving the increase in labor productivity shown in Table 4. Rather, they suggest that reorganization of production across existing suppliers is important.

A unique feature of our data is that we observe detailed characteristics of the workers of both the focal firm and its foreign (Swedish/Danish) suppliers. We thus explore whether the occupational structure of the focal firm grows more similar, or less similar, as compared with that of its foreign suppliers.

In column (1) of Table 6, the dependent variable is the change in the wage-bill share of the focal firm's top occupation, as defined by equation (1). In column (2), we examine the change in the wage-bill share of the focal firm's top occupation relative to its suppliers, as defined by equation (2). The coefficient estimate is positive and statistically significant, suggesting that the focal firm's comparative-advantage occupations, relative to its foreign suppliers, become more important.

We compare the vector of the focal firm's occupational wage-bill shares with that of its foreign (Swedish/Danish) suppliers in column (3) of Table 6, by using the change in the similarity index constructed from equation (3), $\Delta sim_i$, as the dependent variable. The coefficient estimate is negative and significant. In column (4), we use the binary version of the similarity index, (4), instead, and obtain similar results. Columns (3) and (4) provide clear evidence that the focal firm and its foreign suppliers are growing apart, in terms of their occupational structures.

Columns (5)-(7) of Table 6 explore whether the change in the similarity index is due to changes of the focal firm or its foreign suppliers. In column (5), we fix the import shares $w_{ij}$ at period-0 levels and recompute $\Delta sim_i$. The coefficient estimate is similar to that in column (3) and serves as a benchmark for columns (6) and (7). In column (6), we fix both the import shares and $j$'s occupational wage-bill shares, $\theta_{jo}$, at period-0 levels. The coefficient estimate remains negative and (marginally) significant, and is slightly more than half the size of the estimate in column (5). In column (7), we fix both the import shares and $\theta_{io}$ at period-0 levels, so that $\Delta sim_i$ only captures the change in the suppliers' occupation structure, and obtain similar results. Columns (5)-(7) suggest that the changes in both the focal firm's and its foreign suppliers' occupational structures contribute to the decrease in the similarity index shown in column (3). In summary, Table 6 provides evidence that firm growth leads to increased labor specialization between the focal firm and its foreign suppliers.

### 3.4 Robustness and Heterogeneity

A potential concern is that the demand shock variable $z$ might affect both the focal firm and its suppliers directly. If, for example, all firms in the supply chain are exporting similar products, then a demand shock to $i$ is also a demand shock to $j$. We deal with this issue by directly controlling for the suppliers' demand shocks, see Appendix C.2. The coefficient estimates are very close to our baseline results.

Another concern may be that the demand shock variable might affect both the focal firm and its customers directly. To address this, we let the unit of analysis be a supplier (instead of a customer) and estimate the direct impact of $z$ on the supplier, and the indirect impact of $z$ from its customers. More details are provided in Appendix C.3.

In summary, our empirical results in this section establish the importance of labor specialization along international supply chains. Interestingly, we find a weak extensive margin response, suggesting that reallocation occurs within existing suppliers. Our empirical results also show that labor specialization goes hand in hand with labor productivity growth and lower labor shares. We now turn to a quantitative model to explore the importance of this mechanism.

# 4 The Model

In this section, we present a parsimonious partial equilibrium model broadly consistent with the reduced-form evidence outlined above. The model explains task outsourcing as a scale-dependent organizational choice. Firms choose whether to produce tasks in-house or outsource them, trading off task-level efficiency gains against fixed outsourcing costs. As such, outsourcing gives rise to cost reductions through task-level comparative advantage.

The model delivers two main analytical predictions. First, positive demand shocks lead firms to outsource a larger set of tasks. Second, increased outsourcing reduces the value-added-to-sales ratio. Because higher-demand firms reorganize production toward lower-cost external task provision, both marginal and average costs decline with scale, even though production of each individual task exhibits constant returns to scale. In the subsequent section, we use the model to quantify these mechanisms.

## 4.1 Economic Environment

Firms produce differentiated final goods by combining a unit continuum of tasks. Each task can be produced either in-house or outsourced. Task-level efficiency varies across both firms and tasks. While outsourcing allows firms to exploit comparative advantage in task production, it is associated with fixed costs, such as transaction, monitoring, and reorganization costs. We model these as a task-specific fixed cost $f$. In equilibrium, firms outsource tasks for which efficiency gains are sufficiently large. We relegate all detailed derivations and proofs to Appendix D.

**Final goods demand** Final goods are sold under monopolistic competition with CES preferences and elasticity of substitution $\gamma > 1$. Final good sales are given by

$$s(\lambda) = \lambda p(\lambda)^{1-\gamma}, \tag{7}$$

where $p(\lambda)$ is the final good price and $\lambda$ is a firm-specific demand shock.[14]

**Technology** Final goods firms produce by combining a unit continuum of firm-specific tasks $\omega$ with the following CES production function:

$$y = \left[\int_0^1 v(\omega)^{(\sigma-1)/\sigma} d\omega\right]^{\sigma/(\sigma-1)},$$

where $\sigma > 1$ is the elasticity of substitution across tasks and $v(\omega)$ is the quantity of task $\omega$. Final goods firms are heterogeneous in two dimensions. First, firms face different demand shocks $\lambda$. Second, there is heterogeneity in the efficiency of producing tasks. Note that we have not included a Hicks-neutral productivity shifter in the production function. In this class of models,

[14] $\lambda$ is a composite of the firm-specific demand shock, the final goods price index and aggregate spending. The latter two variables do not vary across buyer firms.

firm-level demand and productivity heterogeneity are isomorphic, but the demand interpretation aligns more closely with our empirical strategy.

**Task production** Tasks are produced using labor under constant returns to scale. In-house task productivity is denoted $\phi^b(\omega)$ ($b$ for buyer) and outsourced task productivity is $\phi^s(\omega)$ ($s$ for supplier). Both $\phi^b(\omega)$ and $\phi^s(\omega)$ vary across firms and tasks (the index for firms is dropped for brevity).[15] For quantitative implementation, we later impose a parametric distribution on task productivities and simulate a large but finite number of tasks. We assume that the market for tasks is perfectly competitive and that wages are the numéraire, so that task prices are $p_t^x(\omega) = 1/\phi^x(\omega)$, $x = \{b, s\}$.

There is a task-specific fixed cost $f$ associated with outsourcing. As a result, firms may optimally produce some tasks in-house even when outsourcing would reduce marginal costs.

**Optimal outsourcing** Firms choose which tasks to outsource to maximize profits. Define relative supplier advantage:

$$\tilde{\phi}(\omega) = \phi^s(\omega)^{\sigma-1} - \phi^b(\omega)^{\sigma-1},$$

and without loss of generality, sort tasks such that $\partial\tilde{\phi}(\omega)/\partial\omega < 0$. This ensures that the sourcing decision admits a cutoff representation. There exists a threshold task $\omega^*(\lambda)$ such that tasks in the interval $[0, \omega^*]$ are outsourced and tasks in $[\omega^*, 1]$ are produced in-house. The CES input price index can then be written as

$$P(\lambda)^{1-\sigma} = \int_0^{\omega^*(\lambda)} \phi^s(\omega)^{\sigma-1} d\omega + \int_{\omega^*(\lambda)}^1 \phi^b(\omega)^{\sigma-1} d\omega.$$

Final good prices are a constant mark-up over costs,

$$p(\lambda) = \bar{m} P(\lambda),$$

where $\bar{m} = \gamma/(\gamma - 1)$. Profits are given by

$$\pi(\lambda) = \frac{s(\lambda)}{\gamma} - \omega^*(\lambda) f.$$

Appendix D shows that the optimal cutoff $\omega^*(\lambda)$ satisfies

$$\tilde{\phi}(\omega^*) = \frac{\gamma f}{\lambda} \frac{\sigma - 1}{\gamma - 1} \bar{m}^{\gamma-1} P(\lambda)^{\gamma-\sigma}. \tag{8}$$

[15] The assumption of firm-specific tasks implies that both $\phi^b(\omega)$ and $\phi^s(\omega)$ vary across firms: For the same task, two final goods firms face different supplier task productivities. $\phi^s(\omega)$ is inclusive of variable trade costs and the relative wage facing the supplier.

Since $\tilde{\phi}(\omega^*)$ is a downward sloping function of $\omega^*$, this equation yields a unique solution for $\omega^*(\lambda)$. The left-hand side is the marginal reduction in the CES unit-cost index from outsourcing the marginal task. The right-hand side is the per-task fixed outsourcing cost converted into marginal-profit units. Higher demand raises the scale over which cost savings are realized, effectively lowering the fixed cost per unit of output

### 4.2 Comparative statics

We now examine how demand affects outsourcing decisions. A higher demand shock increases the scale of production, making fixed outsourcing costs less important relative to the gains from specialization.

To obtain closed-form comparative statics, we focus on the case $\gamma = \sigma$, under which the price index drops out of the first-order condition. This restriction implies that equation (18) can be solved directly - otherwise it becomes a fixed point problem which can only be solved numerically. This restriction simplifies the analysis but is not essential for the economic mechanism. In the quantitative analysis, we solve the model numerically without imposing this restriction.[16]

**Proposition 1** *For $\gamma = \sigma$, a positive demand shock increases the outsourcing cutoff:*

$$\frac{\partial \omega^*}{\partial \lambda} = -\frac{\tilde{\phi}(\omega^*)}{\left[\partial \tilde{\phi}/\partial \omega^*\right]\lambda} > 0. \tag{9}$$

**Proposition 2** *For $\gamma = \sigma$, a positive demand shock decreases the ratio of value-added-to-sales ratio:*

$$\frac{\partial (VA/s)}{\partial \lambda} = -\frac{1}{\bar{m}} P^{\sigma-1} \frac{\partial \omega^*}{\partial \lambda} \bar{\phi}(\omega^*) < 0, \tag{10}$$

*where $\bar{\phi}(\omega^*)$ is a weighted average of buyer and supplier productivity at the cutoff point: $\bar{\phi}(\omega^*) = (1-\Pi)\phi^s(\omega^*)^{\sigma-1} + \Pi\phi^b(\omega^*)^{\sigma-1}$, where the weight $\Pi$ is the cost of outsourced tasks relative to total variable costs.*

The proofs are in Appendix D. The intuition is straightforward. Higher demand raises the scale over which outsourcing generates cost savings, while fixed outsourcing costs remain unchanged. As a result, firms outsource more tasks. Increased outsourcing raises the share of intermediate inputs in production and lowers the value-added-to-sales ratio. Qualitatively, these model predictions match our empirical results from Section 3. To gauge the quantitative fit of the model, the next section estimates the model and compares the reduced form results with estimates using simulated data.

