Growing Together and Apart: Scale Economies and Specialization*

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Abstract

We construct a novel data set where the universe of cross-border transactions between Danish and Swedish firms is merged with the administrative matched worker-firm data from both countries. Our empirical analyses show that when output demand increases exogenously, the buyer firm experiences an increase in both labor productivity and labor specialization relative to foreign suppliers, and that these results only hold for relationship-specific buyer firms. These firms also decrease the wage-bill and employment shares of production-related workers but increase the shares of college graduated workers. We propose a parsimonious model with relationship specificity, task specialization and outsourcing and calibrate key model parameters. Our quantification and counterfactual show that for the buyer firms with foreign suppliers, labor specialization is a quantitatively important economic mechanism for labor productivity. For example, our model simulation accounts for one third of the 90-10 dispersion 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 25 percent lower and the final goods price index 25 percent higher.

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 modern economies, the division of labor is increasingly taking place between firms, as firms fragment production along the supply chain. Yet, the empirical evidence on the magnitude of these gains is limited. This paper attempts to fill the gap in the literature by studying specialization and the division of labor across firms in supply chains.

One of the reasons for the lack of progress is that the division of labor is typically unobserved in standard data sets of supply chains and production networks. In this paper, we merge the universe of transactions between Danish and Swedish firms with the administrative matched worker-firm data from both countries. Using the novel data set, we first provide novel evidence on the impact of exogenous demand shocks on the division of labor and labor productivity in the supply chain. Second, we propose a simple model with relationship specificity, task specialization and outsourcing that is broadly consistent with the evidence. Third, we calibrate key model parameters by simulated method of moments and quantify how much division of labor contributes to labor productivity. Finally, we provide validation to the quantitative model by showing novel empirical evidence that relationship specificity matters for the effects of exogenous demand shocks.

The keystone of our data is that, among the universe of Swedish (Danish) firms, we observe all their purchases from Danish (Swedish) suppliers over the time period 2012-2018, the data of which we obtain from Danish and Swedish tax authorities. Because these VAT (value-added tax) based data use the same firm identifiers as the other administrative data from Denmark and Sweden, we are able to merge them with the matched worker-firm data from both countries. Our novel data set thus provides rich details about firms, workers, and product level trade, like in previous studies using a single country's administrative data (e.g. Hummels et al. 2014). It also covers buyer and supplier firms on both sides of international trade, like in previous studies that match customs data from importing and exporting countries (e.g. Blum et al. 2009). For the purpose of our study, our data provide rich variation in firm size and labor productivity; e.g. the value added per worker of the 90th percentile buyer firm is roughly 50% higher than the 10th percentile firm. In addition, we observe employment, wage costs and narrowly defined occupation codes for workers for *both* buyer firms and their foreign suppliers. This enables us to measure the degree of occupation similarity between buyers and suppliers, i.e. a measure of specialization across firms in the supply chain.

In order to study how buyer firms' labor productivity relates to labor specialization, we estimate how buyer firms respond to fluctuations in output demand. An empirical challenge is to find an exogenous demand shifter. Here, we turn to the trade literature, which commonly

uses so-called world import demand (WID) shocks as exogenous variation for firm-level output demand (Hummels et al., 2014). The idea is simple: In some baseline period, a firm exports a portfolio of products $\mathcal{P}$, which is observed in our data. The firm-level instrument is then the weighted average of global imports of these products, from all other sources than Sweden and Denmark. Our empirical analysis reveals that positive demand shocks are raising firm sales, employment and labor productivity, while reducing the value added to sales ratio and the labor share. Moreover, we find evidence of increasing specialization: occupation similarity between the Swedish (Danish) firms and their Danish (Swedish) suppliers declines. Therefore, our results suggest that firms and their suppliers grow together, but that they also grow apart - in the sense that they increasingly do different things. On the other hand, we find no empirical evidence that the buyer firms establish new supplier links in Denmark or Sweden after exogenous increases in output demand.

Motivated by these empirical results, we set up a parsimonious model of task specialization and outsourcing for the buyer firm. The firm produces output by combining a unit continuum of tasks, and it is matched to a given foreign supplier because of relationship specificity. Tasks can either be produced in-house or outsourced, and there is heterogeneity in task efficiency, varying both across tasks and firms. The main trade-off is the potential savings in unit production costs from outsourcing and specialization, vs. the task-specific fixed outsourcing cost, which may represent trade costs, monitoring costs or costs associated with reorganizing production. When output demand increases exogenously, sales and profits go up for the buyer firm and so the marginal gain from specialization and outsourcing increases, whereas the outsourcing cost is fixed. Therefore, the buyer firm will have: (i) more specialization relative to its foreign supplier, as it reallocates labor away from in-house production towards outsourcing costs; (ii) a lower value added to sales ratio and labor share; and (iii) higher labor productivity (value added per worker). Importantly, these testable predictions are broadly in line with the reduced-form results described above. Overall, our model builds on the assumption of relationship specificity, as is standard in the global-supply-chains literature (e.g. Antras et al. 2017). Our focus, however, is on the intensive margin, or the changes of outsourcing and labor specialization from existing foreign suppliers, like in the task-trade literature (e.g. Grossman and Rossi-Hansberg 2008). This approach complements the global-supply-chains literature, where the focus is on the extensive margin, or the establishment of new supplier links.

We calibrate the key parameters of the model by simulated method of moments. Our results reveal that fixed outsourcing costs account for 2.4 percent of the average buyer firm's total wage costs, and that they are also more than 10,000 greater than marginal costs, highlighting that buyer firms need scale to engage in division of labor along the supply chain. Simulating the estimated model, we find that the elasticity of output to labor (the returns to scale coefficient) is 1.07, suggesting that labor specialization along the supply chain gives rise to substantial scale economies. To be specific, the labor productivity for the 90th percentile firm is 17 percent higher than the 10th percentile firm. This means that the mechanism of labor specialization, the only one at work in our model, accounts for roughly one third (17%/50%) of the 90-10

dispersion of labor productivity in the data. We also simulate the WID shocks in the model and estimate the same reduced-form regressions described above on simulated data. We find that the simulated coefficient estimates are 1/10th to 1/5th relative to the actual coefficient estimates. These simulation results suggest that for the buyer firms with foreign suppliers, labor specialization is a quantitatively important economic mechanism for labor productivity. [1]

For the 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. We find that for the average buyer firm, labor productivity would be roughly 25 percent lower in the counterfactual and the final goods price index 25 percent higher. Our results are driven by the intensive margin adjustment, because we abstract away from the adjustment through the number of suppliers. On the other hand, Antras et al. (2017) abstract away from the intensive margin, and show that if all foreign supplier links were lost, the average buyer firm would experience a 9 percent increase in marginal cost. Therefore, our counterfactual analysis suggests that the intensive margin of increased outsourcing and labor specialization with existing foreign suppliers could be as economically significant as the extensive margin of new supplier links.

