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DISCUSSION PAPER SERIES

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ABSTRACT

Offshoring, Matching, and Wage Inequality: Theory and Evidence*

This paper examines how offshoring affects worker skill demands and studies its implications for wage inequality. Using Danish administrative data, we find that offshoring increases firm-level demand for higher skills in occupations with high exposure to foreign competition. This effect is more pronounced in low-productivity firms, highlighting distributional impacts across firms. By constructing a Becker-type worker-firm matching model in a global economy, we demonstrate underlying mechanisms and quantify the role of offshoring-induced adjustments. Offshoring increases firm similarity in worker skill and wages within high-exposed jobs, leading to a decrease in between-firm inequality—a contrast to the effects of technological change.

JEL Classification: C78, F14, F16, J24, J31

Keywords: offshoring, worker-firm matching, segregation by skill, wage inequality, between-firm inequality

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1 Introduction

The last two decades have witnessed a momentous shift in the paradigm of international trade from exchange in final goods to trade in tasks (Grossman and Rossi-Hansberg, 2006). Recent advances in Information and Communication Technology (ICT), together with changes in economic institutions, have facilitated the fragmentation of production processes in disparate locations across borders, a phenomenon commonly referred to as "offshoring." In response to changes in the nature of production, firms adjust by re-optimizing the mix of occupations and the skill-type of workers to keep in-house.

Previous work has mainly focused on studying the types of jobs replaced by offshoring—typically associated with routine, easily codifiable tasks that do not require geographic proximity (Blinder, 2009; Blinder and Krueger, 2013)—and their labor market effects (Autor et al., 2003; Oldenski, 2012; Goos et al., 2014; Hummels et al., 2014). More recently, Bernard et al. (2020) shows how offshoring has shifted firm-level occupational demand toward jobs intensive in non-offshorable innovation-related tasks. While much of the literature has focused on studying offshoring-induced compositional shifts across occupations (i.e., the between-occupation channel adjustment), the specific mechanisms through which occupational exposure to foreign competition affects firm-level adjustments in skill demands within occupations, as well as their implications for domestic labor market inequality, remain underexplored.

In this paper, we examine how offshoring affects worker skill demands and study its implications for wage inequality using rich administrative data from Denmark. Our analysis broadly consists of two complementary parts. First, we identify the causal effect of offshoring on firm-level demand for worker skills by employing a shift-share instrumental variable research design. Second, we demonstrate mechanisms that can explain our reduced-form findings by building a worker-firm matching model in a global economy, where offshoring affects the domestic labor market by changing the effective supply of workers. We then quantify the role of offshoring in explaining changes in labor market inequality through counterfactual experiments.

Our analysis of changes in the skill demands within occupations critically relies on the rich data on worker education and job training information, which allows us to construct detailed measures of individual-level worker skills. Specifically, we transform detailed text information on specific degrees and training content into quantifiable skill measures by (i) mapping each education record to the most relevant occupation code and (ii) merging these records with occupation-specific descriptors from O*NET to extract skill information. A key underlying assumption in our approach is that an individual's educational attainment or job training reflects their ability to perform tasks required in a particular occupation. We demonstrate that our skill measures exhibit significant variations within detailed occupational groups and show positive, statistically significant correlations with wages.

Using these skill measures, we begin by analyzing the firm-level response to offshoring exposure in terms of changes in the average quality of worker skills employed. Since our objective is to empirically test for firms' adjustments in jobs that are potentially substitutable with foreign workers in the data, we focus on workers in high-offshorable occupations. Throughout the paper, we conceptualize offshoring as a firm's decision to hire foreign workers instead of home workers. To operationalize this concept in the data, we focus on firm-level purchases of foreign goods, which can be interpreted as embodiments of foreign workers' human capital and value-added. Specifically, we restrict to products that firms both export and import (excluding raw materials), which is consistent with the notion of "narrow offshoring" (Feenstra and Hanson, 1999; Hummels et al., 2014). We further focus on offshoring to low-wage countries, namely China, as we restrict our analysis to a North-South framework where only the North finds offshoring a less expensive production alternative (Feenstra and Hanson, 1997; Grossman and Rossi-Hansberg, 2008). We then aggregate at the industry level to construct measures of offshoring exposure.

Our research design leverages industry-level variations in offshoring exposure to examine within-firm changes in the skill types hired over time. A key identification challenge is that industry- or firm-level shocks to demand or productivity may simultaneously affect industry-level offshoring exposures and worker-firm matches. To address endogeneity issues, we build on Hummels et al. (2014) and construct a Bartik-type instrumental variable of world export supply—the aggregation of product-level export supply from China to the world (excluding Denmark), weighted by initial product shares imported by each Danish manufacturing industry in the pre-sample year. The instrument, which has a product-time variation, is correlated with the value of Danish firms' purchases from China but is external to the firm-level outcomes in Denmark. We also show that none of the shifters (i.e., products) in our instrument dominates in terms of growth rates of offshoring values, further supporting its validity (Borusyak et al., 2022).

We find that offshoring has a positive impact on the average skills of workers employed in occupations exposed to foreign competition. That is, a doubling in the offshoring values to China triggers a rise in the average skills by 0.14, which corresponds to a 0.3 percent increase relative to the sample mean. This increase in average skills pertains only to firms classified as low-productivity firms, which we define as firms with average sales per employee below the median of the distribution (high-productivity firms are above this threshold) in the pre-sample period. The baseline results are driven by firms replacing low-skilled workers with high-skilled ones rather than individual workers improving their skills through training. Together with the distributional effects across firms—where the positive effects are primarily observed in low-productivity firms—our findings suggest that significant adjustments occur through changes in worker-firm matching.

To demonstrate and quantify mechanisms through which offshoring affects these firm-level adjustments, the second part of our paper constructs a Becker-type worker-firm matching model with transferable utility and a continuum of characteristics. In particular, we build on Dupuy and Galichon (2014), which allows for unobserved heterogeneity in preferences and thus theoretically supports "non-pure" matching while also examining complementarity in the matching surplus function. The model consists of workers and firms that form a set of acquaintances according to their matching intensity technology (e.g., the average number of job ads workers observe and job applications firms review) and competitively find matches to produce a joint surplus, which is shared as wages and profits. Similar to Antràs et al. (2006) and Kremer and Maskin (2006), offshoring is captured as an additional supply of foreign workers available for firms to match with. In our model, foreign matching, compared to domestic matching, involves a different matching intensity technology and additional production cost.

Our model features three key innovations: (i) applying the matching model and its estimation to the context of worker-firm matching; (ii) introducing the unemployment margin and incorporating different matching intensity technologies between workers and firms—which affect both matching at the extensive margin and bargaining power in the surplus division conditional on matching—thereby effectively adapting the marriage market analysis to a worker-firm matching context; and (iii) extending the framework to a global economy setting. These innovations are, in fact, closely interrelated and crucial. In analyses of matching in marriage markets, how surplus is divided is rarely observed. However, in worker-firm matching, how much is extracted from the matched surplus, particularly wage, is one of the main outcomes of interest. Here, introducing the extensive margin with an explicit outside option is crucial for determining the division of surplus. Moreover, worker displacement is another important consequence of offshoring, making the role of the extensive margin even more essential. Finally, the economic forces demonstrated through the matching intensity technology become relevant only in the presence of an extensive margin.