**Discussion** The model abstracts from several margins that may also contribute to scale economies. In particular, we do not model supplier choice, or learning and reorganization within

[16] Numerical simulations of the model show that the qualitative predictions hold more generally.

firms. The model is therefore not intended to capture all sources of scale economies, but rather to isolate the role of task outsourcing.

To connect the model to the data, we interpret occupations as bundles of non-overlapping tasks. Under this interpretation, a firm's occupational employment shares correspond to the distribution of tasks it performs in-house. As firms outsource a larger set of tasks, the set of tasks performed internally becomes more concentrated. This implies that occupational employment becomes more specialized and less similar to that of supplier firms, which perform a different subset of tasks.

We end this section by providing more intuition behind the model and comparative statics. Figure 4 shows the $\tilde{\phi}(\omega)$ function for one particular parameterization. [17] If buyer and seller productivities $\phi^k$ are drawn from the same distribution, the final good firm would want to outsource half of the tasks in the absence of outsourcing costs. This is denoted by $\bar{\omega}$ in the figure. With $f > 0$, the equilibrium is at $\omega^* < \bar{\omega}$. An increase in $f$ leads to a higher value on the right hand side of equation 18. This translates into a movement along the vertical axis in the figure, which yields a lower $\omega^*$ (less outsourcing). In contrast, more dispersion in task productivities $\phi$ translates into a steeper $\tilde{\phi}(\omega)$ function, which means that the gains from outsourcing will be greater. As such, we can think of dispersion in $\phi$ as a measure of comparative advantage. If task productivity is on average higher for the supplier than the buyer, then the $\tilde{\phi}(\omega)$ function would shift to the right. As such, the mean of $\phi$ for the supplier relative to the buyer is a measure of absolute advantage.

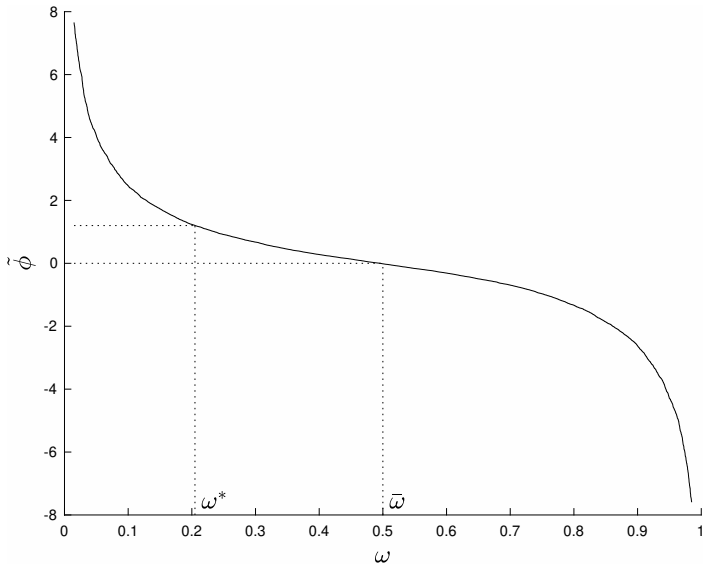
Figure 5 shows how firms responds to demand shocks, using the same parameterization as above. The top two graphs confirm Propositions 1 and 2 - higher demand leads to a larger share of outsourced tasks and a lower value added to sales ratio. The bottom two graphs show that this translates into higher value added per worker and a lower labor share (wage costs relative to total costs).

# 5 Structural Estimation and Counterfactuals

In this section, we estimate key parameters of the model using simulated methods of moments (SMM), and then simulate the model to quantify the economic significance of labor specialization along the global supply chain. We present the estimation methodology, discuss the estimated parameter values, and discuss model fit. We then conduct a counterfactual with prohibitively costly outsourcing and assess the impact on firms' labor productivity and input costs. Finally, we consider alternative model specifications and robustness analyses.

[17] $\ln \phi^k \sim \mathcal{N}(0,1)$, $\sigma = \gamma = 2, \lambda = 1, f = 0.3$.

Figure 4: Determination of cutoff task.




### 5.1 Setting and Key Parameters

Task productivities, $\phi^b(\omega)$ and $\phi^s(\omega)$, are drawn from the log normal distribution,

$$\left(\ln \phi^b, \ln \phi^s\right) \sim \mathcal{N}(\Gamma, \Omega), \quad \Gamma = (0, \mu^s), \quad \Omega = \begin{pmatrix} \sigma_\phi^2 & \rho\sigma_\phi^2 \\ \rho\sigma_\phi^2 & \sigma_\phi^2 \end{pmatrix}, \tag{11}$$

where $\Gamma$ is the mean and $\Omega$ is the covariance matrix. Equation (11) says that we have normalized the mean of the buyer firm's task productivity draws to 0, and that $\mu^s$ captures the average productivity advantage of the supplier. As a result, $\mu^s$ represents the supplier's absolute advantage in the model. $\sigma_\phi^2$ is the variance of task productivity draws. As such, $\sigma_\phi^2$ represents firms' comparative advantage across tasks. Finally, equation (11) says that the productivity draws, $\phi^b(\omega)$ and $\phi^s(\omega)$, might be correlated, summarized by the correlation coefficient $\rho$. This may happen, for example, if the buyer firm and supplier are from the same industry.

Demand shocks are also drawn from the log normal distribution,

$$\lambda = \epsilon^\xi, \quad \ln \epsilon \sim \mathcal{N}\left(\mu_\epsilon, \sigma_\epsilon^2\right), \tag{12}$$

where $\mu_\epsilon$ is the mean, $\sigma_\epsilon$ is the standard deviation and $\xi$ is a scaling parameter. In equation (12), $\ln \epsilon$ corresponds to the demand shock $z_i$ that is used in our empirical analyses and given in equation (6), and so equation (12) translates the model variable of $\lambda$ into the data variable of $z_i$.

The full set of parameters to estimate is $\Upsilon = \left\{\xi, \mu_\epsilon, \sigma_\epsilon, \mu^s, \sigma_\phi, \rho, f\right\}$. The elasticities of substitution $\sigma$ and $\gamma$ are not identified and we therefore choose pre-determined parameters $\gamma = \sigma = 4$. We list the seven parameters to estimate in the 3rd column of Table 7.

We estimate the model by simulated method of moments. We simulate 1,000 firms by drawing their demand shifter, $\lambda$, using equation ((12)). For each firm, we approximate the unit

Figure 5: Demand and outsourcing.

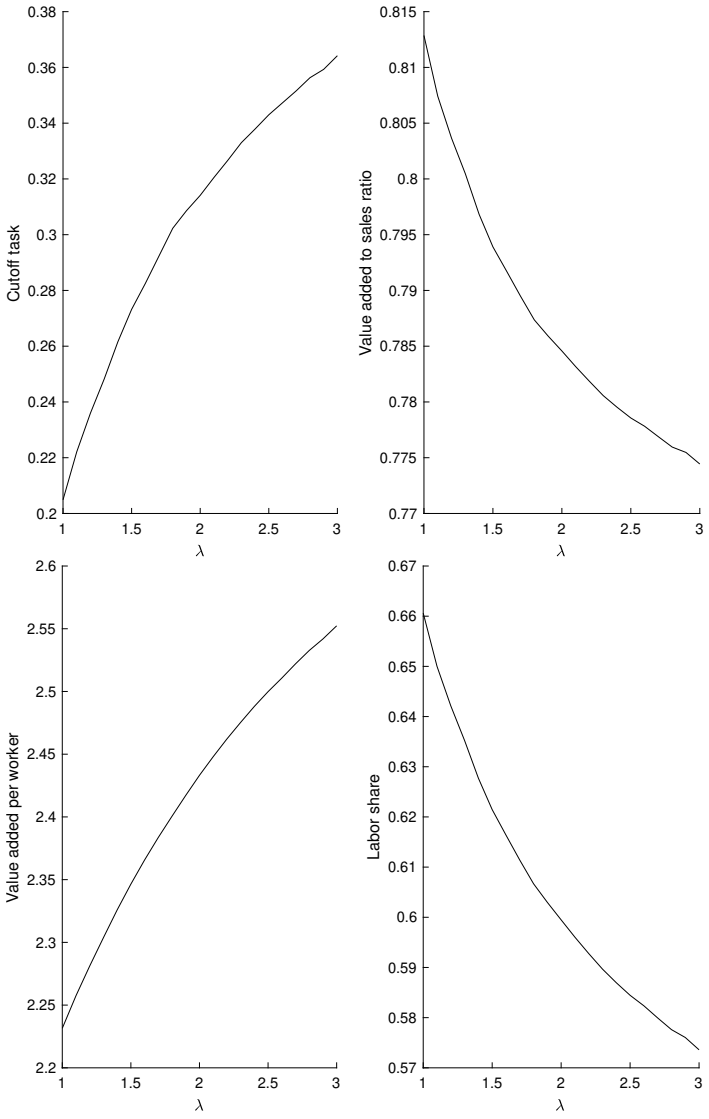



Table 7: Identification of Model Parameters.

| Targeted Moments | Data | Identifies | Par. Values |
|---|---|---|---|
| *Demand-side*: | | | |
| Regression of log sales on $z$ | 0.12 | $\xi$ | $\xi = 0.12$ |
| mean(lnSales) | 18.28 | $\mu_\epsilon$ | $\mu_\epsilon = 101.48$ |
| stdev(lnSales) | 1.67 | $\sigma_\epsilon$ | $\sigma_\epsilon = 13.62$ |
| *Supply-side*: | | | |
| stdev($\ln \theta$) (mean) | 1.61 | $\sigma_\phi$ | $\sigma_\phi = 0.50$ |
| mean(*cosim* similarity index) | 0.45 | $\rho$ | $\rho = 0.91$ |
| mean(Labor share), top decile $S$ | .42 | $\mu^s$ | $\mu^s = 0.046$ |
| mean(Labor share), bottom decile $S$ | .58 | $\mu^s, f$ | $f = 1851.26$ |

The data regression coefficient of log sales on $z$ is given in Table 4, column (1).

*Notes:*

continuum of tasks with 250 discrete tasks and draw their task productivities for the buyer and the potential supplier using equation (11).[18] We obtain the estimated parameter values by minimizing the difference between empirical and simulated moments.