In the final part of the paper, we present empirical evidence for our model assumption of relationship specificity and model mechanism of within-firm labor reallocation. We first show that the average degree of relationship specificity, which is based on Nunn (2007)'s measure, is high among the buyer-supplier relationships in our data. We next show that when output demand increases exogenously, it is the relationship-specific buyer firms that experience increases in value added per worker and decreases in occupational similarities with their foreign suppliers'. In addition, they decrease the wage-bill and employment shares of production-related workers but increase the shares of college graduated workers. In contrast, for generic-inputs buyer firms, our coefficient estimates often show the *opposite* signs. These results provide validation for the key assumption and 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,[2] the empirical evidence for how relationship specificity matters at the micro level is more limited.[3] Our results provide novel empirical evidence that relationship specificity, as measured by Nunn (2007), matters for productivity, within-firm labor allocation, and between-firm labor specialization.

This paper relates to the following distinct bodies of work. The first is the literature on global value chains (e.g. Baldwin and Venables (2010), Costinot et al. (2013), Antras and Chor (2013), Antràs et al. (2017), Blaum et al. (2018), Grossman, Helpman and Lhuillier 2023).[4] This literature emphasizes the relationship specificity between firms and their foreign suppliers, which is also a key element of our analyses. Our work also relates to an earlier literature on offshoring

[1] 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.

[2] Relationship specificity is also commonly used in the studies of multinationals (e.g. Antras and Helpman 2004), the theory of contracts (e.g. Hart and Moore 1988) and theory of the firm (e.g. Grossman and Hart 1986).

[3] For developing countries, Macchiavello and Morjaria (2015) study the Kenyan rose export market, and Startz (2016) studies Nigerian traders.

[4] Antras and Chor (2021) provide a recent survey.

and task trade (e.g. Feenstra and Hanson 1997, Grossman and Rossi-Hansberg 2008).[5]

The second is the literature that shows that foreign sourcing typically raises measured productivity and lowers marginal costs (e.g. Amiti and Konings (2007), Goldberg et al. (2010), Loecker et al. (2016), Halpern et al. (2015), Gopinath and Neiman (2014)). Relative to this literature, our results highlight a novel mechanism for productivity gains; namely, reorganization of production across tasks and occupations.

The third is the empirical literature on the division of labor, which showsthat market size (demand) affects specialization among workers (e.g., Baumgardner (1988), Garicano and Hubbard (2009), Duranton and Jayet (2011), Becker et al. (2018), Tian (2021) and Atalay et al. (2023)).[6] The fourth is the literature on production networks, which typically uses data on domestic firm-to-firm links to study how such links are formed and their economic consequences (e.g. Bernard et al. (2018), Lim (2018), Bernard et al. (2019), Tintelnot et al. (2021), Demir et al. (2021), Dhyne et al. (2022), and Bernard et al. (2022)).[7] Compared to these studies, our paper focuses on the division of labor across firms along the international supply chain and how it relates to labor productivity and relationship specificity.

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 the quantitative model, section 5 calibrates and quantifies 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 keystone of our data is the universe of cross-border firm-to-firm 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.[8] 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.[9]

[5] Hummels et al. (2018) provide a recent survey.

[6] For the theoretical literature on the division of labor, see Costinot 2013 and Chaney and Ossa 2013. On the other hand, in related work, Boehm and Oberfield (2022) uses data on plants' input and output mix to explore the relationship between fragmentation of production and growth, by focusing on plants' vertical spans of production.

[7] Bernard and Moxnes (2018) provide an early review of the literature. In recent work, Cajal-Grossi et al. (2023) studies the buyer firms and their Bangladesh suppliers in the garments industry, and Eaton et al. (2022) use French customs data to disentangle iceberg trade costs and match frictions in firm-to-firm matching.

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

[9] 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

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/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 in a single location and secondly have ensured that all VAT numbers are anonymized with the same key, this enables us to link Swedish (Danish) VAT numbers reported in Denmark (Swedish) to firm identifiers in other Danish (Swedish) register data (see below). We use annual aggregates of the sales-form data where each observation shows the export value by year, by (Swedish or Danish) supplier, by customer, and by types of exports (goods, services, or triangulation). For most of the analysis, we will focus on firm-to-firm relationships between Danish (Swedish) firms and their Swedish (Danish) suppliers.

We merge the VAT register data with the following administrative data for 2012-2018. (i) 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 cover the universe of private sector firms, and provide data on firm characteristics such as revenue, value added, employment, and industry affiliation. (ii) The Employment Statistics for Employees and the Education Attainment Register from Denmark and the Longitudinal Integrated Database (LISA) from Sweden cover the population of private-sector workers, and provide links to every firm and data on worker characteristics such as salary, occupation, and education. (iii) The Statistics for International Trade in Goods from Denmark and the Foreign Trade Register from Sweden provide imports (exports) for each firm by origin (destination) country by 8-digit Combined Nomenclature (CN) products. In all these administrative data, both firms and employees are characterized by unique identifiers.

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.[10] 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), pre-

customer without entering the intermediaries country of origin.

[10]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.

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 3rd countries	94.7	94.1	95.1	97.3	86.1

pared 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+'.[11]

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 thus 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 within the focal firm. Second, the focal firm must have at least one Swedish/Danish supplier in both periods.[12] This is necessary in order to study how the focal firm has changed relative to its foreign suppliers. Third, the focal firm must be an exporter in the initial period according to the customs data, to other countries than Sweden and Denmark (a "third-country exporter"). This is necessary for constructing the exogenous demand shock. As for the focal firm's foreign suppliers, we only impose the first restriction, but not the latter two.

Table 1 shows that our sample has decent coverage. 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 clarifies why our sample has decent coverage. 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 values of international trade.

[11] Statistics Sweden provides a many-to-many concordance file between SSYK12 and ISCO08. We construct ISCO+ as the most disaggregate 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.

[12] 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			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
VA / Employment						
- 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
Exports to 3rd 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: VA/emp in thousands euros, the rest in million euros.

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 x-axis and log value added per worker on the y-axis. 2-digit industry (NACE) and country (Denmark/Sweden) fixed effects are included, so that cross-industry and cross-country variation is excluded from the analysis.