We then use our model to quantify the impact of offshoring on the quality of worker-firm matching and related labor market consequences. We exploit the equilibrium properties of the model to estimate the key structural parameters, a subset of which are calibrated based on external data sources. A significant challenge in the estimation arises from the lack of data on the number of foreign matches. To make progress on this end, we assume that the ratio between the hypothetical number of foreign workers and the actual domestic workers is equal to the ratio between the value of offshoring and the value added in the domestic economy, with appropriate normalization to the unit of labor to adjust for cross-country differences in productivity. Using this assumption, we can then infer the number of offshored matches from the data.

The estimation results reveal three key aspects. The estimated production technology indicates positive assortative matching based on observed worker and firm characteristics. Over time, the importance of these observable characteristics relative to unobservables in the estimated complementarity increased by more than twofold (from 0.6930 to 2.011). Additionally, the estimated cost of offshoring decreased by 20 percent (from 101.93 to 87.96 Danish Kroner (DKK) per hour). Finally, the estimated matching intensities were higher for domestic matching than foreign matching initially; however, the differences in these intensities decreased over time. That is, offshoring became more accessible both through lower offshoring costs and increased foreign matching rates.

Finally, we use the estimated model to conduct counterfactual experiments. While the mechanisms of our model apply to workers more generally in other job categories, the quantitative exercises focus on workers employed in high-offshorable occupations—those facing significant competition from foreign workers given the offshoring technology in the considered sample period. Our analysis proceeds in two major parts.

In our first exercise, we assess the differential effects of offshoring and technology-related channels. Compared to the baseline scenario, the counterfactual simulations with either zero offshoring costs or increased foreign matching intensities reveal that offshoring places downward pressure on wages and increases the share of unmatched workers at Home, particularly among lower-skilled workers. Additionally, offshoring leads to an increase in the overall skill quality of workers hired by firms. These results contrast sharply with counterfactual simulations using greater skill complementarity in the production technology. Increased positive assortative matching raises average wages, with larger gains for higher-skilled workers, while the share of unmatched workers does not increase. Due to increased sorting, the average quality of matched worker skills increases for the top of the firms' productivity distribution, while it decreases for the bottom.

In our second exercise, we assess how offshoring contributed to rising inequality between 1996 and 2006. Specifically, we compare the baseline results for 2006 with counterfactual results derived using structural parameter estimates from 1996. Over the decade, the average wage increased by 10 percent, which would have increased by 11 percent if offshoring costs had remained at 1996 levels. Further accounting for changes in foreign matching intensity, the counterfactual average wage would have increased by an additional 2 percentage points. A similar pattern emerges in the overall wage dispersion, measured by the standard deviation of wages. In terms of wage inequality between firms—measured by the difference in average wages between the top and bottom deciles of firms—the actual increase in between-firm inequality exceeded 200 percent over the decade, which would have reached more than 300 percent under the 1996 levels.

Our analysis extends existing findings documenting adverse employment and wage effects of offshoring on high-exposed occupations by (i) demonstrating how these effects are driven by offshoring-induced changes in domestic worker-firm matching and (ii) showing that this reallocation leads firms, on average, to hire higher-skilled workers and become more similar in both skill and wage levels within these jobs (i.e., a decrease in between-firm inequality). The key mechanisms of how exposure to foreign competition affects domestic worker-firm matching, as presented in our model, and the corresponding consequences on labor market inequality, as demonstrated in our results, have broader implications for workers in other occupations with low offshorability due to institutional constraints (e.g., occupational licensing) or the current state of offshoring technology. This is particularly relevant given the rapid changes in technology and globalization, which continuously reshape the nature of tasks, including the offshorability of jobs.

Contribution to the Literature

Our work is associated with three strands of studies. It is related to a growing trade literature that uses matching models to study the distributional effects of globalization: heterogeneous effects of international trade within sectors, firms, and occupations (Kremer and Maskin, 2006; Costinot and Vogel, 2010; Grossman et al., 2017; Bonfiglioli et al., 2021; Galle et al., 2022). Our innovation lies in (i) bringing the marriage market analysis of matching models (Choo and Siow, 2006; Dupuy and Galichon, 2014) to a worker-firm matching context by introducing the unemployment margin and incorporating different matching intensity technologies between workers and firms; and (ii) extending the framework to incorporate offshoring. In addition, by proposing a novel strategy to estimate offshored matches in the data, we quantify the role of offshoring on domestic labor market outcomes and inequality.

Next, this paper contributes to studies examining the labor market effects of offshoring. Previous work has focused on changes in wage and employment outcomes in response to offshoring, comparing across occupations and education groups (Feenstra and Hanson, 1997; Hsieh and Woo, 2005; Biscourp and Kramarz, 2007). Recently, the focus has shifted to examine the impact of offshoring at a more disaggregate level using administrative data (Baumgarten et al., 2013; Becker et al., 2013; Hummels et al., 2014; Bernard et al., 2020; Dorn and Levell, 2021; Pulito, 2024; Colella, 2024). Our analysis using high-quality Danish data together with a comprehensive characterization of worker skills enables us to examine the distributional effects of offshoring on workers within occupations, thereby complementing closely related recent studies such as Bernard et al. (2020) that show offshoring-led reallocation of workers from production to non-production jobs to update product quality. Furthermore, we study changes in the firm-level skill demands, not only within offshoring firms, as in Pulito (2024) and Colella (2024), but also among their low-productivity counterparts that keep production entirely in the domestic economy.

Finally, this project contributes to the burgeoning literature on worker sorting or segregation of workers by skill. Previous studies have documented evidence of growing segregation by skill in recent decades, notably in developed countries.[1] The potential mechanisms proposed in the literature include: technological change (Autor et al., 2003; Acemoglu and Autor, 2011), the expansion of the ICT sector (Håkanson et al., 2020), outsourcing (Abraham and Taylor, 1996; Goldschmidt and Schmieder, 2017; Handwerker, 2023), international trade (Helpman et al., 2010; Davidson et al., 2014)[2], and rising skill dispersion (Kremer and Maskin, 1996; Acemoglu, 1999). We propose offshoring as an important channel that affects between-firm inequality through changes in domestic worker-firm matching. Our quantitative analysis, in particular, sheds light on the importance of these competing hypotheses (for example, technology versus globalization) in explaining changes in labor market inequality.

The rest of the paper proceeds as follows. Section 2 describes the data and the construction of measurements. Section 3 presents stylized facts and regression analyses. Section 4 introduces the worker-firm matching model with offshoring. Section 5 presents the structural estimates of the model and counterfactual results. Section 6 concludes.

[1]For example, studies include focusing on the US (Song et al., 2019), United Kingdoms (Faggio et al., 2010), Germany (Card et al., 2013), France (Abowd et al., 1999), Sweden (Baziki et al., 2016; Håkanson et al., 2020), and Denmark (Bagger et al., 2013; Bagger and Lentz, 2018).

[2]Davidson et al. (2014) empirically examines the idea that globalization improves matching for high-productivity firms in the exporting sector. This is in line with Helpman et al. (2010) that show how worker-firm matching is affected by exporting firms' intensity in screening their workers to gain competitiveness.