### 5.2 Empirical Moments and Identification

Table 7 summarizes the data moments used for identification, their values and which parameters they help identify. The model is exactly identified with 7 parameters and 7 moments. While all parameters are jointly determined in estimation, each moment primarily loads on a specific economic margin in the model. This structure provides a transparent mapping between model primitives and observable outcomes.

**Firm Demand** We begin with parameters governing firm heterogeneity in demand. The model implies that firm sales are proportional to the demand shifter $\lambda$, which we model as a monotone transformation of the empirical demand shock $z$. The parameter $\xi$ therefore governs how variation in the empirical shock translates into dispersion in firm scale. We identify $\xi$ using the regression coefficient of log sales on $z_i$. Intuitively, $\xi$ determines the elasticity of firm size with respect to the underlying demand shock.

Conditional on $\xi$, the distribution of $\ln \lambda$ is pinned down by the distribution of $\ln \epsilon$. We therefore use the cross-sectional mean and standard deviation of log sales to identify $\mu_\epsilon$ and $\sigma_\epsilon$, which govern the level and dispersion of firm size in the model.[19]

**Dispersion in task productivity** We next turn to parameters governing task-level heterogeneity and outsourcing. The parameter $\sigma_\phi$ controls the dispersion in task productivities within firms and therefore the strength of comparative advantage across tasks.

In the model, this dispersion determines how concentrated production is across tasks. When $\sigma_\phi$ is high, firms have stronger comparative advantage in a subset of tasks and allocate more resources toward those tasks. We map this to the data using the dispersion of occupational wage-bill shares within firms. Specifically, we target the mean standard deviation of $\ln \theta_{io}$, where $\theta_{io}$ denotes the wage-bill share of occupation $o$ in firm $i$. Under the mapping from tasks to occupations, this moment provides a direct measure of within-firm specialization and therefore identifies $\sigma_\phi$.

**Correlation in task productivity** The parameter $\rho$ captures the correlation between buyer and supplier task productivities. It governs the extent to which firms share comparative advantage in similar tasks.

This parameter directly affects the similarity of task allocations between firms. When $\rho$ is high, buyers and suppliers tend to specialize in similar tasks; when $\rho$ is low, they specialize in

[18] This discretization provides a close approximation to the continuum model. Increasing the number of tasks does not affect the parameter estimates to a large degree, see Section 5.3.

[19] We have also regressed log sales on country and 2-digit industry fixed effects and then using the residual to compute the mean and standard deviation. The results are very similar to Table 7.

different tasks.

We identify $\rho$ using the similarity index based on occupational wage-bill shares between buyer and supplier firms.[20] This moment captures how similar firms are in their production structure and therefore directly maps to the correlation in task-level comparative advantage.

**Absolute advantage and fixed costs** The parameters $\mu^s$ and $f$ jointly determine the extent of outsourcing in the model.

The parameter $\mu^s$ captures the supplier's absolute productivity advantage and shifts the gains from outsourcing uniformly across firms. In contrast, the fixed outsourcing cost $f$ introduces scale dependence: larger firms are less affected by fixed costs and therefore outsource more tasks.

Because the model does not directly observe the outsourcing share $\omega^*$, we use the labor share (wage costs relative to total variable costs) as a sufficient statistic for the extent of outsourcing. Higher outsourcing implies greater use of intermediate inputs and therefore a lower labor share. To separately identify $\mu^s$ and $f$, we exploit heterogeneity across firm size. We target the average labor share for firms in the top and bottom deciles of the size distribution. The key identification comes from differential sensitivity: for large firms, outsourcing decisions are primarily driven by productivity differences (and therefore $\mu^s$), while for small firms, fixed costs $f$ play a central role. This allows us to disentangle level effects from scale-dependent frictions.

In sum, the identification strategy exploits three distinct sources of variation: (i) cross-firm variation in size to identify demand parameters, (ii) within-firm dispersion in task allocation to identify comparative advantage and (iii) between-firm similarity in task allocation and size-dependent outsourcing behavior to identify correlation and fixed costs.

While our data captures only cross-border links between Danish and Swedish firms, our identification relies on moments that aggregate across all sourcing relationships (e.g., labor share) or are unlikely to vary systematically across locations (e.g., similarity indices). As such, the limited availability of firm-to-firm data is not a constraint for the structural estimation,.

### 5.3 Results

**Parameter Estimates** Table 7 reports the estimated parameters. The estimates imply that suppliers have, on average, a modest productivity advantage over buyers, with $\mu^s = 0.046$, corresponding to roughly a 5 percent difference in task productivity. At the same time, task productivities exhibit substantial dispersion, governed by $\sigma_\phi = 0.50$, indicating meaningful scope for comparative advantage across tasks.

A key feature of the estimates is the high correlation in task productivities between buyers and suppliers, $\rho = 0.91$. This suggests that firms tend to be productive in similar tasks, limiting the scope for extreme specialization and implying that outsourcing reallocates tasks at the margin rather than across entirely distinct production domains.

The estimated fixed cost of outsourcing is $f = 1851$ DKK (approximately 300 USD) per

[20] Since the model does not feature round-about production, the task cost shares for the supplier are all greater than zero, i.e., the supplier is not itself outsourcing tasks.

task. For the average firm, the share of outsourcing costs in total labor costs are 1.1 percent (i.e, the mean of $\omega^* f/L$).[21] While small relative to total firm costs, this fixed cost is sufficient to generate substantial scale dependence: larger firms outsource more tasks because they can spread these costs over a greater volume of output.

Taken together, these estimates imply that outsourcing is driven by a combination of modest absolute advantage, meaningful dispersion in comparative advantage, and scale-dependent frictions.

**Model fit** We evaluate the model by comparing non-targeted moments in the simulated data to their empirical counterparts.

First, Table 8 shows that the model generates substantial dispersion in labor productivity across firms. In the simulated data, value added per worker at the 90th percentile is 30 percent higher than at the 10th percentile, compared to 50 percent in the data. This indicates that task reallocation through outsourcing accounts for a significant share of productivity differences across firms.[22]

Second, the model reproduces the relationship between firm size and input use. In particular, the estimated coefficient from a regression of labor share on log sales is $-0.028$ in the model, closely matching the empirical estimate of $-0.029$ (see Figure 1). This provides direct support for the model's central mechanism: larger firms rely more on intermediate inputs due to increased outsourcing.

The model also generates a positive relationship between firm size and labor productivity, but the magnitude is smaller than in the data. The estimated elasticity of value added per worker with respect to sales is 0.029 in the model, compared to 0.10 in the data. This suggests that while outsourcing contributes to productivity gains, additional mechanisms—such as learning-by-doing, managerial improvements, or within-firm reorganization—likely play an important role. We also find that the average value added to sales ratio is higher in the model compared to the data (0.58 versus 0.32)

**Scale economies** The model implies increasing returns to scale at the firm level, even though production of each task exhibits constant returns to scale.

To quantify this effect, we regress log output on log employment using simulated data. The estimated elasticity is 1.05, implying that a doubling of employment increases output per worker by approximately 5 percent. These increasing returns arise endogenously from task reallocation: as firms grow, they outsource a larger set of tasks and concentrate production on activities where they have a comparative advantage.

[21] In recent work, Antras et al. (2017) estimate that the fixed sourcing cost is 10,000-56,000 USD per source country for the median U.S. buyer firm. Halpern et al. (2015) find that the average Hungarian buyer firm's total fixed import cost, for accessing all products and all source countries, accounts for 2.2 percent of total production cost. While these estimates are based on different data and model than our estimate, they are qualitatively similar to ours and help place ours into context.

[22] In comparison, in a model with no task specialization, but with heterogeneity in demand and/or total factor productivity, labor productivity (along with the labor share and the value added to sales ratio) is constant across firms.

Table 8: Variation in Labor Productivity, Data and Model.

| Moment | Data | Model |
|---|---|---|
| Value added per worker, P90/P10 | 1.50 | 1.30 |
| VA/Sales, mean | .32 | .58 |
| Regression of labor share on ln sales | -0.029 | -0.028 |
| Regression of ln VA/L on ln sales | 0.10 | 0.029 |

*Notes:* The coefficient estimate of the regression of log $VA/L$ on log sales is displayed in Figure 1, and that of labor share on log sales displayed in Figure 2.

This result highlights a central contribution of the model: increasing returns to scale emerge endogenously from organizational choices, even in the absence of technological non-convexities.

**Response to demand shocks** Next, we simulate firms' response to demand shocks and compare them with our empirical estimates from Tables 4 and 6. This exercise puts the model and data on the same statistical footing and allows for a direct comparison of reduced-form elasticities.

For each firm $i$, we draw a new demand shock, $\epsilon_i'$, using equation (12) and hold all the other parameters fixed. We then compute $i$'s optimal choices of outcome variables under this new scenario with demand shocks, $y_i'$, and run the following regression using simulated data:

$$\Delta \ln y_i = \alpha + \beta \Delta \ln \epsilon_i + \nu_i, \tag{13}$$

where $\nu_i$ is an error term and $\Delta$ denotes the change of $y_i'$ and $\epsilon_i'$ relative to the baseline scenario. The lower panels of Tables 9 and 10 report the $\beta$ estimates of regression (13) and the upper panels recap the estimates of the corresponding data regression of (5).

Column (1) of Table 9 re-iterates that, because the model targets the data regression coefficient for log sales, it is the same as the model regression coefficient. The rest of Table 9 shows that the model regression coefficients are qualitatively similar to the data regression coefficients for log value-added-to-sales ratio, log labor share, and log value added per worker. In general, the magnitudes are smaller in the model compared to the data, but this is also as expected since the model isolates one mechanism - task outsourcing - and therefore captures a lower bound of the total effect.

**Labor specialization** We now turn to the model's implications for labor specialization.

In the model, increased outsourcing reduces the set of tasks performed in-house, leading firms to concentrate production on a narrower set of activities. Under the mapping between tasks and occupations, this implies greater specialization in occupational employment and reduced similarity between buyer and supplier firms.

Table 10 reports the results. Columns (1) and (2) show the wage-bill share and relative wage-bill share of the top occupation, as defined in equations (1) and (2), respectively. Column

Table 9: The Simulated Effects of Demand Shocks on Scale and Labor Productivity

| | (1) $\Delta \ln Sales$ | (2) $\Delta \ln \frac{VA}{Sales}$ | (3) $\Delta \ln LaborShare$ | (4) $\Delta \ln \frac{VA}{L}$ |
|---|---|---|---|---|
| Actual Data: | | | | |
| $z$ | 0.12*** | -0.028** | -0.045*** | 0.037*** |
| Simulated Data: | | | | |
| $\ln \epsilon$ | 0.12*** | -0.004*** | -0.007*** | 0.003*** |
| | (0.02) | (0.01) | (0.01) | (0.01) |

*Notes:* Significance levels: $*p < 0.1, **p < 0.05, ***p < 0.01$. The data regression coefficients are taken from Table 4, and the standard errors are shown over there. The model regressions all have 1000 observations, and the standard errors of their coefficient estimates are in parentheses. The dependent variables of the model regressions are the changes of the scenario with demand shocks relative to the baseline scenario.