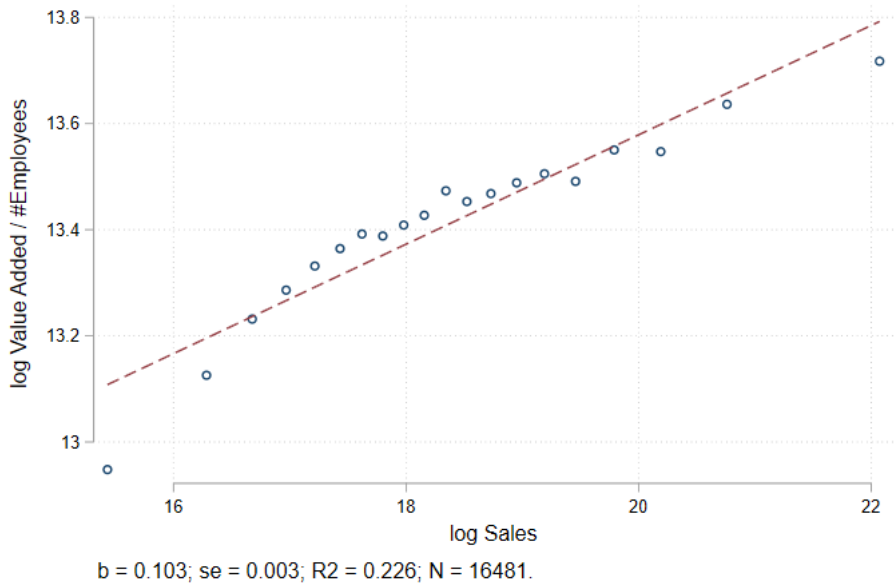
The figure shows a strong positive correlation between size and labor productivity. The slope coefficient is 0.103 and the R^2 of 0.23. A firm at the 90th percentile of the sales distribution has 50% higher value added per worker than the one at the 10th percentile.

Figure 2 shows a binned scatter plot with log sales on the x-axis and the labor share, defined as the wage bill relative to total costs, on the y-axis. Total costs are constructed as the sum of all 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, 2-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 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

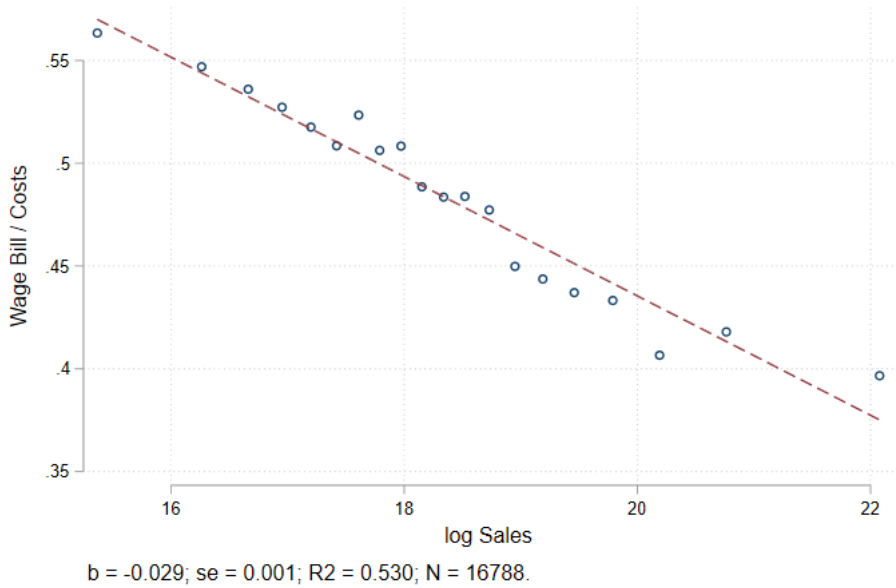
labor share compared to small firms.

Figure 1: Sales and Labor Productivity



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

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 (foreign supplier, j), that is engaged in goods trade according to the customs data, we compute rs_i (rs_j), or the share of goods imports (exports) that are differentiated according to the Rauch (1999) classification.[13] rs_i range 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. 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.

Finally, service trade is an important feature of our sample. By count, 59% of focal firms in Denmark (Sweden) are engaged in service imports from Sweden (Denmark), and for this group, service accounts for 40% of the import value. Meanwhile, 50% of focal firms import both goods and services, and for this group, service accounts for 30% of imports.

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 a large wage-bill share, the focal firm relies more heavily on a single occupation and so is 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 θ_{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 1st measure of labor specialization, $\theta(o_i^{*1})$.

The second definition is based on the value of θ_{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 i and 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 $\theta_{io} > \Theta_{io}$, 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 2nd measure of labor specialization, $\theta(o_i^{*2})$.

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

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 is 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).[14] We obtain the 3rd 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: Occupation Similarity

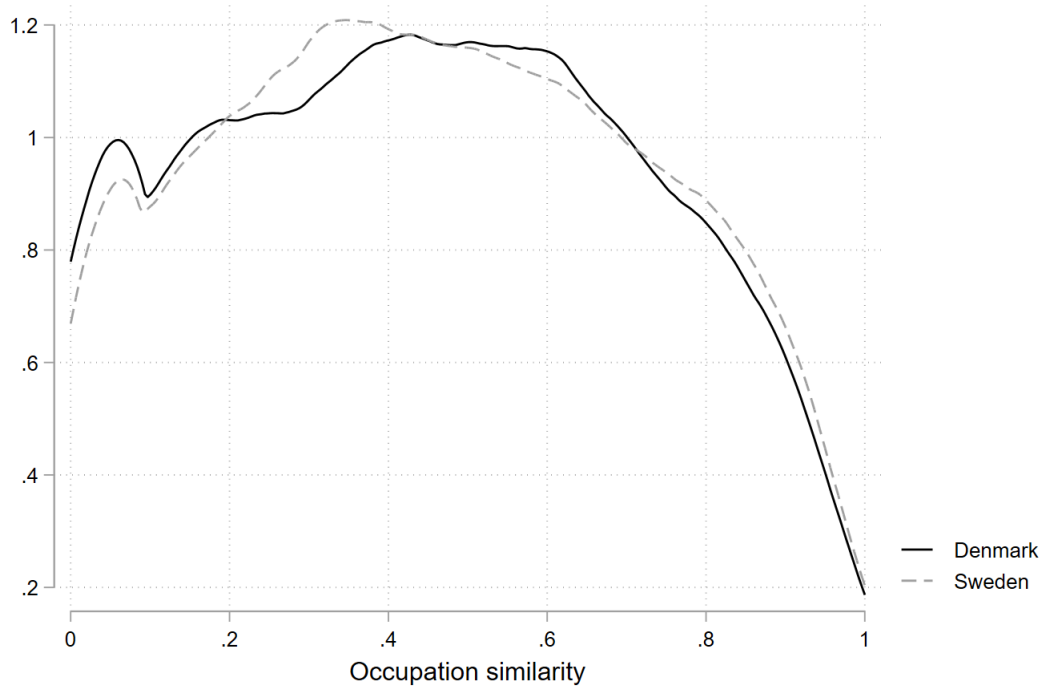


Figure 3 is the density plot of sim_i for the initial period, 2012-13. The dashed curve is for firms in Sweden and the solid one for firms in Denmark, and the areas under both curves are equal to 1 by construction. Figure 3 shows that sim_i varies substantially across focal firms.