2 Data and Measurements

2.1 Data Sources

Our baseline data rely on the Danish matched employer-employee sample, which leverages three sources of information over the sample period from 1995 through 2006, with 1995 serving as the base year in our analysis: (i) the "Integrated Database for Labor Market Research" (*IDA*), (ii) the "Accounting Statistics Registers" (*FirmStat*), and (iii) the "Foreign Trade Statistics Register" (*UHDI*).

The *IDA* provides individual-level data on socioeconomic and labor market characteristics, such as education, occupation, and place of work, at the annual frequency for all individuals employed in the recorded population of Danish firms since 1980. The *FirmStat* covers the universe of private sector firms and includes variables related to key financial items, such as total sales and size, which are included in the empirical analysis as control variables.[3] We then complement the first two registers with the *UHDI*, which contains firm-product-country-level data on international trade. Both imports and exports are recorded in Danish kroner (DKK) according to the 8-digit Combined Nomenclature as long as the transaction is worth at least 7500 DKK or involves goods that weigh at least 1000kg. We use UHDI and UNComtrade—which provide cross-country product-level trade flows—to construct our main measures of offshoring and the corresponding instrumental variables.

We further utilize the US Department of Labor's Occupational Characteristics Database (O*NET), the successor to the Dictionary of Occupational Titles (DOT), to obtain factor descriptions of occupation-specific skill and task requirements for the skill construction. O*NET provides standardized measures of occupation-specific requirements for knowledge, skills, and abilities across nearly 1,000 occupations. The data is collected through surveys of job incumbents or occupational experts and is frequently updated to reflect changes in occupational structures over time. We implement an occupational crosswalk between O*NET's SOC codes and ISCO codes to combine with the *IDA*.

2.2 Measurements

2.2.1 Workers' Skills

We use variables *hfaudd* (the highest obtained education) and *erhaudd* (the highest completed professional training), which provide 2449 different types of education and job

[3] All monetary figures (including workers' wages) are CPI-adjusted to the level of 1995.

training records, to construct individual-level skills.[4] We convert rich text information on specific degrees and the content of job training into quantifiable skill measures in the following three steps.

First, we map each education record to a relevant occupation code, assuming that an individual's educational attainment or job training reflects one's ability to perform tasks required in a particular occupation.[5] The mapping is generated using the O*NET *code connector*, which connects keywords extracted from education and job training records to relevant occupations.[6] Second, we use the occupation-specific descriptors in O*NET's Abilities files related to cognitive abilities (1.A.1.a.1 - 1.A.1.g.2) and conduct principal component analysis (PCA) to construct a scalar measure of cognitive skills.[7] Since there is no Danish version of the O*NET data, we assume that the occupation-specific task and skill requirements measured in the US are similar to those in Denmark. Finally, we assign these skill measures to each individual based on the education and job training information reported in a given year in the data. Thus, our skill measures would vary over time for individuals who pursue further schooling or engage in additional job training. For education records that do not correspond to a specific occupation code—such as when the education content is too general—we assign the average skills obtained, weighted by the occupation distribution in the pre-shock period.[8]

Finally, we show that our skill measures demonstrate positive and statistically significant correlations with wages. Here, we run an individual-level pooled OLS regression of log wages on our measures of cognitive skills, workers' characteristics, and year fixed effects. The unit of observation is a person-year pair.[9] Table 1 presents results. Column (1) mainly includes the covariates: years of education, years of work experience, and years of work experience squared. Column (2) adds our skill measures. Column (3) includes additional covariates: gender, age, and nationality. Our results in Columns (2) and (3)

[4]Vocational and post-secondary training programs are heavily subsidized by the Danish government, spending around 0.5 percent of GDP each year. The government provides and finances worker training at off-the-job training sites and offers generous wage subsidies for firms offering training during work hours. This results in an unusually high incidence of training participation among employed workers. The training courses can be grouped into basic, vocational, and postsecondary training (`https://www.ug.dk`). Vocational education includes periods of formal schooling and apprenticeships providing opportunities to practice in actual workplaces (Keller and Utar, 2023). Post-secondary training typically takes place during off-work hours and consists of polytechnical, college, or MBA-type courses.

[5]The idea is similar to Lindenlaub (2017), where education records are considered as a reflection of individual capabilities to perform tasks in particular jobs.

[6]See Appendix A for further details.

[7]The approach is similar to existing studies such as Lise and Postel-Vinay (2020) and Goos et al. (2014), which utilize the O*NET data to construct measures of skills or tasks.

[8]For example, *hfaudd* codes from 1006 through 1011 correspond to general education.

[9]Descriptive statistics on worker-level variables are reported in Table A.3.

Table 1: Wage Regression with Skill Measures

	(1)	(2)	(3)
Education	0.0809***	0.0784***	0.0732***
	(0.000136)	(0.000183)	(0.000178)
Experience	0.0305***	0.0305***	0.0325***
	(0.000191)	(0.000191)	(0.000195)
Experience^2	-0.000518***	-0.000517***	-0.000657***
	(6.53e-06)	(6.53e-06)	(6.48e-06)
Cognitive Skills		0.0607***	0.115***
		(0.00275)	(0.00267)
Observations	1,393,640	1,393,598	1,393,598
R-squared	0.320	0.321	0.362

Notes: This table presents the OLS correlation results obtained from regressing individual log wages on individual-level measures of workers' characteristics, including our measures of cognitive skills. We pool all observations in our sample. The unit of observation is a person-year pair. All regressions include year fixed effects. Column (1) mainly includes the covariates: years of education, years of work experience, and years of work experience squared. Column (2) adds our skill measures. Column (3) includes additional covariates: gender, age, and nationality. Significance levels: ***1%, **5%, *10%.

show that the estimated coefficients for our skill measures are positive and statistically significant for both specifications.

2.2.2 Offshoring

Throughout the paper, we conceptualize offshoring as a firm's decision to match with foreign workers instead of home workers. Empirically, we operationalize this notion by focusing on firm-level purchases of goods that contribute to the firm's production, which we interpret as the embodiment of foreign workers' human capital and value added.[10]

It is important that these purchases are used in the production process and potentially substitute in-house workers (Feenstra and Hanson, 1999). Thus, our measurement of offshoring focuses on purchases of product categories (excluding raw materials) that firms both import and export, which effectively captures the notion of "narrow offshoring."[11] Note that our focus on the manufacturing sector alleviates concerns related to firm-level purchases intended for reselling to consumers for direct consumption, which is also articulated in Hummels et al. (2014). Our approach focusing on purchases from abroad

[10] For example, if a Danish firm producing furniture purchases a table from China, this can be interpreted as the Danish firm matching with Chinese workers whose value-added is captured in the form of tables.