(3) shows the *cosim* index of occupation similarity, and column (4) shows the binary version of *cosim*, as defined in equation (4). Table 10 shows that the model regression coefficients are all qualitatively similar to the data regression coefficients.

These patterns are a direct implication of Proposition 1: as firms outsource a larger set of tasks, the set of in-house activities becomes more concentrated, leading to increased specialization and reduced overlap with suppliers.

As with other outcomes, the magnitude of these effects is smaller than in the data, again suggesting that outsourcing is one of several forces shaping labor specialization.

**Counterfactual: No Outsourcing** We use the estimated model to quantify the economic importance of outsourcing by conducting a counterfactual in which outsourcing is prohibitively costly: $f = \infty$.

In this scenario, firms produce all tasks in-house, and differences across firms are driven solely by demand shocks. As a result, there is no variation in input prices or labor productivity arising from task reallocation.

Figure 6 shows the distribution of changes in labor productivity and the input price index across firms. The top panel of Table 11 summarizes the results. The counterfactual reveals substantial gains from outsourcing. On average, value added per worker declines by 0.29 log points (approximately 34 percent) when outsourcing is eliminated. At the same time, the input price index increases by 0.096 log points (approximately 10 percent), reflecting the loss of access to lower-cost external production.

These effects are highly heterogeneous across firms. Firms that rely heavily on outsourcing in the baseline experience large declines in productivity, while firms that outsource little are less affected. This heterogeneity mirrors the dispersion in labor productivity observed in the data.

Overall, this counterfactual isolates the contribution of global task specialization to firm performance and shows that outsourcing is a quantitatively important source of productivity

Table 10: The Simulated Effects of Demand Shocks on Labor Specialization

| | (1) $\Delta\theta\left(o_i^{1*}\right)$ | (2) $\Delta\theta\left(o_i^{2*}\right)$ | (3) $\Delta cosim_i$ | (4) $\Delta bisim_i$ |
|---|---|---|---|---|
| Actual Data: | | | | |
| $z$ | 0.014* | 0.019*** | -0.016** | -0.010** |
| Simulated Data: | | | | |
| $\ln \epsilon$ | 0.005*** | 0.005*** | -0.001*** | -0.006** |
| | (0.01) | (0.01) | (0.01) | (0.00) |

*Notes:* Significance levels: $*p < 0.1, **p < 0.05, ***p < 0.01$.. The dependent variables in columns (1)-(4) are defined in equations (1), (2), (3) and (4), respectively. The coefficient estimates with actual data are taken from Table 6. The coefficient estimates with simulated data have 1000 observations, and their standard errors are in parentheses. The dependent variables of the model regressions are the changes of the scenario with demand shocks relative to the baseline scenario.

Table 11: The Gains from Outsourcing

| | Mean | Weighted mean | Median | St. dev. |
|---|---|---|---|---|
| Baseline Model, $\rho = 0.91$ | | | | |
| $\Delta \ln(VA/worker)$ | -0.29 | -0.30 | -0.28 | 0.11 |
| $\Delta \ln$(input price index) | 0.096 | 0.11 | 0.094 | 0.024 |
| The Model with $\rho = 0$ | | | | |
| $\Delta \ln(VA/worker)$ | -0.26 | -0.30 | -0.26 | 0.11 |
| $\Delta \ln$(input price index) | 0.24 | 0.25 | 0.24 | 0.062 |

*Notes:* The weighted mean uses employment as weights.

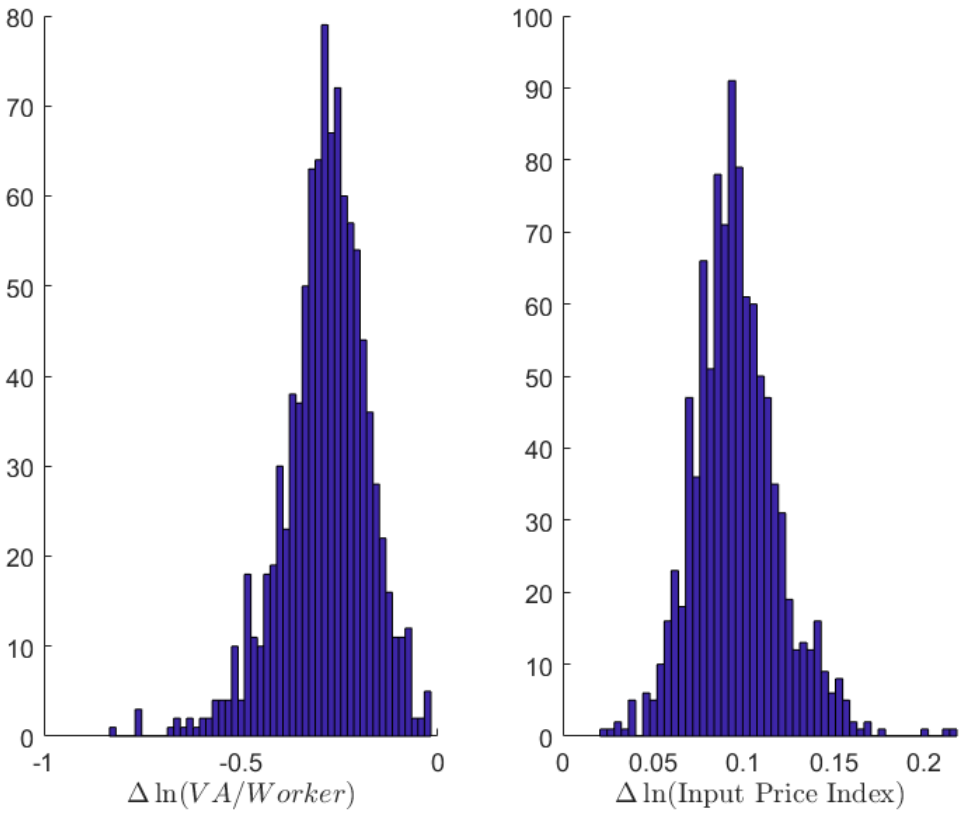
gains.

Taken together, the structural estimates and counterfactual exercises show that task outsourcing is a quantitatively important source of firm-level scale economies and productivity differences. In the model, reallocating tasks across firm boundaries generates substantial dispersion in value added per worker and produces increasing returns to scale, even though production at the task level is constant returns to scale. Eliminating outsourcing reduces average labor productivity by roughly one-third and raises input costs by about 10 percent, indicating sizable gains from global task specialization. At the same time, the model explains only part of the empirical responses of productivity and specialization to demand shocks, suggesting that outsourcing is a central—but not exclusive—channel through which scale affects firm performance.

### 5.4 Alternative Specifications and Robustness

We end this section by performing a series of robustness checks.

Figure 6: Counterfactual: No Outsourcing




*Notes:* Changes in log value added per worker and log input price index refer for the change from the baseline to the counterfactual.

**Role of buyer–supplier similarity** Finally, we assess the importance of modeling buyer–supplier similarity by estimating a restricted version of the model in which task productivities are uncorrelated across firms ($\rho = 0$).

While the restricted model can match the remaining moments, it generates a counterfactually low level of similarity between firms and substantially overstates the gains from outsourcing. In particular, as shown in the lower panel of Table 11, the implied increase in input costs under the no-outsourcing counterfactual is much larger than in the baseline model.

The intuition is straightforward. When task productivities are highly correlated, firms share similar comparative advantage, limiting the scope for mutually beneficial outsourcing. Failing to account for this correlation leads to a substantial overstatement of the gains from outsourcing, highlighting the importance of modeling buyer–supplier similarity.

**Adding Capital** Finally, we have experimented with adding capital into the model and using alternative values of $\sigma$. Appendix D shows that these modifications do not impact our results substantially.

**More Tasks** We increase the number of tasks in the SMM estimation from 250 in the baseline model to 10,000. The estimated parameters are overall very similar to the baseline. One exception is the per-task fixed cost - this parameter is by construction a function of the number of tasks, and as such this is as expected.

# 6 Additional Empirical Evidence

In this section, we use our novel linked worker-firm data from Denmark and Sweden to provide additional empirical evidence for our model. We first clarify that, because of high relationship specificity in our sample (section 2), the empirical results from section 3 are driven by relationship-specific buyer firms. We then show that these buyer firms' labor reallocation in response to exogenous demand shocks is consistent with the predictions of our model.

## 6.1 Relationship-specific Buyer Firms

Recall, from sub-section 2.3, that relationship specificity, based on Nunn (2007)'s measure, is high among the buyer-supplier relationships between Danish and Swedish firms. In this sub-section, we explore whether, and how, relationship specificity matters for the effects of exogenous demand shocks on the buyer firms' size, labor productivity, and labor specialization.

We split the sample used for Tables 4 and 6 as follows. The relationship-specific sub-sample consists of the buyer firms with $rs_i > 0.68$, the 75th percentile of the differentiated-goods share in Nunn (2007)'s data, and the generic-inputs sub-sample consists of the remaining buyer firms. We then estimate the same regressions as in Tables 4 and 6 by sub-sample, and report the results in Tables 12 and 13, where panel A (B) shows the results for the relationship-specific

(generic-inputs) sub-sample. We see that the vast majority, or more than four out of five, of the buyer firms in our sample are in the relationship-specific sub-sample.

Columns (1)-(2) of Table 12 show that the buyer firms in both sub-samples grow in sales and employment in response to positive exogenous demand shocks. Column (3) shows that the two sub-samples also exhibit similar responses in labor share, or the share of wage costs in total costs. Columns (4) and (5) show that the buyer firms in the relationship-specific sub-sample increase log value added per worker and log TFP when demand increases exogenously, and these results are similar to the results for the full sample in Table 4. On the other hand, the results for log value added per worker and log TFP are statistically insignificant for the generic-inputs sub-sample.