We supplement sim_{ij} with a similarity index where wage bill shares θ_{io} are replaced by

[14] 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.

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 4th, 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.

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), Δ is the change from period 0 (2012-13) to period 1 (2017-18), i indexes the focal firm, $\alpha_{s(i)}$ represents the 2-digit industry fixed effect, and $\gamma_{r(i)}$ represents the 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 the 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, ϵ_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:

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

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 ω_{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, β, as causal effects. 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, ϵ_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.

Table 3: 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***	0.14**	-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	16788	16788	16788	16297	16628	16297	13074

Note: Labor share is defined as the wage bill relative to total costs. Industry FE refers to NACE 2-digit fixed effects. Country FE is a dummy for whether the firm is Swedish or Danish. Standard errors in parentheses.

3.2 Results : Firm-level Outcomes

Table 3 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 2-digit industry,[15], and report the results in column (7). These results are suggestive of economies of scale in production.

In summary, Table 3 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.

3.3 Results: Between-Firm Outcomes

We start by exploring whether focal firms establish new foreign (Danish/Swedish) supplier links and report our results in Table 4. 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 4 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 3. Rather, they suggest that reorganization of production across existing suppliers is important.

[15]TFP is computed using the Ackerberg–Caves–Frazer method ("acfest" in Stata), using deflated revenue, labor, capital and materials.

Table 4: 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	16788	16788	16788	16788

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.

Table 5: Between-Firm Outcomes.

	(1) $\Delta\theta\left(o^{*1}\right)$	(2) $\Delta\theta\left(o^{*2}\right)$	(3) Δsim	(4) $\Delta bisim$	(5) Δsim fix imp shares	(6) Δsim fix θ_j	(7) Δsim fix θ_i
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	16788	16788	16788	16788	16788	16788	16788

Note: Standard errors in parentheses. Significance levels: $*p < 0.1, **p < 0.05, ***p < 0.01$.

In column (1) of Table 5, 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 5, by using the change in the similarity index constructed from equation (3), Δsim_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 5 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 Δsim_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, θ_{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 θ_{io} at period-0 levels, so that Δsim_i only captures 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 5 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.1. The coefficient estimates are very close to our baseline results.

Another concern is 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.2.

In summary, our empirical results in this section establish the importance of labor specialization along international supply chains, a novel element that has been largely overlooked in the literature. The labor specialization is with respect to existing foreign suppliers (i.e. the intensive margin), and so complements the literature's focus on new supplier links (i.e. the extensive margin). Our empirical results also suggest that qualitatively, the increase in the focal firm's labor specialization may contribute to the increase in its labor productivity. We now turn to a quantitative model to explore the quantitative importance of this mechanism.

4 A Quantitative Model

4.1 Economic Environment

In this section, we present a parsimonious model broadly consistent with the reduced-form evidence outlined above. Heterogeneous final goods firms produce output by combining a unit continuum of tasks. Tasks can either be produced in-house or purchased, and there is heterogeneity in task efficiency, varying both across tasks and firms. There are potential gains from specialization, as in-house task production may not be very efficient. But outsourcing is costly, due to e.g. transaction costs, monitoring costs or costs associated with reorganizing production. We model this as a task-specific fixed cost. In equilibrium, firms will outsource tasks where the efficiency gains from doing so are relatively large. Under some regularity conditions, 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, whereas the marginal transaction cost is fixed. In the subsequent section, we will estimate the model to gauge the quantitative importance of across-firm specialization for firm productivity and growth.

Firms produce differentiated final goods, which are sold to consumers, and may also sell intermediate goods or services (tasks) to other firms.

Final goods production: Firms produce final goods y by combining a unit continuum of firm-specific tasks ω with the following CES production function:

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

where $\sigma > 1$ is the elasticity of substitution across tasks and $v\left(\omega\right)$ is the quantity of task ω. Firms are heterogeneous in two dimensions. First, firms face different demand shocks φ.[16] Second, there is heterogeneity in the efficiency of producing tasks. The market structure is monopolistic competition.

Task production: Firms can choose between producing tasks in-house or purchase them at arms length. Tasks are produced with labor under constant-returns-to-scale technologies. In-house task productivity is $\phi^b\left(\omega\right)$ (b for buyer). Arms length task productivity is $\phi^s\left(\omega\right)$ (s for supplier). Both $\phi^b\left(\omega\right)$ and $\phi^s\left(\omega\right)$ vary across firms and tasks (the index for firms is dropped for brevity).[17] We assume that the market for tasks is perfectly competitive, so that the task price is $p_t^x\left(\omega\right) = 1/\phi^x\left(\omega\right), x = \{b, s\}$. There is a task-specific transaction cost f associated with purchasing a task at arms length. Therefore, a final goods firm might produce a task in-house even if $p_t^b\left(\omega\right) > p_t^s\left(\omega\right)$.

Final demand: Individuals have CES preferences over final goods with an elasticity of substitution $\gamma > 1$. Final good sales is then

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

where $p\left(\varphi\right)$ is the final good price and φ is a demand shock (to ease notation, φ is a composite of the firm-specific demand shock, the final goods price index and aggregate spending).

Equilibrium. Final goods firms are maximizing profits by selecting the set of tasks to produce in-house and the set of tasks to outsource. Define relative task productivity

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

[16] See below. The demand shock is isomorphic to heterogeneity in total factor productivity (TFP). To ease notation, we do not include TFP heterogeneity in the analysis.

[17] The assumption of firm-specific tasks implies that both $\phi^b\left(\omega\right)$ and $\phi^s\left(\omega\right)$ vary across firms: For the same task, firm 1 faces a different supplier task productivity than firm 2.

and without loss of generality, sort tasks such that $\partial\tilde{\phi}(\omega)/\partial\omega < 0$. Assume that there is an optimal cutoff task $\omega^*(\varphi)$, such that tasks in the interval $[0, \omega^*]$ are outsourced and tasks in the interval $[\omega^*, 1]$ are produced in-house. Appendix **??** proves that $\omega^*(\varphi)$ indeed exists. The CES input price index can then be written as

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

With monopolistic competition, final good prices are a constant mark-up over costs,

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

where $\bar{m} = \gamma/(\gamma - 1)$. Gross profits are proportional to sales, $s(\varphi)/\gamma$ and therefore net profits are

$$\pi(\varphi) = s(\varphi)/\gamma - \omega^*(\varphi) f.$$

The firm finds the $\omega^*(\varphi)$ that maximizes $\pi(\varphi)$. Appendix **??** shows that the first order condition is

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

Since $\tilde{\phi}(\omega^*)$ is a downward sloping function of ω^*, this equation yields a unique solution for $\omega^*(\varphi)$.