[11] We follow Eurostat's definition of raw materials: Section 2 (crude materials, inedible, except fuels) and Section 4 (animal and vegetable oils, fats, and waxes) in the fourth revision of Standard International Trade Classification (SITC rev. 4).

is similar to Olney and Pozzoli (2021) and is further supported by survey data, which indicate that 95% of Danish firms that offshore to a particular region also import from that region (Bernard et al., 2020). Finally, an appealing aspect of our offshoring measure is that it does not distinguish between carrying out production at Danish firms' own affiliates in a foreign country versus producing through arm's-length contracts with foreign firms. In that sense, our measure is a general one, as it captures different modes of offshoring.[12]

Given our focus on the North-South framework where only the North finds offshoring a less expensive production alternative (Feenstra and Hanson, 1997; Grossman and Rossi-Hansberg, 2008), we further restrict our analysis to offshoring to low-wage countries, in particular, China. Previous studies document the importance of China's integration into the global economy in the early 2000s with its accession to the WTO (Autor et al., 2013; Pierce and Schott, 2016)—arguably one of the most important trade shocks from low-wage countries to hit northern economies, including Denmark (Keller and Utar, 2023).[13] In our context, China's rise has facilitated access to labor with different skill levels and types, which plays a crucial role in shaping how domestic workers and firms match.

2.2.3 Occupational Offshorability

We follow Blinder and Krueger (2013) to measure occupational offshorability. Offshorable occupations are generally associated with routine tasks that are easily codifiable (Autor et al., 2003; Oldenski, 2012) and the work performance in these jobs does not require direct physical contact; and geographic proximity is less important (Blinder, 2009; Blinder and Krueger, 2013; Goos et al., 2014).[14] Table A.1 lists the 1-digit ISCO codes and the corresponding offshorability index scores, where higher values indicate high offshorability. Given our focus on manufacturing firms, we classify ISCO codes 7 and 8, which are (i) Craftsmanship and (ii) Process and Machine Operators; Transportation and Construction Work, as *high-offshorable*. These occupations, which are intensive in manual production work, also demonstrate the highest offshorability scores when using alternative measures proposed in Goos et al. (2014), calculated based on summaries of news reports on cases of offshoring by companies located in Europe in the European Restructuring Monitor (ERM).

[12]Note that the Danish industries most engaged in offshoring are Machinery and Equipment, Textiles, Plastics, and Furniture, which typically do not have supply chains as complex as those in the automotive industry (Olney and Pozzoli, 2021).

[13]China's share of imports to the United States and 12 EU countries more than doubled between 2000 and 2007 from 5.7% to 12.4% (Bloom et al., 2016).

[14]These jobs are not necessarily low in skill content. Anecdotally, offshorable tasks that require high skills, such as software programming, reading X-rays, or preparing tax forms, have been offshored to low-wage countries (Baumgarten, 2015).

2.3 Sample Construction and Description

Our construction of the final sample proceeds in the following steps. We first limit our focus exclusively to firms operating in the manufacturing sector between 1995 and 2006. We then exclude firms with fewer than three employees. We further require these firms to be present throughout our sample period. Using the employer-employee matches, we next identify workers who are employed by these firms at least once and track their labor market outcomes and education records over time. When examining firm outcomes based on worker characteristics to construct the average skill of in-house workers, we focus on worker observations whose employment status is recorded as employed and linked with a valid firm identifier (*cvrnr*).[15] Finally, we focus on workers aged between 20 and 65.

Table A.2 reports the descriptive statistics of our main sample at the firm level. Panel A shows the mean and standard deviation of the firm's average skills, calculated for the entire workforce and separately by occupation group. We categorize occupations into three groups using the 1-digit ISCO codes: 1 and 2; 3 through 5; and 7 and 8.[16] The first two groups include occupations related to management, high-skill professionals, clerical and sales (low offshorability); the last group involves occupations intensive in manual production work (high offshorability) and shows, on average, lower cognitive skills compared to other occupation groups.

Panel B reports the descriptive statistics of the independent variables used in our reduced-form analysis. Our measure of offshoring is the log of industry-level offshoring to China. The instrumental variable is the log of export values from China to the world, excluding Denmark, aggregated at the industry level.[17] Panel C includes the descriptive statistics of the rest of the firm variables that are included in the empirical analysis: firms' sales, size, importer, and exporter status. Our sample of firms is relatively large, employing, on average, 50 workers, and has average sales of roughly 9 million DKK. More than half of the firms in our sample engage in import or export activities.

[15] Therefore, we exclude observations with records indicating retirement, temporary absence, or leave (for example, for education purposes).

[16] We exclude 1-digit ISCO codes 6, 9, and 10, which correspond to farming, other work, and military occupations.

[17] See Section 3.2.1 for further details on the construction of our instrumental variable.

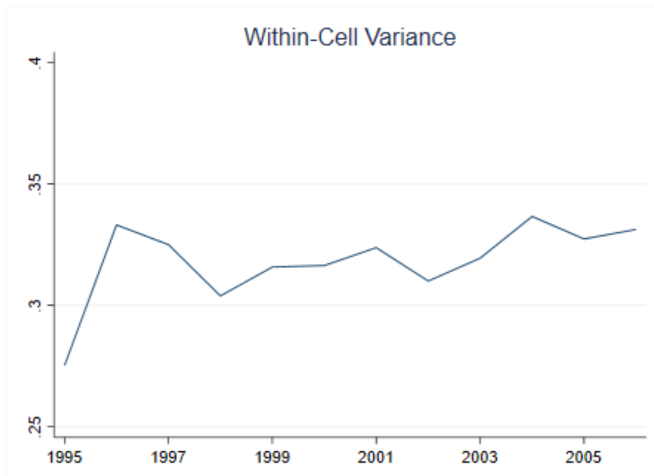
3 Stylized Facts and Regression Analysis

3.1 Stylized Facts

This section presents descriptive patterns of our sample, which we summarize as three important stylized facts.

Fact 1. The within-cell variance of skill increases over time.

Figure 1: The Share of Within-Industry-Occupation-Education Variance of Skills



Notes: This figure shows the share of the within-cell variance in total variance calculated using Equation (1), where a cell is defined as a triplet of education-occupation-industry (441 4-digit occupations, 5 education types, and 300 6-digit industries).

To demonstrate the importance of our skill construction, in addition to the wage regressions, we conduct a simple variance decomposition exercise to examine the within-cell variance of skills, where cell (l) is defined as a triplet of education-occupation-industry. Specifically, we compute,

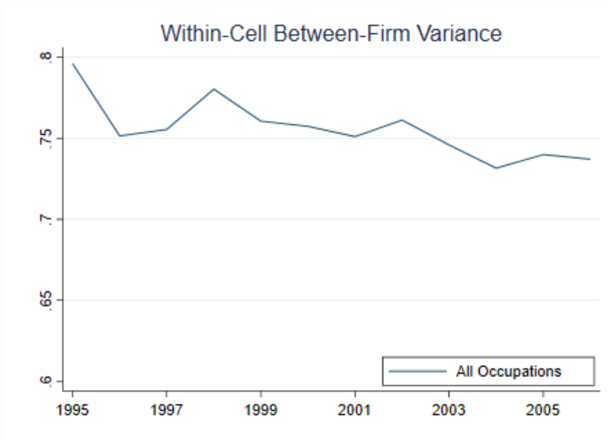
$$\frac{1}{N_t}\sum_{l}\sum_{i\in l}(s_{it}-\bar{s}_t)^2 = \frac{1}{N_t}\sum_{l}\sum_{i\in l}(s_{it}-\bar{s}_{lt})^2 + \frac{1}{N_t}\sum_{l}\sum_{i\in l}(\bar{s}_{lt}-\bar{s}_t)^2 \tag{1}$$