Table 12: Expansion and Scale Economies by Relationship Specificity Sub-samples

| | (1) $\Delta \ln Sales$ | (2) $\Delta \ln L$ | (3) $\Delta \ln LaborShare$ | (4) $\Delta \ln \frac{ValueAdded}{L}$ | (5) $\Delta \ln TFP$ |
|---|---|---|---|---|---|
| *Panel A Relationship Specific ($rs_i > 0.68$)* | | | | | |
| z | 0.109*** | 0.054*** | -0.043*** | 0.043*** | 0.024* |
| | (0.022) | (0.016) | (0.014) | (0.015) | (0.013) |
| Observations | 13954 | 13954 | 13841 | 13547 | 10816 |
| *Panel B Generic Inputs ($rs_i < 0.68$)* | | | | | |
| z | 0.189*** | 0.091** | -0.053* | -0.001 | 0.024 |
| | (0.061) | (0.043) | (0.031) | (0.033) | (0.031) |
| Observations | 2671 | 2671 | 2641 | 2609 | 2246 |

Panel A of Table 13 shows that the relationship specific buyer firms increase the wage-bill shares of their top occupations and decrease the similarity of their occupational structure relative to their foreign suppliers, and these results are similar to Table 6. On the other hand, panel B of Table 13 shows that the coefficient estimates of the generic-inputs buyer firms have the same signs as in panel A, but they lack statistical significance.

Table 13: Between-Firm Labor Specialization by Relationship Specificity Sub-sample

| | (1) $\Delta\ \theta(o_i^{1*})$ | (2) $\Delta\ \theta(o_i^{2*})$ | (3) Similarity | (4) Similarity (binary) |
|---|---|---|---|---|
| *Panel A Relationship Specific ($rs_i > 0.68$)* | | | | |
| z | 0.013 | 0.019*** | -0.015** | -0.010** |
| | (0.009) | (0.007) | (0.008) | (0.004) |
| Observations | 13954 | 13954 | 13954 | 13954 |
| *Panel B Generic Inputs ($rs_i < 0.68$)* | | | | |
| z | 0.024 | 0.018 | -0.017 | -0.008 |
| | (0.019) | (0.017) | (0.017) | (0.012) |
| Observations | 2671 | 2671 | 2671 | 2671 |

Overall, the results in Tables 12 and 13 show that the earlier results from Tables 4 and 6 are driven by relationship-specific buyer firms, given that they account for most of the observations in our sample. These results clarify that our work fits in well with the GVC literature, where relationship specificity plays an important role.

## 6.2 Within-firm Labor Reallocation

Next, we note that a key mechanism of our quantitative model is that when output demand increases, the buyer firm allocates labor away from in-house production towards fixed outsourcing cost. In this sub-section, we explore whether these model predictions are consistent with our data.

We start with the model prediction that the buyer firm allocates labor away from in-house production. The management-layers literature (e.g. Caliendo et al. 2015) shows that the lowest-layer workers are present in almost all plants and firms, and it also provides these workers' occupation codes. We thus interpret these workers as primarily related to in-house production, and map their occupation codes to those in our data. We then estimate regression (5) with the change in the wage-bill or employment share of the production occupations as the dependent variable.

Column 1 of Table 14 reports the results for the change in wage-bill share and column 2 reports those for the change in employment share. In panel A, we include all observations, and obtain negative and statistically significant coefficient estimates for both wage-bill and employment shares. In panel B, we find that the coefficient estimates remain negative and significant for the relationship-specific sub-sample. Panel C shows that the coefficient estimates are statistically insignificant for the generic-inputs sub-sample. These results provide clear evidence that relationship-specific buyer firms allocate labor away from in-house production, as consistent with our quantitative model.

Table 14: Within-Firm Labor Reallocation: Production Occupations

| | (1) Δ Wage-bill share | (2) Δ Employment share |
|---|---|---|
| *Panel A: All* | | |
| z | -0.012** | -0.011** |
| | (0.006) | (0.005) |
| Observations | 16788 | 16788 |
| *Panel B Relationship Specific ($rs_i > 0.68$)* | | |
| z | -0.016*** | -0.016*** |
| | (0.006) | (0.006) |
| Observations | 13954 | 13954 |
| *Panel C Generic Inputs ($rs_i < 0.68$)* | | |
| z | 0.009 | 0.017 |
| | (0.013) | (0.013) |
| Observations | 2671 | 2671 |

Table 15 examines the model prediction that the buyer firm allocates labor towards outsourcing costs. We measure outsourcing-costs labor by using college-educated workers, because previous studies, such as Matsuyama (2007), have hypothesized that trade costs, including outsourcing costs, are skilled-labor intensive relative to in-house production. Column 1 of Table 15 reports the results for the change in the wage-bill share of college-educated workers, and column 2 reports the change in employment share. With all observations included, in panel A, we obtain positive coefficient estimates, but their statistical significance is marginal at best. With relationship-specific buyer firms only, in panel B, however, we obtain statistical significance for the wage-bill share, and the coefficient estimates remain positive, and become larger in magnitude. In panel C, with generic-inputs buyer firms, we obtain statistically insignificant coefficient estimates. These results suggest that relationship-specific buyer firms allocate labor towards outsourcing costs, as consistent with our quantitative model.[23]

[23]Our results in Table 15 and earlier ones in Table 4 show that the buyer firms become more skilled-labor intensive and also achieves higher labor productivity. This positive correlation between changes in skill and productivity over time complements previous studies with the productivity-skill-complementarity hypothesis, such as Burstein and Vogel (2017).

Table 15: Within-Firm Labor Reallocation: College-Educated Workers

| | (1) Δ Wage-bill share | (2) Δ Employment share |
|---|---|---|
| *Panel A: All* | | |
| z | 0.007* | 0.005 |
| | (0.004) | (0.004) |
| Observations | 16788 | 16788 |
| *Panel B: Relationship Specific ($rs_i > 0.68$)* | | |
| z | 0.009** | 0.008* |
| | (0.004) | (0.004) |
| Observations | 13954 | 13954 |
| *Panel C: Generic Inputs ($rs_i < 0.68$)* | | |
| z | -0.011 | -0.016* |
| | (0.010) | (0.010) |
| Observations | 2671 | 2671 |

Note that the in-house-production labor and outsourcing-cost labor in our model do not exactly map into the production workers and college educated workers in Tables 14 and 15. For example, college educated engineers might be involved in in-house production as well. As a result, unlike the regressions in Tables 4 and 6, those in Tables 14 and 15 do not have corresponding model regressions, and so the empirical evidence in Tables 14 and 15 is qualitative in nature.

Summarizing this section, we have shown that in response to positive exogenous demand shocks, the relationship-specific buyer firms increase value added per worker, allocate labor away from in-house production towards outsourcing costs, and their occupational structures grow apart from their foreign suppliers'. These results are consistent with the key mechanisms of our quantitative model. In addition, while relationship specificity is a theoretical assumption that is commonly used in the literature of global supply chains, the empirical evidence for how relationship specificity matters at the micro level is more limited. Our results in this section provide novel empirical evidence that relationship specificity, as measured by Nunn (2007), matters for productivity, within-firm labor allocation, and between-firm labor specialization for the global supply links between Denmark and Sweden.

# 7 Conclusion

In this paper, we put together a novel dataset, where the universe of cross-border transactions between Danish and Swedish firms is merged with the administrative matched worker-firm data from both countries. This novel data allows us to explore labor specialization across firms, labor productivity, relationship specificity, and within-firm labor allocation along international supply

chains.

To be specific, we first provide novel empirical evidence that when output demand increases exogenously, the buyer firm experiences an increase in labor productivity but a decrease in occupational similarity with foreign suppliers, which suggests increased labor specialization. Second, we propose a simple model with task specialization and outsourcing that is broadly consistent with the evidence, in which the buyer firm substitutes its own labor used in in-house production for imported inputs when output demand increases exogenously. Third, we use our novel data to structurally estimate key model parameters, and our quantification and counterfactual show that for the buyer firms with foreign suppliers, labor specialization is a quantitatively important economic mechanism for higher labor productivity and lower input costs. For example, our model simulation accounts for a substantial portion of the cross-section variation of value-added per worker in the data, and that in the absence of labor specialization and outsourcing, the average buyer firm's labor productivity would be 34 percent lower and the input price index 10 percent higher. Finally, we show that our main empirical results are driven by the relationship-specific buyer firms, which account for the majority of our sample. They also decrease the wage-bill and employment shares of production-related workers but increase the shares of college graduated workers, and these results provide additional empirical evidence for the key mechanisms of our quantitative model.

In our work, we have used data of international supply chains for our empirical analyses. Our quantitative model, on the other hand, is equally applicable to labor specialization with domestic suppliers, and so could be useful to the study of domestic supply chains, especially if the domestic-supply-chains data can be merged with matched worker-firm data in future research.

Finally, our study emphasizes the substitution margin between the buyer firm's own in-house production labor and imported inputs, and so complements the existing GVC literature's emphasis on the margin of which suppliers to choose. It could be fruitful for future research to incorporate both substitution margins in the same framework.

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# Appendix

# A Data

Table 16: Data Sources

| | Denmark | | Sweden | |
|---|---|---|---|---|
| Variable name (abb.) | Data source | Original variable name | Data source | Original variable name |
| Total sales (*Sales*) | Firm Statistics Register (FIRM) | gf_oms | The VAT Register (MOMS) | oms_exkl_moms |
| Employment in full-time equivalents ($L$) | Firm Statistics Register (FIRM) | gf_aarsv | Structural Business Statistics (FEK) | AntalAnstallda |
| Value added (*ValueAdded*) | Firm Statistics Register (FIRM) | gf_vtv | Structural Business Statistics (FEK) | ForadlingsVarde |
| Wage costs (-) | Firm Statistics Register (FIRM) | gf_lgagmv | Structural Business Statistics (FEK) | SummaPersonalkostnader |
| Total costs (-) | Firm Statistics Register (FIRM) | gf_kob + gf_lgagmv | The VAT Register (MOMS) & Structural Business Statistics (FEK) | M20_25_InkopVarEG+M21_InkopTjaEG+M22_InkopTjaUtEG+ M50_MomsUlagImport+M23_InkopVarSverige+M24_InkopTjaSverige+ SummaPersonalkostnader |
| Capital (-) | Firm Account Statistics (FIRE) | iaat+grby+atam+fmaa+aadi | Structural business statistics (FEK) | SummaEgetKapitalInklHBKBEnskilda |
| Materials (-) | Firm Account Statistics (FIRE) | krhe+fvv (-2016), frhe+fvv (2017-) | Structural business statistics (FEK) | KostnaderForRavaror |
| Industry ($s$) | Firm Statistics Register (FIRM) | gf_nace_db07 (first two digits) | Structural business statistics (FEK) | bransch_sni2007 (first two digits) |
| 3rd-country exports (-) | Statistics for International Trade in Goods (uhdm) | vrd | Foreign trade - exports and imports of goods (UHV) | vrd |
| National occupation code (-) | Employment Statistics for Employees (BFL) | vmo_disco_kode | Longitudinal integrated database for health insurance and labour market studies (LISA) | Ssyk4_J16 (-2013), SSyk4_2012_J16 (2014-) |
| Occupation-specific wage bill ($WL$) | Employment Statistics for Employees (BFL) | ajo_smalt_loenbeloeb | Longitudinal integrated database for health insurance and labour market studies (LISA) | loneink |
| Workers' education (-) | The Attainment register (UDDA) | hfaudd (aggregated by level) | Longitudinal integrated database for health insurance and labour market studies (LISA) | Sun2000niva |

Notes: Labor share is defined as Wage costs divided by Total costs. Capital and Materials are used for TFP estimation only. National occupation codes are used to construct ISCO+ codes as described in Appendix X.