4.2 Comparative statics

From our economic framework we derive two propositions on the impact an exogenous increase in final-good demand, φ. The proofs are in Appendix **??**.

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

$$\frac{\partial \omega^*}{\partial \varphi} = -\frac{\tilde{\phi}(\omega^*)}{\left[\partial\tilde{\phi}/\partial\omega^*\right]\varphi} > 0. \tag{8}$$

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

$$\frac{\partial\left(ValueAdded/Sales\right)}{\partial\varphi} = -\frac{1}{\bar{m}} P^{\sigma-1} \frac{\partial\omega^*}{\partial\varphi} \bar{\phi}(\omega^*) < 0, \tag{9}$$

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 Π is the cost of outsourced tasks relative to total variable costs.

The intuition behind these propositions is as follows. Higher demand implies that the marginal gains from outsourcing a task increases, while the marginal cost remains the same. Therefore, the cutoff task increases. As a consequence, the value added to sales ratio, a common measure

of vertical (dis)integration, declines. The propositions hold for $\gamma = \sigma$. Unfortunately, we have not been able to show analytically that Propositions 1 and 2 also hold for other values of γ and σ . However, numerical simulations of the model show that the sign of the propositions also hold more generally.

Two remarks regarding our framework are in order. First, the model emphasizes the make-or-buy decision of tasks, but abstracts away from the decision of which supplier to choose. One could extend the model in this direction, so that one subset of tasks is outsourced to firm x, and a different subset is outsourced to firm y. However, as shown above, according to our estimates, the set of suppliers is not significantly affected by demand shocks. Therefore, we have chosen to simplify the model and abstract from the extensive margin of supplier choice. In the quantitative exercise below, we will assume that the firm-to-firm network is exogenous, and that firms are randomly matched with a supplier.

Second, when mapping the model to the data, we require a link between occupations and tasks. E.g., the empirical measures of labor specialization above, such as the similarity measure, need a theoretical counterpart. We choose to interpret an occupation as a set of non-overlapping tasks, such that a subset of tasks is performed by occupation O_1, and a different subset of tasks of performed by occupation O_2.

5 Structural Estimation and Counterfactual Exercises

In this section, we estimate our model using simulated methods of moments. This serves three main purposes. First, we can identify key parameters of the model, which informs us about the economic significance of labor specialization. Second, we can compare the reduced-form coefficients from Tables 3 and 5 to corresponding coefficients based on regressions on simulated data from the estimated model. This allows us to assess the importance of our economic mechanism compared to competing hypotheses. Third, we can conduct counterfactuals. In our main counterfactual, we make outsourcing prohibitively costly, and assess the impact on firms' productivity, costs and labor specialization.

A potential challenge in estimating the model, is that our data only includes firm-to-firm links between Danish (Swedish) firms and its Swedish (Danish) counterparts, e.g. domestic links links are unobserved. We sidestep this issue by not using this information when estimating the model, instead relying on more broader measures of outsourcing, such as the wage bill relative to total costs.

5.1 Setting and Key Parameters

We start by simulating firms. Each firm is represented by one independent draw from the following distribution of φ, the demand shifter, $\varphi = \epsilon^{\xi}, \ln \epsilon \sim \mathcal{N}(0, \sigma_{\ln \epsilon})$. $\sigma_{\ln \epsilon}$ measures the standard deviation of the distribution. The parameter ξ will be used to target the elasticity of the WID shock from equation (6) on log sales (see further discussion below).

We simulate 1,000 firms. For each firm, we approximate the unit continuum of tasks

Table 6: Identification.

Moment	Data	Identifies
stdev($\ln\theta$) (mean)	1.61	$\sigma_{\ln\phi}$
stdev(lnSales)	1.67	$\sigma_{\ln\epsilon}$
mean(Labor share), top decile S	.42	$\mu^s_{\ln\phi}$
mean(Labor share), bottom decile S	.58	$\mu^s_{\ln\phi}, f$
Regression of log sales on z	0.121	ξ

with 10,000 discrete ones, and draw from the following distributions of buyer and supplier productivities, $\ln\phi^k \sim \mathcal{N}(\mu^k_{\ln\phi}, \sigma_{\ln\phi})$. We normalize $\mu^b_{\ln\phi} = 0$, such that $\mu^s_{\ln\phi}$ captures the average productivity advantage of suppliers over the focal firm. Meanwhile, $\sigma_{\ln\phi}$ represents the standard deviation of productivity across tasks, which we assume to be the same for both suppliers and the focal firm. As mentioned above, we assume that the firm-to-firm network is exogenous, and that each firm is randomly matched with exactly one supplier. The set of parameters to estimate is thus $\Upsilon = \left\{\sigma_{\ln\epsilon}, \xi, \mu^s_{\ln\phi}, \sigma_{\ln\phi}, f\right\}$, where f is the fixed outsourcing cost.

The elasticities of substitution σ and γ are not identified with our methodology. In the baseline estimation, we set σ=γ=5.

5.2 Empirical Moments and Identification

Table 6 summarizes the data moments used for identification, their values and which parameters they help identify. While formally, all moments jointly identify all parameters, there is an intuitive mapping between moments and parameters.

According to equation (7), log sales is closely related to $\ln\varphi$, and as such the standard deviation of log sales across firms helps identify $\sigma_{\ln\epsilon}$.

In the model, the cost of a task ω relative to total variable costs is $\phi(\omega)^{\sigma-1} P^{\sigma-1}$. This variable is the counterpart to the occupational wage-bill share, θ_{io}, in equation (3). As a result, the mean, across i, of the standard deviation, across o within i, of $\ln\theta_{io}$, helps identify $\sigma_{\ln\phi}$.

In the model, the labor share is the cost share of in-house tasks, i.e. the wage bill, relative to total variable costs. Intuitively, the labor share is lower the greater the productivity advantage of suppliers relative to buyers. Furthermore, the labor share is greater the higher the task fixed cost. For large firms, the task fixed cost is relatively unimportant in determining which tasks to outsource. For small firms, the task fixed cost will more binding. Therefore, the mean labor share for large firms, defined as the top decile of the firm size distribution, helps identify $\mu^s_{\ln\phi}$. The mean labor share for small firms, defined as the bottom decile of the firm size distribution, helps identify both $\mu^s_{\ln\phi}$ and f.

According to equation (7) and $\varphi = \epsilon^{\xi}$, ξ is the elasticity of log sales with respect to $\ln\epsilon$. We let $\ln\epsilon$ correspond to the exogenous demand shock of z_i from equation (6). Therefore, the regression coefficient of log firm sales on z_i (Table 3 column (1)) directly identifies ξ.