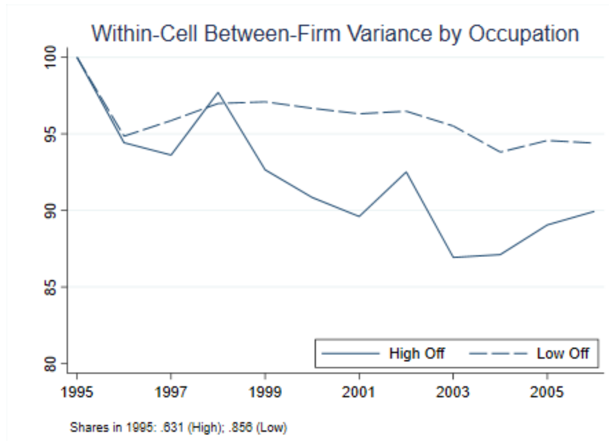
where s_{it} is the individual skill, $\bar{s}_{lt}$ is the average skill of cell l, and $\bar{s}_t$ is the aggregate mean. We work with 441 4-digit occupations, 5 education types, and 300 6-digit industries in our sample, and thus, roughly 55,827 cells.

Figure 1 shows the share of the within-cell variance in total variance for our constructed skill measures. Given our very narrowly defined cell, the share of within-cell variance is lower than the share of between-cell variance. At the beginning of our sample period, the share of within-cell variance is less than 0.30. However, we find an upward trend, particularly from the late 1990s, which reinforces the importance of our skill construction to capture heterogeneity within these observable categories.

Fact 2. The between-firm shares in explaining the within-cell variance of skill decrease over time, which is pronounced in high-offshorable occupations.

Figure 2: The Share of Within-Cell-Between-Firm Variance of Skills: All and By Occupation





Notes: This figure shows the results of the share of within-cell between-firm variation of the total variance. We compute, for each cell, the between-firm shares using Equation (3) and aggregate results using employment weights of each cell in a given year. The left graph shows results combining all occupations. The right graph contrasts results for high-offshorable occupations (1-digit ISCO codes 7 and 8) in solid lines with low-offshoring occupations (1-digit ISCO codes 1 through 5) in dashed lines.

Our next step is to understand the role of firms in explaining these within-cell variations in skill. We use the same definition of the cell defined above using education-occupation-industry. Similar to Helpman et al. (2016), for each cell l, we estimate the following:

$$s_{it} = \psi_{jlt} + \omega_{it}, \tag{2}$$

where ψ_{jlt} are the firm-cell-specific estimated dummies in time t. We then conduct a variance decomposition as follows:

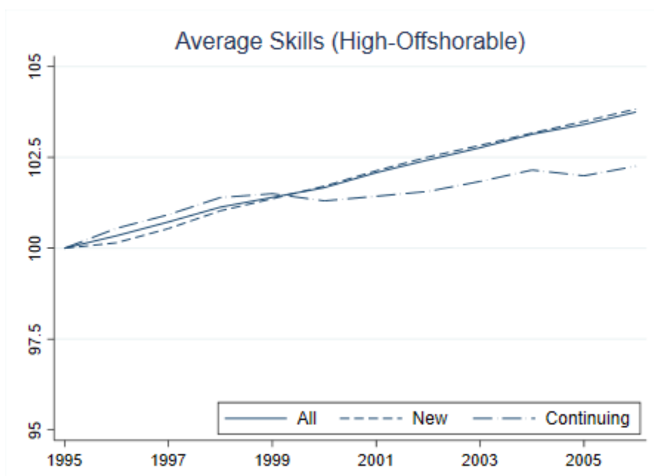
$$var(s_{it}) = var(\hat{\psi}_{jlt}) + var(\hat{\omega}_{it}). \tag{3}$$

Finally, we compute the share of within-cell-between-firm variance of the total variance and aggregate results using employment weights of each cell in a given year.[18]

Figure 2 presents the results of the share of within-cell between-firm variation of the total variance. The left graph shows results combining all occupations; the right graph presents results separately for high- (1-digit ISCO codes 7 and 8) and low-offshorable occupations (1-digit ISCO codes 1 through 5), shown in solid and dashed lines, respectively. The share of the between-firm component is greater than the within-firm component, as it ranges between 0.70 and 0.80 during our sample period. However, there is a notable downward trend in these shares over time post-2000s, which is particularly pronounced for high-offshorable occupations. For low-offshorable occupations, on the other hand, the between-firm share decreases over time but to a smaller extent.

Fact 3. For high-offshorable occupations, the within-firm average of cognitive skills increases, with the contribution of new matches increasing over time.

Figure 3: Within-Firm Average Skills: All versus Continuing Workers



Notes: This figure shows trends in the quality of matches for high-offshorable occupations (1-digit ISCO codes 7 and 8) using the average within-firm worker skills for all workers (solid lines), new hires (dashed lines), and continuing workers (dashed-dotted lines). The cohort of workers who were employed in a given firm in 1995 is categorized as "continuing" workers, and the subsequent cohorts are classified as "new" workers. All values are normalized to the level observed in 1995.

The results for high-offshorable occupations illustrated in **Fact 2** suggest that the types of skills firms hire in these jobs tend to become similar over time. We then study changes in

[18]When including worker-level controls, the variance decomposition becomes:

$$var(s_{it}) = var(X_{it}'\hat{\beta}_{lt}) + var(\hat{\psi}_{jlt}) + 2Cov(X_{it}'\hat{\beta}_{lt}, \hat{\psi}_{jlt}) + var(\hat{\omega}_{it}). \quad (4)$$

the quality of worker-firm matches by examining trends in the average within-firm worker skills. Figure 3 presents this for all workers (solid line) as well as separately for the cohort of workers who were employed in a given firm in 1995 ("continuing" workers, dashed-dotted line) and those hired in subsequent years ("new" workers, dashed line). There is an overall increase in the average skills of workers employed over time, which is mainly due to "new" hires—consistent with the high labor market flexibility in Denmark (Appendix Section D). Examining the results for "continuing" workers—which essentially provides the counterfactual average skills if firms do not form new matches—reveals that the extent to which firms improve skills is lower compared to the actual trend. These results highlight the important contribution of firms' adjustments by changing their worker matches.

3.2 Regression Analysis

Motivated by these descriptive patterns, this section investigates the connection between offshoring and firm-level adjustments in terms of changes in the average quality of worker skills employed and further studies distributional effects across the firm distribution. Since our objective is to empirically test for firms' adjustments in jobs that are potentially substitutable with foreign workers in the data, we focus on high-offshorable occupations.

3.2.1 Empirical Strategy

Our research design leverages industry-level variations in offshoring exposure to examine within-firm changes in the skill types hired over time. In doing so, we use firm-level imports of intermediate and final goods from China and aggregate at 6-digit industry codes provided in *FirmStat* using variables *gf_branche_93* and *gf_branche_03*.[19] Thus, firms operating in the same industry, regardless of their offshoring status, face the same level of offshoring exposure. If we were to measure offshoring at the firm rather than the industry level, we would fail to capture the skill implications for firms that do not offshore (typically the low-productivity ones) but operate in the same industry as firms that do offshore (typically the high-productivity ones). This approach is also consistent with the model we present in Section 4, which considers the effects of offshoring not only on firms that engage in it but also on their domestic counterparts.