# B Occupation Codes

Occupation codes in Denmark and Sweden:

- Denmark: Danish occupation codes, DISCO-08, have been in use since 2010 (that is, during our full sample period). They are a 6-digit extension of 4-digit ISCO-08. Without further ado we collapse 6-digit DISCO-08 to 4-digit ISCO-08.
- Sweden: Swedish occupation codes changed between 2014 and 2015 from SSYK96 to SSYK12. The latter are still in use. SSYK96 (SSYK12) are 4-digit codes based on, but different from, ISCO-88 (ISCO-08).

To examine questions like "do Danish sellers share occupation codes with their Swedish buyers?" we need a set of occupation codes that are both consistent over time and comparable across Denmark and Sweden.

## B.1 Aligning Swedish occupation codes over time

We wish to translate SSYK96 codes into SSYK12 codes. SCB provides an official many-to-many key. This means that for some SSYK96 we have multiple SSYK12 "candidates". We need a rule to choose between these candidates (in other words, we wish to collapse the many-to-many key to a many-to-one key). The rule is defined as follows:

1. Consider all employees working in the same firm in 2013 (the last year of SSYK96) and 2014 (the first year of SSYK12).
2. Disregard employees with missing occupation code in either year (after simple imputation using data for the adjacent years, 2012 and 2015). This means that all employees are associated with a SSYK96-SSYK12 pair.
3. Disregard employees with SSYK96-SSYK12 pairs not in accordance with the many-to-many key. For each SSYK96, choose the SSYK12 with the most observed SSYK96-SSYK12 pairs.

## B.2 Aligning occupation codes across Denmark and Sweden

We wish to compare Danish (ISCO08) and Swedish (SSYK12) occupation codes. SCB provides an official many-to-many key. This means that for some SSYK12 we have multiple ISCO08 candidates. Unlike above, we have no data to help us form a rule between these candidates. Instead, we construct an occupation grouping, call it ISCO+, as the most dis-aggregate grouping that ensures

1. there exists at many-to-one key between ISCO08 and ISCO+, and
2. there exists at many-to-one key between SSYK12 and ISCO+.

This is akin to the so-called CN8+ product classification, suggested by Van Beveren et al. (2012), which ensures a many-to-one mapping between all year-specific CN classifications and CN8+.

Table 17: Aggregate statistics for occupation codes, Sweden

| Digits | Four | | Three | | Two | | One | |
|---|---|---|---|---|---|---|---|---|
| | t=0 | t=1 | t=0 | t=1 | t=0 | t=1 | t=0 | t=1 |
| *Panel A: SSYK96* | | | | | | | | |
| #Occ codes | 355 | . | 113 | . | 27 | . | 10 | . |
| Non-mis share | 94 | . | 94 | . | 94 | . | 94 | . |
| Top share | 6 | . | 8 | . | 13 | . | 22 | . |
| *Panel B: SSYK12* | | | | | | | | |
| #Occ codes | 289 | 429 | 91 | 148 | 24 | 46 | 10 | 10 |
| Non-mis share | 94 | 91 | 94 | 91 | 94 | 91 | 94 | 91 |
| Top share | 6 | 6 | 8 | 7 | 16 | 10 | 22 | 20 |
| *Panel C: ISCO+* | | | | | | | | |
| #Occ codes | 179 | 207 | 30 | 36 | 3 | 4 | 2 | 2 |
| Non-mis share | 94 | 91 | 94 | 91 | 94 | 91 | 94 | 91 |
| Top share | 33 | 32 | 80 | 83 | 100 | 100 | 100 | 100 |

Note: "Non-mis share" is share of workforce with observed occupation code (in percent). "Top share" is the share of the workforce in the largest occupation code (in percent).

Table 18: Aggregate statistics for occupation codes, Denmark

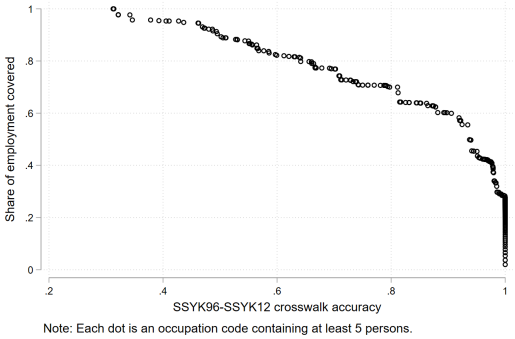
| Digits | Four | | Three | | Two | | One | |
|---|---|---|---|---|---|---|---|---|
| | t=0 | t=1 | t=0 | t=1 | t=0 | t=1 | t=0 | t=1 |
| *Panel A: ISCO08* | | | | | | | | |
| #Occ codes | 539 | 499 | 172 | 164 | 52 | 52 | 10 | 10 |
| Non-mis share | 95 | 96 | 95 | 96 | 95 | 96 | 95 | 96 |
| Top share | 10 | 10 | 11 | 10 | 13 | 15 | 16 | 17 |
| *Panel B: ISCO+* | | | | | | | | |
| #Occ codes | 202 | 204 | 36 | 36 | 4 | 4 | 2 | 2 |
| Non-mis share | 93 | 96 | 94 | 96 | 95 | 96 | 95 | 96 |
| Top share | 33 | 34 | 73 | 76 | 100 | 100 | 100 | 100 |

Note: "Non-mis share" is share of workforce with observed occupation code (in percent). "Top share" is the share of the workforce in the largest occupation code (in percent).

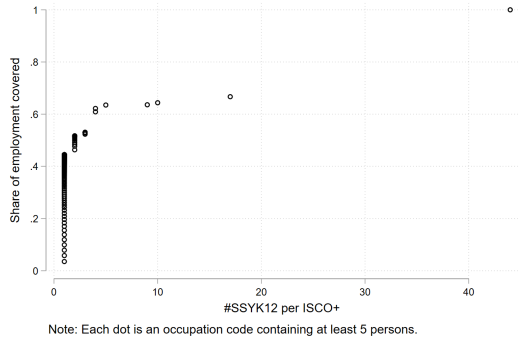
Figure 7: Occupation Code Concordance



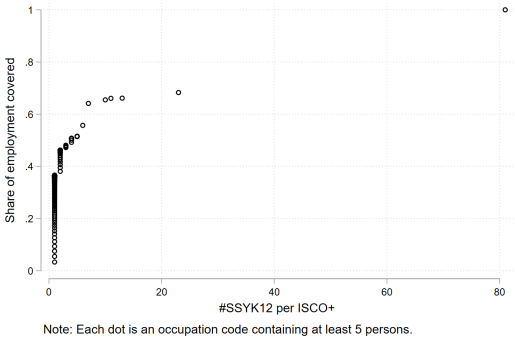

(a) SSYK96 to SSYK12



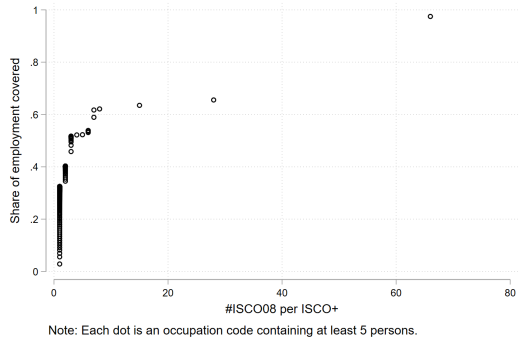

(b) SSYK96 to SSYK12



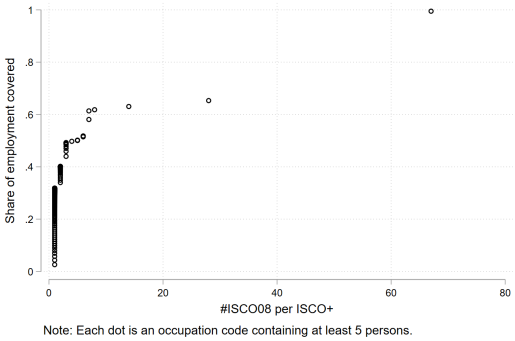

(c) SSYK12 to ISCO+, t=0




(d) SSYK12 to ISCO+, t=1




(e) ISCO08 to ISCO+, t=0




(f) ISCO08 to ISCO+, t=1

Notes: In all subfigures, except subfigure (b), occupation codes are ordered according to the number of "observed occupation codes" per "imputed occupation code", and we plot the empirical CDF of employment. In subfigure (b), we rank SSYK12 occupation codes according to the share of employees with the chosen SSYK12 among the candidate SSYK12's, and we plot the empirical CDF of employment.