5.3 Structural Estimates and Model Fit

The estimated coefficients are as follows: $\sigma_{\ln\phi} = 0.56$, $\sigma_{\ln\epsilon} = 13.61$, $\mu^s_{\ln\phi} = 0.09$, $f = 0.07$ and $\xi = 0.12$. The results suggest that there are significant gains from outsourcing: The productivity advantage of suppliers are, on average, around 10 percent ($\mu^s_{\ln\phi} = 0.09$). However, the costs of outsourcing is also significant. According to the estimates, firms' outsourcing costs ($\omega^* f$) are 2.4 percent of total costs, on average. But for the average firm, transaction costs are more than 10,000 greater than marginal costs, highlighting that firms need scale to engage in division of labor along the supply chain.

Our model can potentially generate economies of scale due to the division of labor across firms in the supply chain. How big is this effect according to our estimates? We gauge this by regressing output on employment (both in logs) on simulated data (using the parameters reported above). The estimated coefficient is 1.07, i.e. a doubling of employment yields 7 percent higher labor productivity (output per worker) due to reallocation of tasks across the supply chain.

We also find that specialization creates significant dispersion in labor productivity. In equilibrium, labor productivity for the 90th percentile firm is 17 percent higher than the 10th percentile firm.[18] 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. Together, results provide evidence that labor specialization along the supply chain is quantitatively significant.

Table 7 evaluates model fit by comparing model predictions for both targeted and untargeted moments. Not surprisingly, we are able to hit targeted moments quite well, as the model is exactly identified. For untargeted moments, the picture is more mixed. The elasticity of the labor share with respect to sales is very close in the data and model (Figure 2), but the elasticity of labor productivity with respect to sales is lower in the model compared to the data (Figure 1). The model also produces a too high value added to sales ratio.

We also evaluate model fit by estimating the same regressions as in Tables 3 and 5, but using model-generated data (using the parameters reported above) instead of actual data. To be specific, for each firm i in our model, one of the 1000 firms that we have simulated, we draw a new demand shock, ϵ, from the same underlying distribution, and hold all the other parameters fixed. We then solve for i's optimal choices of outcome variables y_i, and run the following regression using simulated data:

$$\Delta \ln y_i = \alpha + \beta \Delta \ln \epsilon_i + v_i \tag{10}$$

where ν_i is an error term.

Tables 8 and 9 report the coefficient estimates of regression (10), and compares them with those of regression (5). The results show that the simulated regression coefficients are 1/10 to 1/5 the size of those from data regressions. Our interpretation of these results is that the

[18] In the data, labor productivity for the 90th percentile firm is 17 percent higher than the 10th percentile firm.

Table 7: Model Fit.

Moment	Data	Model
Targeted:		
std($\ln\theta$) (mean)	1.61	1.61
stdev(lnSales)	1.67	1.67
mean(Labor share), top decile S	.41	.42
mean(Labor share), bottom decile S	.58	.58
Regression of log sales on z	.12	.12
Untargeted:		
VA/Sales (mean)	.32	.58
Regression of labor share on ln sales	-0.029	-0.027
Regression of ln labor productivity on ln sales	0.103	0.027

Table 8: Firm Outcomes. Simulated and Actual Data.

	(1) $\Delta \ln Sales$	(2) $\Delta \ln L$	(3) $\Delta \ln \frac{ValueAdded}{Sales}$	(4) $\Delta \ln LaborShare$	(5) $\Delta \ln \frac{ValueAdded}{L}$
Simulated:					
$\ln \epsilon$	0.124***	0.117***	-0.003***	-0.007***	0.004***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Data:					
z	0.121***	0.059***	-0.028**	-0.045***	0.037***
N	1,000	1,000	1,000	1,000	1,000

Note: Standard errors in parentheses. Significance levels: $*p < 0.1, **p < 0.05, ***p < 0.01$.

quantified model is consistent with the reduced-form evidence in many respects, but that the model-generated magnitudes are somewhat weaker compared to the data. Our conclusion is that our economic mechanism is quantitatively important, but that there are also other sources of scale economies operating at the same time, e.g. division of labor within the firm itself or learning-by-doing, which is captured in the reduced-form analysis but not part of our model.

5.4 A Counterfactual

We end this section by performing the following counterfactual. We make outsourcing prohibitively expensive, by setting $f = +\infty$ in the model.

According to Table 10, average labor productivity declines by 25 percent, while the final goods price index increases by 24 percent. Hence, our results point to relatively large efficiency gains due to labor specialization along the supply chain.

Figure 4 shows the distribution of the change in log value added per worker. Interestingly,

Table 9: Specialization. Simulated and Actual Data.

	(1) $\Delta\theta\left(o_i^{1*}\right)$	(2) $\Delta\theta\left(o_i^{2*}\right)$	(3) Δ similarity	(4) Δsimilarity (binary)
Simulated:				
$\ln\epsilon$	0.003***	0.003***	-0.0002***	-0.006**
	(0.01)	(0.01)	(0.01)	(0.00)
Data:				
z	0.014*	0.019***	-0.016**	-0.010**
N	1,000	1,000	1,000	1,000

Note: Standard errors in parentheses. Significance levels: $*p < 0.1, **p < 0.05, ***p < 0.01$.

Table 10: Prohibitive outsourcing costs.

	Mean	Weighted mean	Median	St. dev.
Change in:				
...log value added per worker	-0.25	-0.30	-0.27	-0.06
...log final goods prices	0.24	0.24	0.24	-0.01
...log final goods price index		0.24		

Notes: The weighted mean uses employment as weights.

the fall in efficiency is highly heterogeneous across firms. On the one hand, the change in labor productivity is small for firms initially not outsourcing many tasks. On the other hand, the change is big for firms highly exposed to outsourcing.

6 Model Validation

In this section, we provide empirical evidence for our key model assumption of relationship specificity and key model mechanism of within-firm labor reallocation using our novel linked worker-firm data from Denmark and Sweden.