Here, the identification challenge is that industry- or firm-level shocks to demand or productivity can possibly affect both industry-level offshoring exposures and worker-firm matches. Specifically, as the industry-level offshoring measure is constructed using the

[19]This classification follows the NACE system where *gf_branche_93* and *gf_branche_03* demonstrate correspondence with NACE Rev. 1 and NACE Rev. 1.1, respectively.

sum of firm-level offshoring, simultaneity concerns potentially arise in the presence of industries with a high concentration ratio.

To address such endogeneity issues, we build on Hummels et al. (2014) and construct a Bartik-type instrumental variable of world export supply,

$$I_{kt} = \sum_{h} s_{hk0} \times \mathrm{WES}_{ht}. \tag{5}$$

We combine the product-level export supply from China to the world excluding Denmark in time t (WES_{ht}) weighted by initial product shares imported by each industry k in the pre-sample year 1995 (s_{hk0}) within Danish manufacturing. The instrument, which has a product-time variation, is correlated with the value of Danish firms' purchases from China but is external to the firm-level outcomes in Denmark.

As discussed in the recent literature on shift-share instruments (Borusyak et al., 2022), the validity of this instrument rests on either the shares or the shifters being exogenous. Table A.4 shows the distribution of the offshoring values by product. There are altogether 135 shifters (i.e., products) in our instrument, and none of them dominates in terms of growth rates of offshoring values, giving support to the assumption required for validity that the shifters need to be large and not very concentrated.

Our baseline specification to examine how the average skill of workers hired in-house responds to changes in industry-specific exposures to offshoring to China is,

$$y_{jkt} = \alpha_0 + \alpha_1 \mathrm{Offshoring}_{kt} + \omega_{kt}\eta + \delta_{k't} + \delta_j + \epsilon_{jt}. \tag{6}$$

We define y_{jkt} as the average cognitive skills of in-house workers in firm j operating in industry k at time t. $\mathrm{Offshoring}_{kt}$ is the offshoring exposure measured at 6-digit industries.[20] By including firm fixed effects and 4-digit industry-by-year fixed effects, we examine within-firm changes over time, controlling for time-varying industry shocks that possibly affect firms' employment decisions. We also add 6-digit industry-level exports to the world to control for time-varying global demand of Danish industries' goods that can affect firms' employment decisions and, therefore, the average skills of in-house workers. Standard errors clustered at 6-digit industries. The coefficient of interest α_1 estimates the effects of offshoring on the average within-firm changes in their workers' skills over time.

[20] Although, in principle, we could calculate the offshoring exposure variable at the industry level for each municipality separately, we prefer a less disaggregated approach, as a non-negligible share of firms in our sample (around 25 percent) are multi-establishment companies with locations spread across several municipalities. Furthermore, the industry-based approach is less prone to endogeneity concerns than one that accounts for both industry and municipality simultaneously.

3.2.2 Results

Table 2 presents our main results focusing on the average skills of workers in high-offshorable occupations. Column (1) presents the non-instrumented ordinary least squares (OLS) coefficients estimated using our offshoring variable, whereas Columns (2) to (7) show the results obtained with the instrumental variable (IV) approach.

The OLS coefficient is not precisely estimated but generally suggests a positive association between industry-level offshoring and average firms' skills.[21] When we turn to the IV results of Column (2), the first stage is strong, as indicated by the fact that the F-statistic on the instrument is above 17.[22] The identification-robust Anderson-Rubin Wald test designed for cases of clustered standard errors also shows that the instrument is strongly related to our endogenous variable.[23] In the second stage, the offshoring coefficients in the IV specification are positive and statistically significant. In terms of magnitudes, a doubling in the offshoring values to China triggers a rise in the average skills within offshorable jobs by 0.14, which corresponds to a 0.3 percent increase relative to the sample mean. The magnitudes are larger than the analogous OLS coefficients—consistent with the presence of unobserved wage or productivity shocks that increase offshoring and are negatively correlated with average skills at the firm level.[24]

Columns (3) and (4) examine the results separately by firm type, where we categorize firms as low (high)-productivity if their average sales per employee in 1995 are below (above) the median of the distribution. We show that the increase in average skills pertains only to firms classified as low-productivity firms—an increase in offshoring by 100 percent leads to a 0.27 increase in average skills within offshorable jobs in low-productivity firms, which corresponds to about a one percent increase relative to the sample mean. High-productivity firms are more likely to offshore production and, thus, respond less in terms of domestic hires in high-offshorable jobs. Low-productivity firms, which mostly operate

[21] Table A.5 shows results for all occupations and workers by occupation group (low-offshorable-high-skill, low-offshorable-low-skill, and high-offshorable). In the top panel, we present the non-instrumented OLS coefficients estimated on our variable of offshoring; in the bottom panel, we show the results using the IV approach. All of the OLS coefficients are not precisely estimated but generally suggest a positive association between industry-level offshoring and average firms' skills. The IV coefficients are positive and statistically significant for both low-offshorable-high-skill occupations and high-offshorable occupations.

[22] Note that the rule of thumb of 10 is meant only for special cases, such as the case of no cross-sectional or time-series correlation in the error term. For more complex autocovariance structures, Olea and Pflueger (2013) suggest an F-statistic threshold of 17 instead. Even considering this higher rule of thumb, we do not face a weak instrument problem in any of our specifications.

[23] The critical value at 5 percent significance with one instrument is approximately 3.841 (Andrews et al., 2019).

[24] Studies using similar identification strategies to tease out the causal effects of trade variables also find that the instrumented coefficients tend to be larger in magnitude compared to the OLS coefficients (e.g., Hummels et al., 2014).

Table 2: Average Skills of High-Offshorables and Offshoring by Firm Productivity

	Dependent Variable: Average Cognitive Skills × 100, High-offshorable						
	OLS	IV-FE					
	All	**All**	By Firm Productivity		**All**	By Firm Productivity	
			Low	**High**		**Low**	**High**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Offshoring (China)	0.0049	0.1365**	0.2701***	-0.2503*	0.1150**	0.2342***	-0.2472*
	(0.0150)	(0.0569)	(0.0640)	(0.1404)	(0.0554)	(0.0632)	(0.1354)
Time-invariant skills	-	-	-	-	✓	✓	✓
Sector by Year FE	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
Mean Y	46.83	46.83	46.42	47.24	46.54	46.12	46.96
First Stage F-stat	-	820.89	686.81	135.59	820.92	686.81	135.59
AR First Stage F-stat	-	6.77	21.90	4.00	5.06	16.75	4.20
N	34,162	34,162	16,856	16,882	34,163	16,856	16,883

Notes: This table reports results examining Equation (6). The dependent variable is the average skills for high-offshorable jobs at the firm level. All skill variables are multiplied by 100. Column (1) reports OLS results; Columns (2) to (7) report IV results. Columns (1) to (4) use time-varying skills information; Columns (5) to (7) fix the skills information to the first time each worker is observed. Columns (3)-(4) and (6)-(7) show results separately examined by firm types: we classify firms as having low (high)-productivity if their average sales per employee in 1995 is below (above) the median of the distribution. Offshoring$_{kt}$ is the offshoring exposure measured at 6-digit industries. We include firm fixed effects and 4-digit industry-by-year fixed effects We also add 6-digit industry-level exports. Robust standard errors clustered at the industry level in parentheses. AR First Stage F-stat on Instrument refers to the identification-robust Anderson-Rubin Wald test. Significance levels: ***1%, **5%, *10%.

domestically, by contrast, actively adjust their workforce by hiring higher-skilled workers than before, possibly including former employees of high-productivity firms. These distributional effects across firms align with Fact 2 (Section 3.1), highlighting the declining between-firm inequality in skills for high-offshorable jobs over time.