Table 19: Top ISCO08 codes, Denmark

| Rank | ISCO08 code | Employment share (%) | Description |
|---|---|---|---|
| *Period t=0* | | | |
| 1 | 5223 | 11.5 | Shop Sales Assistants |
| 2 | 9334 | 5.7 | Shelf Fillers |
| 3 | 4110 | 3.6 | General Office Clerks |
| 4 | 3322 | 2.8 | Commercial Sales Representatives |
| 5 | 8160 | 2.7 | Food and Related Products Machine Operators |
| *Period t=1* | | | |
| 1 | 5223 | 10.7 | Shop Sales Assistants |
| 2 | 9334 | 4.0 | Shelf Fillers |
| 3 | 4110 | 3.8 | General Office Clerks |
| 4 | 3322 | 3.5 | Commercial Sales Representatives |
| 5 | 5230 | 3.5 | Stall and Market Salespersons |

Table 20: Top SSYK12 codes, Sweden

| Rank | SSYK12 code | Employment share (%) | Description |
|---|---|---|---|
| *Period t=0* | | | |
| 1 | 5223 | 5.1 | shop sales, specialty stores |
| 2 | 3322 | 4.7 | Commercial sales representatives |
| 3 | 4322 | 3.7 | Warehouse and terminal Staff |
| 4 | 4119 | 3.7 | Office clerks not elsewhere classified |
| 5 | 9120 | 2.8 | Car reconditioning labourers, window cleaners and other hand cleaning workers |
| *Period t=1* | | | |
| 1 | 5223 | 5.1 | shop sales, specialty stores |
| 2 | 4322 | 5.0 | Warehouse and terminal Staff |
| 3 | 3322 | 4.3 | Commercial sales representatives |
| 4 | 7223 | 3.3 | Machine-tool operators |
| 5 | 9629 | 2.6 | Other service workers not elsewhere classified |

Table 21: Top ISCO+ codes, Denmark

| Rank | ISCO+ | Emp. share (%) | #ISCO08 | Top ISCO08 | Emp. share (%), top ISCO08 | Description, top ISCO08 |
|---|---|---|---|---|---|---|
| *Period t=0* | | | | | | |
| 1 | A | 33.2 | 67 | 5223 | 34.7 | Shop Sales Assistants |
| 2 | B | 5.6 | 3 | 9334 | 98.1 | Shelf Fillers |
| 3 | C | 5.3 | 7 | 3322 | 53.4 | Commercial Sales Representatives |
| 4 | D | 2.7 | 1 | 8160 | 100 | Food and Related Products Machine Operators |
| 5 | E | 2.6 | 28 | 9313 | 18.9 | Building Construction Labourers |
| *Period t=1* | | | | | | |
| 1 | A | 34.8 | 68 | 5223 | 30.7 | Shop Sales Assistants |
| 2 | C | 6.3 | 7 | 3322 | 55.2 | Commercial Sales Representatives |
| 3 | B | 4.2 | 3 | 9334 | 96.6 | Shelf Fillers |
| 4 | E | 2.8 | 28 | 9313 | 15.8 | Building Construction Labourers |
| 5 | F | 2.5 | 7 | 2512 | 52.4 | Software Developers |

Table 22: Top ISCO+ codes, Sweden

| Rank | ISCO+ | Emp. share (%) | #SSYK12 | Top SSYK12 | Emp. share (%), top SSYK12 | Description, top SSYK12 |
|---|---|---|---|---|---|---|
| *Period t=0* | | | | | | |
| 1 | A | 33.9 | 44 | 5223 | 15.0 | shop sales, specialty stores |
| 2 | B | 6.6 | 4 | 3322 | 71.7 | Commercial sales representatives |
| 3 | C | 3.1 | 17 | 7111 | 20.0 | Woodworkers, carpenters |
| 4 | D | 2.7 | 1 | 2512 | 100 | Software- and system developers |
| 5 | E | 2.4 | 1 | 7232 | 100 | Aircraft mechanics and repairers |
| *Period t=1* | | | | | | |
| 1 | A | 32.6 | 81 | 5223 | 15.5 | shop sales, specialty stores |
| 2 | B | 7.0 | 7 | 3322 | 61.1 | Commercial sales representatives |
| 3 | E | 3.3 | 1 | 7232 | 100 | Aircraft mechanics and repairers |
| 4 | D | 3.3 | 6 | 2512 | 63.3 | Software- and system developers |
| 5 | C | 2.8 | 23 | 7111 | 18.0 | Woodworkers, carpenters |

# C Additional Results

## C.1 Extensive margin

Table 23 shows how the demand shock impacts the focal firms broader import activity using customs data covering all source countries. Column (1) shows that firms do not start importing in response to the shock. Conditioning on firms that are importers in both periods, the demand shock raises import value, the number of source countries, and the probability of sourcing from a new country (columns 2-6).

Table 23: Import status, import value, and import countries

| | (1) $\Delta 1\{Value > 0\}$ | (2) $\Delta \ln Value$ | (3) $\Delta \ln \#Countries$ | (4) $\Delta \#Countries$ | (5) $1\{\Delta \#Countries > 0\}$ | (6) $1\{NewCountry\}$ |
|---|---|---|---|---|---|---|
| $z$ | -0.010 | 0.211*** | 0.045** | 0.378*** | 0.057*** | 0.040*** |
| | (0.010) | (0.063) | (0.020) | (0.119) | (0.014) | (0.013) |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 16,788 | 13,777 | 13,777 | 13,777 | 13,777 | 13,777 |

## C.2 Controlling for WID shocks to suppliers

The following table is identical to Table 4 in the main text, but add suppliers' (buyers') average WID shock as a control: $\overline{z}_i = \sum_j w_{ij,t=0} z_j$, where $w_{ij,t=0}$ is export (import) share to supplier (from buyer) $j$. For suppliers and buyers that are not 3rd country exporters, we assign $z_j = 0$. For focal firms without buyers, we assign $\overline{z}_i = 0$.

Table 24: Same as Table 4 in main text, but controlling for suppliers' and buyers' average WID shock

| | (1) Δ ln Sales | (2) Δ ln L | (3) Δ log(imports from DK/SE) | (4) Δ ln ValueAdded / Sales | (5) Δ ln(LaborShare) | (6) Δ ln ValueAdded / L | (7) $\Delta \ln TFP$ |
|---|---|---|---|---|---|---|---|
| *Panel A: Controlling for average shock to suppliers* | | | | | | | |
| z | 0.120*** | 0.059*** | 0.141** | -0.027** | -0.045*** | 0.037*** | 0.030** |
| | (0.020) | (0.015) | (0.056) | (0.013) | (0.013) | (0.014) | (0.012) |
| $\overline{z}$ | 0.042 | 0.012 | -0.142 | -0.051** | 0.010 | -0.014 | -0.022 |
| | (0.030) | (0.028) | (0.098) | (0.022) | (0.021) | (0.027) | (0.024) |
| *Panel B: Controlling for average shock to buyers* | | | | | | | |
| z | 0.119*** | 0.059*** | 0.139** | -0.029** | -0.045*** | 0.034** | 0.030** |
| | (0.020) | (0.015) | (0.056) | (0.013) | (0.013) | (0.014) | (0.012) |
| $\overline{z}$ | 0.059* | 0.016 | -0.042 | 0.039 | -0.002 | 0.083** | -0.018 |
| | (0.033) | (0.027) | (0.109) | (0.030) | (0.021) | (0.035) | (0.031) |
| Observations | 16788 | 16788 | 16788 | 16297 | 16628 | 16297 | 13074 |

## C.3 Supplier-level regressions

Consider the regression equation

$$\Delta \ln y_j = \alpha_{s(j)} + \gamma_{r(j)} + \delta z_j + \theta \bar{z}_j + \varepsilon_j \tag{14}$$

This differs from equation (5) in the main text in two regards. First, the unit of observation is a supplier $j$ rather than a focal firm $i$. Second, we add an additional regressor $\bar{z}_j = \sum_i w_{ij} z_i$, where $w_{ij}$ is the share of $j$'s DK/SE exports in period 0 allocated to $i$ and $z_i$ is the focal firm's WID shock as defined in the main text. Hence, $\bar{z}_j$ measures the shock received by the supplier through its buyers (the focal firms). $z_j$ is $j$'s WID shock and enters as a control variable. Note we haven't restricted suppliers to be 3rd country exporters. If $j$ was not a 3rd country exporter in period 0 then it didn't receive a WID shock. In this case, we assign $z_j = 0$.

In the draft, the only sampling requirement we impose on suppliers is that they report positive total sales and employment in both periods 0 and 1. In Table 1, however, we impose an additional requirement: Suppliers must have some DK/SE buyers in period 0. This is necessary for constructing $\bar{z}_j$.

Table 25: Supplier-level regressions. Suppliers are required to have DK/SE buyers in period 0.

| | (1) Δ ln Sales | (2) Δ ln L | (3) Δ log(exports to DK/SE) | (4) Δ ln ValueAdded / Sales | (5) Δ ln(LaborShare) | (6) Δ ln ValueAdded / L |
|---|---|---|---|---|---|---|
| $\bar{z}$ | 0.099*** | 0.046** | 0.218*** | 0.051*** | 0.007 | 0.101*** |
| | (0.025) | (0.021) | (0.080) | (0.017) | (0.015) | (0.021) |
| z | 0.105*** | 0.054** | 0.052 | -0.021 | -0.071*** | 0.056*** |
| | (0.029) | (0.022) | (0.082) | (0.018) | (0.020) | (0.020) |
| Observations | 18118 | 18118 | 13069 | 17568 | 17935 | 17568 |

Note from the previous table that columns (1) and (2) are based on more observations than column (3) (the slightly smaller number of observations in 4-6 are due to some missing outcome, similar to the main text). In the next table, we restrict the sample to suppliers with DK/SE buyers in both periods 0 and 1. Now columns 1-3 are based on the same sample.

Table 26: Supplier-level regressions. Suppliers are required to have DK/SE buyers in both periods 0 and 1.

| | (1) Δ ln Sales | (2) Δ ln L | (3) Δ log(exports to DK/SE) | (4) Δ ln ValueAdded / Sales | (5) Δ ln(LaborShare) | (6) Δ ln ValueAdded / L |
|---|---|---|---|---|---|---|
| $\bar{z}$ | 0.089*** | 0.031 | 0.218*** | 0.063*** | 0.001 | 0.119*** |
| | (0.025) | (0.022) | (0.080) | (0.020) | (0.017) | (0.024) |
| z | 0.140*** | 0.071*** | 0.052 | -0.018 | -0.087*** | 0.069*** |
| | (0.028) | (0.020) | (0.082) | (0.022) | (0.018) | (0.023) |
| Observations | 13069 | 13069 | 13069 | 12756 | 12959 | 12756 |

## C.4 Robustness: Excluding smallest firms

Table 27: Same as Table 4 in main text, but dropping 5% smallest firms

| | (1) Δ ln Sales | (2) Δ ln L | (3) Δ ln DK/SE Imp | (4) Δ ln ValueAdded / Sales | (5) Δ ln(LaborShare) | (6) Δ ln ValueAdded / L | (7) Δ ln $TFP$ |
|---|---|---|---|---|---|---|---|
| z | 0.120*** | 0.067*** | 0.174*** | -0.028** | -0.045*** | 0.029** | 0.021* |
| | (0.021) | (0.015) | (0.057) | (0.013) | (0.013) | (0.014) | (0.012) |
| Observations | 15750 | 15750 | 15750 | 15314 | 15612 | 15314 | 12355 |

Notes: For Danish and Swedish firms, separately, we drop the 5% smallest firms measured by the number of (full-time equivalent) employees measured in period 0.