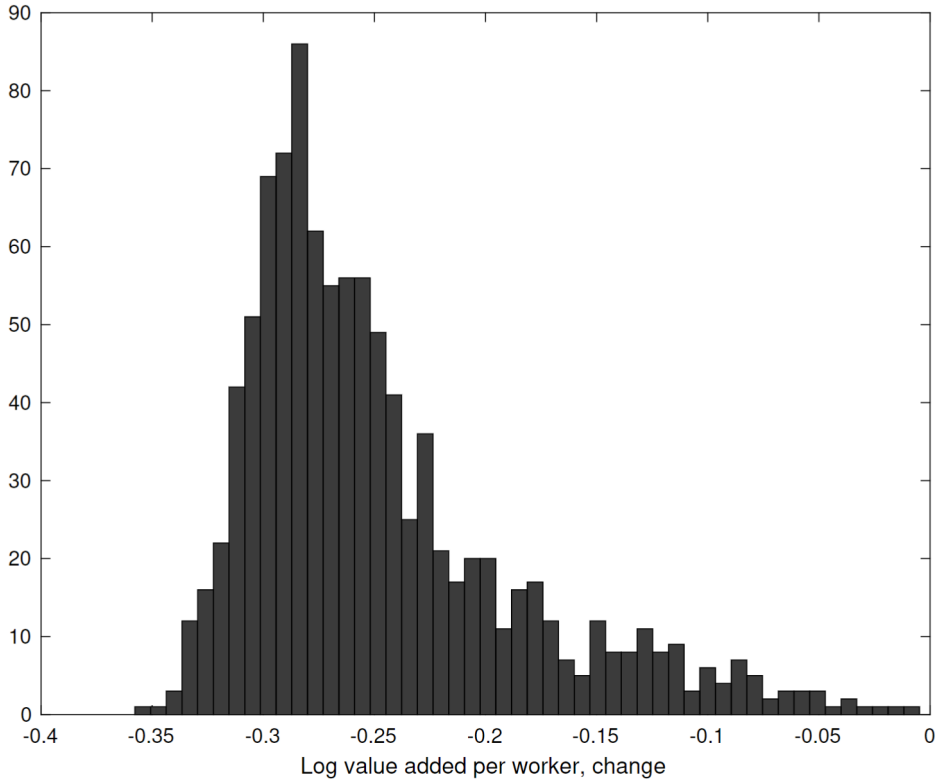
6.1 Relationship-specificity and the Effects of Demand Shocks

To start, we note that our model is premised on the assumption of relationship specificity,[19] as is common in the literature of global supply chains. In sub-section 2.3 above, we have shown 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 focal firms' size, labor productivity, and labor specialization.

We split the sample used for Tables 3 and 5 as follows. The focal firms with $rs_i < 0.68$, the 75th percentile of the differentiated-goods share in Nunn (2007)'s data, and the remaining focal

[19]For example, the buyer firm faces a unique set of specific task productivity draws from its suppliers.

Figure 4: Prohibitive Outsourcing Costs.



firms are in the relationship-specific sub-sample. We then estimate the same regressions as in Tables 3 and 5 by sub-sample, and report the results in Tables 11 and 12, where panel A (B) shows the results for the relationship-specific (generic-inputs) sub-sample.

Columns (1)-(2) of Table 11 show that, despite the differences in relationship specificity, the focal firms in both sub-samples grow in sales and employment, in response to positive exogenous demand shocks. In addition, the growth is larger in magnitude for the generic-inputs sub-sample. Column (3) shows that the two sub-samples also exhibit similar responses in the share of wage costs in total costs. Columns (4) and (5) show that while the coefficient estimate is positive, statistically significant, and fairly large in size for the relationship-specific focal firms, just like in Table 3, it is close to 0 in magnitude for the generic-inputs focal firms.

Table 11: 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 Inputs (the rest)					
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 12 shows that the relationship specific focal 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 5. On the other hand, panel B of Table 12 shows that the coefficient estimates of the generic-inputs focal firms have the same signs as in panel A, but they lack statistical significance.

Table 12: 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 Inputs (the rest)				
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 11 and 12 provide empirical evidence that relationship-specific local firms, and only these focal firms, increase labor productivity and increase labor specialization relative to their foreign suppliers in response to positive exogenous demand shocks. These results provide validation for our quantitative model whose key assumption is relationship specificity.

6.2 Within-firm Labor Reallocation and Relationship Specificity

Next, we note that a key mechanism of our quantitative model is that when output demand increases, the focal firm allocates labor away from in-house production (e.g. Proposition 1) towards the fixed outsourcing cost, f.

Table 13 explores whether our data is consistent with the hypothesis that the focal firm allocates labor away from in-house production. Our measure of in-house-production labor is motivated by the management-layers literature (e.g. Caliendo et al. 2015). This literature 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.

Column 1 of Table 13 reports the results for the wage-bill share of production occupations, and column 2 reports those for the 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 include the relationship-specific focal firms only, and find that the coefficient estimates remain negative and significant. In panel C, however, we find that the coefficient estimates are *positive* for the generic-inputs focal firms, the opposite patterns to panels A and B. These results provide clear evidence that relationship-specific focal firms, but not generic-inputs ones, allocate labor away from in-house production, as consistent with our quantitative model.

Table 13: Within-Firm Labor Reallocation: Production Occupations

	(1)	(2)
	Δ Wage-bill share	Δ Employment share
Panel A: All		
z	-0.012**	-0.011**
	(0.006)	(0.005)
Observations	16788	16788
Panel B Relationship Specific Inputs ($rs_i > 0.68$)		
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 14 explores whether our data is consistent with the hypothesis that the focal 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 14 reports the results for the wage-bill share of college-educated workers, and column 2 reports the employment share of these workers. With all observations included, in panel A, we obtain positive coefficient estimates, but their statistical significance is marginal at best. With relationship-specific focal 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 focal firms, we obtain *negative* coefficient estimates, with marginal statistical significance for the employment share, the opposite patterns to panels A and B. These results suggest that relationship-specific focal firms, but not generic-inputs ones, allocate labor towards outsourcing costs, as consistent with our quantitative model. Our results in Table 14 and earlier ones in Table 3 show that the focal 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 14: Within-Firm Labor Reallocation: College-Educated Workers

	(1)	(2)
	Δ Wage-bill share	Δ Employment share
Panel A: All		
z	0.007*	0.005
	(0.004)	(0.004)
Observations	16788	16788
Panel B: Relationship Specific Inputs ($rs_i > 0.68$)		
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

Summarizing this section, we have shown that in response to positive exogenous demand shocks, the relationship-specific focal firm increases value added per worker, allocates labor away from in-house production towards outsourcing costs, and its occupational structure grows apart from its foreign suppliers'. In addition, these results do not for generic-inputs ones, for which our coefficient estimates often show opposite signs. These results provide validation for the key assumption and 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.

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 relationship specificity, task specialization and outsourcing that is broadly consistent with the evidence, in which the buyer firm allocates labor away from in-house production towards outsourcing costs when output demand increases exogenously. Third, we calibrate 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 labor productivity. For example, our model simulation accounts for one third of the 90-10 dispersion 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 25 percent lower and the final goods price index 25 percent higher. Finally, we show that when output demand increases exogenously, the relationship-specific buyer firms, and *only* the relationship-specific buyer firms, experience increases value added per worker but decreases in occupational structure relative to foreign suppliers. They also decrease the wage-bill and employment shares of production-related workers but increase the shares of college graduated workers. These results provide validation for the key assumption and 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, highlights the economic mechanism that increased labor specialization contributes to increased labor productivity, and could be applicable to domestic supply chains as well. We look forward to such data becoming available for future research.