The positive effects may also reflect offshoring-induced skill updating, as workers undergo job training or pursue further education. To investigate this margin, Columns (5) to (7) repeat the analysis using a time-invariant definition of skills—specifically, the initial skills information recorded for each individual in the data—to construct the outcome variables. The results remain qualitatively similar but yield smaller estimates, which suggests that, while the skill-updating channel positively contributes to these responses, it does not drive our main findings. These results add support to the importance of adjustments through worker-firm matching, which is consistent with Fact 3 (Section 3.1).

Our findings on the positive effect of offshoring should not be confused with the reallocation effects induced by import competition from China. Gu et al. (2024) shows, in fact, that import competition also triggers a reallocation of Danish workers from production to R&D occupations through the hiring of new employees. However, contrary to the effects of offshoring, the reallocation effects driven by import competition are mainly relevant to high- rather than low-productivity firms.

3.2.3 Robustness Checks

Table A.6 presents a host of robustness checks to test the sensitivity of our main results, namely the positive effects of offshoring exposures on firms' average skills, the magnitude of which is more pronounced for low-productivity firms within high-offshorable jobs. We begin by verifying that our findings are confirmed when we use alternate measures of productivity to classify firms into high- and low-productivity ones: Columns (1) and (2) use sales per capital stock, and Columns (3) and (4) use residuals estimated from firm-level regressions of value added on labor and capital.

Columns (5) and (6) explore whether our main findings are confirmed when using an alternate measure of offshoring based on trade data collected for low-wage countries—defined as those with a GDP per capita of less than 5% relative to that of the US from 1972 to 2001 including China (Bernard et al., 2006)—instead of focusing only on China. An increase in offshoring using this alternate definition triggers a rise in the average share of skills within offshorable jobs for low-productivity firms by 0.18, which is very close to the magnitude estimated in the main analysis.

We then proceed with robustness checks by (i) weighting our regressions using the firms' employment as weights (Columns (7) and (8)), (ii) excluding firms located in Copenhagen and environs from the main sample (Columns (9) and (10)), and (iii) adding (potentially endogenous) time-varying covariates at the firm level, such as firms' sales, size, and trade status (Columns (11) and (12)). The last set of refinement, in particular, helps rule out the possibility that the effect of offshoring on firms' skills estimated in the main analysis is driven by a scale effect rather than a change in firms' demand for skills resulting from offshoring, as we control for firms' productivity. We find that our main results are confirmed by this set of robustness checks.

Columns (13) to (15) examine whether our findings vary across labor-intensive and capital-intensive industries. Capital-intensive industries are those with an average capital-to-labor ratio above the 75th percentile of the capital intensity distribution in 1995. The estimated coefficient on offshoring is positive and precise only among low-productivity firms operating in labor-intensive industries. This is consistent with the notion that firms in labor-intensive industries are more responsive to industry-level offshoring shocks, while the average skills of firms that rely on capital-intensive production methods are less responsive (Olney and Pozzoli, 2021). Finally, Columns (16) and (17) instrument the control for exports at the industry level using the shocks to the world import demand—the construction of this instrument is analogous to Equation (5).[25] We confirm that our baseline findings are not sensitive to this robustness exercise.

4 Model

In this section, we construct a Becker-type matching model with transferable utility (Becker, 1973) and a continuum of characteristics. Our model builds on Dupuy and Galichon (2014)—which extends Choo and Siow (2006) considering a discrete and finite number of characteristics—but with two key innovations: (i) introducing the unemployment margin and incorporating different matching intensity technologies between workers and firms—which affect both matching and bargaining power in the surplus division—thereby effectively adapting the marriage market analysis to a worker-firm matching context; and (ii) extending the framework to a global economy setting. Appendix C contains the proof of all the theoretical results of this section.

4.1 Baseline Economy

The economy is populated by a continuum of workers and firms. Workers are characterized by an N-dimensional observable vector of skills $x \in \mathcal{X} \subseteq \mathbb{R}^n$. Similarly, firms are characterized by an M-dimensional observable vector of characteristics $y \in \mathcal{Y} \subseteq \mathbb{R}^m$, where $\mathcal{X}, \mathcal{Y}$ are bounded. The distribution of workers and firms is given by $\overline{f}(x)$ and $\overline{g}(y)$, respectively—not necessarily of the same mass.

4.1.1 Model Environment

Output, or the matched surplus, is produced when a match between a worker and a firm is formed and is given by

$$q(x,y) = x'\Phi y + C. \tag{7}$$

That is, output consists of an additively separable constant term and the set of bilinear terms in each combination of (x_i, y_j). We normalize (x,y) through affine transformation such that $\mathcal{X} = [0,1]^n$ and $\mathcal{Y} = [0,1]^m$. A production technology with $\Phi_{i,j} > 0$ ($\Phi_{i,j} < 0$)

[25] Specifically, we use the product-level import demand of China from the world excluding Denmark in time t (WID_{ht}) weighted by initial product shares exported by each industry k in the pre-sample year 1995 (s_{hk0}) within Danish manufacturing.

generates a positive (negative) assortative matching between the worker's skill x_i and the firm's characteristic y_j.

We first focus on describing the worker's problem, but the model environment is symmetric between workers and firms. As in Dupuy and Galichon (2014), we posit that the matching process requires forming *acquaintances*. A worker i with skill x^i has a countable set of acquaintances $S^i = \{y_1^i, y_2^i, \cdots\}$, and each acquaintance y_k^i is associated with an i.i.d. preference shock ϵ_k^i. The pairs (y_k^i, ϵ_k^i) are modeled as a Poisson point process with density $\exp(\nu_x) \cdot \exp(-e)\, de\, dy$ over the set $\mathcal{Y} \times \mathbb{R}$. Note that our framework additionally introduces the scalar ν_x, which is a parameter that controls the overall chance of finding matches and can be interpreted as the matching intensity technology.

The utility of a worker i with skill x^i when matched with a firm $y_k^i \in S^i$ is given as $w(x^i, y_k^i) + \lambda_x \epsilon_k^i$, where $w(x, y)$ is the wage schedule faced by all workers and firms to be determined in equilibrium. It is a function of both x and y since the scarcity of both distributions plays a role in the division of surplus. λ_x governs the importance of the idiosyncratic preference relative to the wage, which is common to all workers. The maximization problem is a continuous generalization of the standard logit problem.