# D Theory

**Optimal outsourcing** The maximization problem of the firm is

$$\max_{\omega^*} \left\{ \frac{1}{\gamma} \lambda \left( \bar{m} P \right)^{1-\gamma} - f\omega^* \right\}.$$

The first order condition is then

$$\lambda \frac{1-\gamma}{\gamma} \bar{m}^{1-\gamma} P^{-\gamma} \frac{\partial P}{\partial \omega^*} = f.$$

We have

$$\frac{\partial P}{\partial \omega^*} = \frac{1}{1-\sigma} \left[ \int_0^{\omega^*} \phi^s \left( \omega \right)^{\sigma-1} d\omega + \int_{\omega^*}^1 \phi^b \left( \omega \right)^{\sigma-1} d\omega \right]^{1/(1-\sigma)-1} X.$$

Using Leibniz rule, $X$ is

$$\begin{aligned} X &= \phi^s \left( \omega^* \right)^{\sigma-1} + \int_0^{\omega^*} \frac{\partial \left[ \phi^s \left( \omega \right)^{\sigma-1} \right]}{\partial \omega^*} d\omega - \phi^b \left( \omega^* \right)^{\sigma-1} + \int_{\omega^*}^1 \frac{\partial \left[ \phi^b \left( \omega \right)^{\sigma-1} \right]}{\partial \omega^*} d\omega \\ &= \phi^s \left( \omega^* \right)^{\sigma-1} - \phi^b \left( \omega^* \right)^{\sigma-1} = \tilde{\phi} \left( \omega^* \right). \end{aligned}$$

Therefore, we get

$$\begin{aligned} \frac{\partial P}{\partial \omega^*} &= \frac{1}{1-\sigma} \frac{P}{P^{1-\sigma}} \tilde{\phi} \left( \omega^* \right) \\ &= \frac{1}{1-\sigma} P^{\sigma} \tilde{\phi} \left( \omega^* \right). \end{aligned}$$

In sum, the first order condition becomes

$$\begin{aligned} \lambda \frac{1-\gamma}{\gamma} P^{-\gamma} \bar{m}^{1-\gamma} \frac{1}{1-\sigma} P^{\sigma} \tilde{\phi} \left( \omega^* \right) &= f \\ \lambda \frac{1}{\gamma} \frac{\gamma - 1}{\sigma - 1} \bar{m}^{1-\gamma} P^{\sigma-\gamma} \tilde{\phi} \left( \omega^* \right) &= f \\ \tilde{\phi} \left( \omega^* \right) &= \frac{f}{\lambda} \gamma \frac{\sigma - 1}{\gamma - 1} \bar{m}^{\gamma-1} P^{\gamma-\sigma}. \end{aligned}$$

At an interior optimum with positive fixed costs, outsourcing the marginal task must reduce unit costs, implying that $\tilde{\phi}(\omega^*) > 0$.

**Proof of Proposition 1** Assume that equation (18) has an interior solution and that $\gamma = \sigma$. Differentiate equation (18),

$$\frac{\partial \tilde{\phi}}{\partial \omega^*}\frac{\partial \omega^*}{\partial \lambda} = -\gamma f \bar{m}^{\gamma-1}\lambda^{-2}$$
$$\frac{\partial \omega^*}{\partial \lambda} = -\frac{\tilde{\phi}(\omega^*)}{\left[\partial \tilde{\phi}/\partial \omega^*\right]\lambda} > 0,$$

which is equation (9). $\frac{\partial \omega^*}{\partial \lambda} > 0$ because $\frac{\partial \tilde{\phi}}{\partial \omega^*} < 0$ and $\tilde{\phi}(\omega^*) > 0$ at the optimum. This completes the proof.

Note that equation (9) can be re-written as the following equation about the elasticity of $\omega^*$

$$\frac{\partial \ln \omega^*}{\partial \ln \lambda} = -\frac{1}{e_{\tilde{\phi}}(\omega^*)}, \tag{15}$$

where $e_{\tilde{\phi}}(\omega^*) = \partial \ln \tilde{\phi}(\omega^*)/\partial \ln \omega^*$.

**Proof of Proposition 2** The share of variable costs allocated to a single task $\left(p(\omega)/P\right)^{1-\sigma}$. Therefore, the cost share of all outsourced tasks relative to variable costs is

$$\Pi = P^{\sigma-1}\int_0^{\omega^*} \phi^s(\omega)^{\sigma-1}\, d\omega.$$

Therefore,

$$\begin{aligned}
\frac{\partial \Pi}{\partial \lambda} &= (\sigma-1)P^{\sigma-2}\frac{\partial P}{\partial \lambda}\int_0^{\omega^*}\phi^s(\omega)^{\sigma-1}\,d\omega + P^{\sigma-1}\left[\phi^s(\omega^*)^{\sigma-1}\frac{\partial \omega^*}{\partial \lambda}\right] \\
&= (\sigma-1)\frac{1}{P}\frac{\partial P}{\partial \lambda}\Pi + P^{\sigma-1}\phi^s(\omega^*)^{\sigma-1}\frac{\partial \omega^*}{\partial \lambda} \\
&= (\sigma-1)\frac{1}{P}\left(\frac{1}{1-\sigma}P^{\sigma}\tilde{\phi}(\omega^*)\frac{\partial \omega^*}{\partial \lambda}\right)\Pi + P^{\sigma-1}\phi^s(\omega^*)^{\sigma-1}\frac{\partial \omega^*}{\partial \lambda} \\
&= P^{\sigma-1}\frac{\partial \omega^*}{\partial \lambda}\left(\phi^s(\omega^*)^{\sigma-1} - \Pi\tilde{\phi}(\omega^*)\right) \\
&= P^{\sigma-1}\frac{\partial \omega^*}{\partial \lambda}\left((1-\Pi)\phi^s(\omega^*)^{\sigma-1} + \Pi\phi^b(\omega^*)^{\sigma-1}\right) \\
&= P^{\sigma-1}\frac{\partial \omega^*}{\partial \lambda}\bar{\phi}(\omega^*) > 0
\end{aligned} \tag{16}$$

where $\bar{\phi} = (1-\Pi)\phi^s(\omega^*)^{\sigma-1} + \Pi\phi^b(\omega^*)^{\sigma-1}$.

In the derivation, we used the following results. First,

$$\frac{\partial P}{\partial \lambda} = \frac{1}{1-\sigma}P^{\sigma}\tilde{\phi}(\omega^*)\frac{\partial \omega^*}{\partial \lambda} = \frac{\partial P}{\partial \omega^*}\frac{\partial \omega^*}{\partial \lambda}. \tag{17}$$

Second,

$$\begin{aligned}\phi^s\left(\omega^*\right)^{\sigma-1}-\Pi\tilde{\phi}\left(\omega^*\right) &= \phi^s\left(\omega^*\right)^{\sigma-1}-\Pi\left(\phi^s\left(\omega^*\right)^{\sigma-1}-\phi^b\left(\omega^*\right)^{\sigma-1}\right)\\ &= (1-\Pi)\,\phi^s\left(\omega^*\right)^{\sigma-1}+\Pi\phi^b\left(\omega^*\right)^{\sigma-1}>0.\end{aligned}$$

The value added to sales ratio is $\frac{VA}{s}=1-\frac{\Pi}{\bar{m}}$. Therefore,

$$\frac{\partial\left(VA/s\right)}{\partial\lambda}=-\frac{1}{\bar{m}}\frac{\partial\Pi}{\partial\lambda}=-\frac{1}{\bar{m}}P^{\sigma-1}\frac{\partial\omega^*}{\partial\lambda}\bar{\phi}\left(\omega^*\right)<0,$$

which is equation (10). This completes the proof.

**Capital in the Model and $\gamma\neq\sigma$** With capital in the model, the first main change is that the production function for the final good is

$$q=\frac{1}{\alpha^\alpha(1-\alpha)^{1-\alpha}}K^{1-\alpha}y^\alpha, y=\left[\int_0^1 v\left(\omega\right)^{(\sigma-1)/\sigma}d\omega\right]^{\sigma/(\sigma-1)}$$

where $1-\alpha$ is capital's share, $K$ is the amount of capital, and $y$ is the amount of task composite whose expression is the same as in section **??**.

The second main change is that the buyer firm's first order condition becomes

$$\frac{1-\gamma}{1-\sigma}\alpha\lambda\tilde{\phi}\left(\omega^*\right)P^{\alpha(1-\gamma)+\sigma-1}=\gamma(\bar{m}r^{1-\alpha})^{\gamma-1}f. \tag{18}$$

In equation (18), $r$ is the rental rate, and the variables $P$ and $\tilde{\phi}(.)$ continue to be defined by equations (**??**) and (**??**). Because $P$ decreases in $\omega^*$ (see equation (17)), the left-hand side of equation (18) decreases in $\omega^*$ as long as $\alpha(1-\gamma)+\sigma-1\geq 0$. In this case, the computational task of solving equations (18) and (**??**) can be handled using standard fixed point procedures.

The final main change is that the parameter of $\alpha$ shows up in the expressions for the variables related to value added. For example, the expression for the labor share becomes

$$LS=\frac{\alpha s/\bar{m}+\omega^* f-Imp}{\alpha s/\bar{m}+\omega^* f}=1-\frac{Imp}{\alpha s/\bar{m}+\omega^* f}. \tag{19}$$

In our first quantification, we assume that $\alpha$ is the same for all buyer firms and set its value to 0.67, the mean of the wage-bill-to-value-added ratio in the data. We continue to have $\gamma=\sigma=4$. These parameter values satisfy the condition of $\alpha(1-\gamma)+\sigma-1\geq 0$, and so we can apply our computational algorithms. Among the calibrated parameter values, $\mu_{\ln\epsilon}$ is larger than the benchmark (120.48) and $f$ is smaller (1287.26), but the rest are almost the same as the benchmark. The model predicted moments are also very similar to Tables 8 and 9.

In our second quantification, we assume away capital (i.e. $\alpha=1$) but experiment with $\sigma=5$ (we still have $\gamma=4$). These parameter values also satisfy $\alpha(1-\gamma)+\sigma-1\geq 0$, and so we can apply our computational algorithms. The calibrated parameter values and model predicted moments are very similar to the first quantification with $\alpha=0.67$ and $\sigma=4$.