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Appendix

A Data

Table 15: 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
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 16: 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 17: Aggregate statistics for occupation codes, Denmark

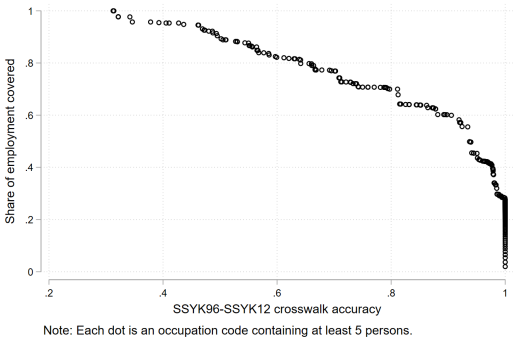
Digits	Four		Three		Two		One	
	t=0	t=1	t=0	t=1	t=0	t=1	t=0	t=1
Panel A: ISCO08								
#Occ codes	539	499	172	164	52	52	10	10
Non-mis share	95	96	95	96	95	96	95	96
Top share	10	10	11	10	13	15	16	17
Panel B: ISCO+								
#Occ codes	202	204	36	36	4	4	2	2
Non-mis share	93	96	94	96	95	96	95	96
Top share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

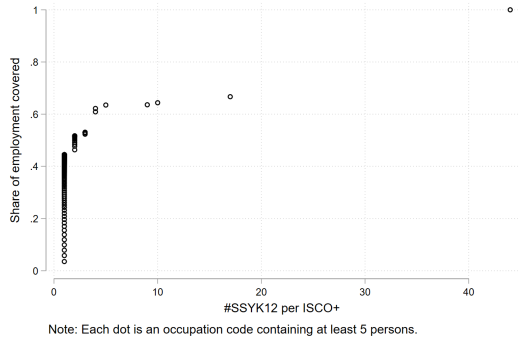
Figure 5: Occupation Code Concordance



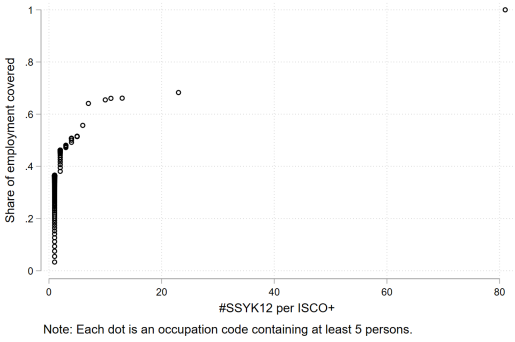
(a) SSYK96 to SSYK12



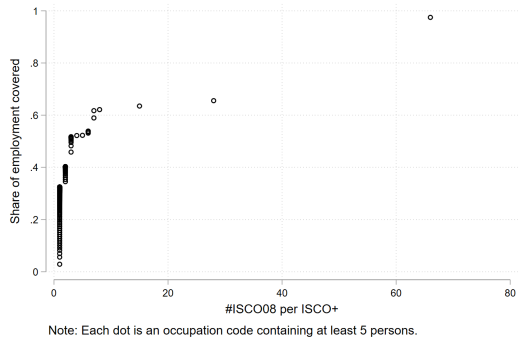
(b) SSYK96 to SSYK12



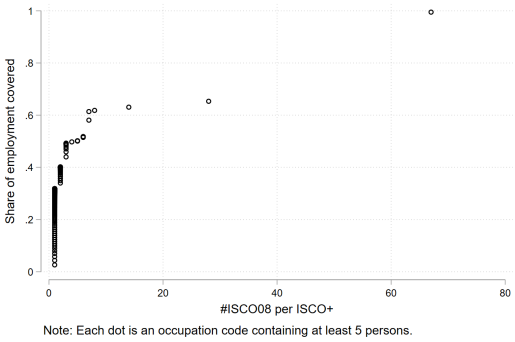
(c) SSYK12 to ISCO+, t=0



(d) SSYK12 to ISCO+, t=1



(e) ISCO08 to ISCO+, t=0



(f) ISCO08 to ISCO+, t=1

Table 18: Top ISCO08 codes, Denmark

Rank	ISCO08 code	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

Note: "Share" is the share of total employment in percent

Table 19: Top SSYK12 codes, Sweden

Rank	SSYK12 code	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 work
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

Note: "Share" is the share of total employment in percent

Table 20: Top ISCO+ codes, Denmark

Rank	ISCO+	Share	#ISCO08	Top ISCO08	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 Machi
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

Note: "Share" is the share of total employment in percent. "Top ISCO08" is the largest ISCO08 within the ISCO+, and "Share, top ISCO08" is the employment share within the ISCO+.

Table 21: Top ISCO+ codes, Sweden

Rank	ISCO+	Share	#SSYK12	Top SSYK12	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

Note: "Share" is the share of total employment in percent. "Top SSYK12" is the largest SSYK12 within the ISCO+, and "Share, top SSYK12" is the employment share within the ISCO+.

C Additional Results

C.1 Controlling for WID shocks to suppliers

The following two tables are identical to Tables 3 and 5 in the main text, but add suppliers' average WID shock as a control: $\bar{z}_i = \sum_j w_{ij,t=0} z_j$. For suppliers that are not 3rd country exporters, we assign $z_j = 0$.

Table 22: Same as Table 3 in main text, but controlling for suppliers' 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
z	0.120***	0.059***	0.141**	-0.027**	-0.045***	0.037***
	(0.020)	(0.015)	(0.056)	(0.013)	(0.013)	(0.014)
$\bar{z}$	0.042	0.012	-0.142	-0.051**	0.010	-0.014
	(0.030)	(0.028)	(0.098)	(0.022)	(0.021)	(0.027)
Observations	16788	16788	16788	16297	16628	16297

Table 23: Same as Table 5 in main text, but controlling for suppliers' average WID shock

	(1) Δ $\theta(o_i^{1*})$	(2) Δ $\theta(o_i^{2*})$	(3) Similarity	(4) Similarity (binary)	(5) Sim. (fix w_{ij})	(6) Sim. (fix w_{ij}, θ_i)	(7) Sim. (fix w_{ij}, θ_j)
z	0.014*	0.018***	-0.016**	-0.010**	-0.017***	-0.009*	-0.009**
	(0.008)	(0.007)	(0.007)	(0.004)	(0.006)	(0.005)	(0.004)
$\bar{z}$	0.001	0.010	0.012	-0.004	-0.008	-0.013	0.014**
	(0.013)	(0.011)	(0.013)	(0.008)	(0.011)	(0.010)	(0.007)
Observations	16788	16788	16788	16788	16788	16788	16788

C.2 Supplier-level regressions

Consider the regression equation

$$\Delta \ln y_j = \alpha_{s(j)} + \gamma_{r(j)} + \delta z_j + \theta \bar{z}_j + \varepsilon_j \tag{11}$$

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 suppliers in period 0. This is necessary for constructing $\bar{z}_j$.

Table 24: 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
$\overline{z}$	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 25: 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
$\overline{z}$	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