In addition to matching with a firm, each worker has an outside option of remaining unmatched and working in the traditional sector (or home production) instead, which yields a utility of $w_0 + \lambda_x \epsilon_0^i$, where w_0 is the outside option common to all workers, and ϵ_0^i is an i.i.d. idiosyncratic component that follows a Gumbel distribution with mean $\gamma \approx 0.577$ and variance 1. A worker first makes a decision at the intensive margin of choosing the best match among the acquaintances, and then at the extensive margin between the best match and the outside option. In sum, worker i's problem can be expressed as

$$U^i = \max\Big[w_0 + \lambda_x \epsilon_0^i,\ \max_{y_k^i \in S^i} \Big(w(x^i, y_k^i) + \lambda_x \epsilon_k^i\Big)\Big] \tag{8}$$

Since ϵ_0^i is independent of ϵ_k^i, the solution at the intensive margin is independent of the decision at the extensive margin. The distribution of the maximized utility at the intensive margin, $\max_{y_k^i \in S^i} \Big(w(x^i, y_k^i) + \lambda_x \epsilon_k^i\Big)$, is the same as that of

$$\lambda_x \log\Big(\int_{\mathcal{Y}} \exp \frac{w(x^i, y)}{\lambda_x} dy\Big) + \lambda_x \nu_x + \lambda_x \widetilde{\epsilon}^i \tag{9}$$

where $\widetilde{\epsilon}^i$ follows a Gumbel distribution with mean γ and variance 1. A higher ν_x implies that it is more likely to find a good match and thus results in a higher realization of utility. Due to the distributional assumption (i.e., exponential), it appears as a constant shift in the distribution by $\lambda_x \nu_x$. Since the two random variables that appear in Equation (8) are both Gumbel with the same variance, this maximization at the extensive margin is also a standard logit problem.

The environment for the firms is symmetric to that of workers. A similar stochastic process (x_k^j, ϵ_k^j) with density $\exp(\nu_y) \cdot \exp(-e)\, de\, dx$ over $\mathcal{X} \times \mathbb{R}$ is assumed for the firm's acquaintances. Note that the matching intensity technologies faced by workers (e.g., the average number of job ads seen by a worker) and firms (e.g., the average number of applications received per vacancy) need not be identical. These two intensities (ν_x, ν_y) affect the overall utility generated by matching as well as the division of surplus in equilibrium. The firm's outside option can represent a firm's exit in case it does not find a good enough match compared to the outside option. The profit maximization of a firm j with y^j implies

$$V^j = \max\left[r_0 + \lambda_y \epsilon_0^j,\ \max_{x_k^j \in S^j} \left(r(x_k^j, y^j) + \lambda_y \epsilon_k^j\right)\right] \tag{10}$$

Given endowments $\overline{f}(x), \overline{g}(y)$, production technology $q(x,y)$, magnitude of unobserved shocks λ_x, λ_y, outside options w_0, r_0, and matching intensities ν_x, ν_y, the equilibrium of the baseline economy is defined as the matching distribution $\pi(x,y)$, the distribution of the unmatched $f_0(x), g_0(y)$, and the wage and profit schedule $w(x,y), r(x,y)$ that satisfies the following three sets of conditions. First, workers and firms solve the optimization problems as described in Equations (8) and (10), respectively, taking as given the equilibrium wages and profits $w(x,y), r(x,y)$. Second, the endowment conditions are satisfied—the overall supply of workers with skill x is equal to the endowment $\overline{f}(x)$, $\forall x \in \mathcal{X}$, and similarly for the firms. Third, the surplus is exhausted (i.e., $w(x,y) + r(x,y) \leq q(x,y)$ holds with equality in equilibrium, $\forall (x,y) \in \mathcal{X} \times \mathcal{Y}$).

4.1.2 Characterization of the Equilibrium

The first two equilibrium conditions (optimization, endowment) imply

$$\pi(y|x) = \frac{\pi(x,y)}{f(x)} = \frac{\exp \frac{w(x,y)}{\lambda_x}}{\int_{\mathcal{Y}} \exp \frac{w(x,y)}{\lambda_x} dy} \tag{11}$$

$$f_0(x) = \frac{\exp \frac{w_0 - \nu_x}{\lambda_x}}{\exp \frac{w_0 - \nu_x}{\lambda_x} + \int_{\mathcal{Y}} \exp \frac{w(x,y)}{\lambda_x} dy} \overline{f}(x), \quad f(x) = \int_{\mathcal{Y}} \pi(x,y) dy = \overline{f}(x) - f_0(x) \tag{12}$$

where $\pi(y|x)$ is the conditional matching distribution, $f_0(x)$ is the mass of unmatched workers, and $f(x)$ is the mass of matched workers. Analogous conditions can be derived for the firms in terms of $\pi(x|y)$ and $g_0(y)$, $g(y)$ (Equations (A8) and (A9) in Appendix C).

Noting that $\pi(x,y) = \pi(y|x)f(x) = \pi(x|y)g(y)$, and that the denominator of the RHS of Equation (11) is a function of x only (and similarly for Equation (A9)), we can collect these separable terms and define:

$$a(x) = \lambda_x \log \frac{\int_{\mathcal{Y}} \exp \frac{w(x,y)}{\lambda_x} dy}{f(x)}, \quad b(y) = \lambda_y \log \frac{\int_{\mathcal{X}} \exp \frac{r(x,y)}{\lambda_y} dx}{g(y)} \tag{13}$$

Then, the equilibrium wages and profits can be expressed using the joint distribution.

$$\begin{aligned} w(x,y) &= a(x) + \lambda_x \log \pi(x,y) \\ r(x,y) &= b(y) + \lambda_y \log \pi(x,y) \end{aligned} \tag{14}$$

Combined with $q(x,y) = w(x,y) + r(x,y)$,

$$\log \pi(x,y) = \frac{q(x,y) - a(x) - b(y)}{\lambda} \tag{15}$$

where $\lambda \equiv \lambda_x + \lambda_y$. Note that $a(x), b(y)$ capture components of $\log \pi(x,y)$ that only depend on x and y, respectively. These terms also correspond to the Lagrange multipliers on the "scarcity constraints," $f(x) = \int_{\mathcal{Y}} \pi(x,y)\, dy$, $g(y) = \int_{\mathcal{X}} \pi(x,y)\, dx$ for the planner's problem.[26] In addition, the choice at the extensive margin implies,

$$\frac{f_0(x)}{f(x)} = \frac{\exp(\frac{w_0}{\lambda_x} - \nu_x)}{\int_{\mathcal{Y}} \exp \frac{w(x,y)}{\lambda_x} dy}, \quad \frac{g_0(y)}{g(y)} = \frac{\exp(\frac{r_0}{\lambda_y} - \nu_y)}{\int_{\mathcal{X}} \exp \frac{r(x,y)}{\lambda_y} dx}. \tag{16}$$

Combined with the definitions for $a(x)$, $b(y)$ in Equation (13),

$$\begin{aligned} \frac{a(x)}{\lambda_x} &= \log \int_{\mathcal{Y}} \exp \frac{w(x,y)}{\lambda_x} dy - \log f(x) = (\frac{w_0}{\lambda_x} - \nu_x) - \log f_0(x) \\ \frac{b(y)}{\lambda_y} &= \log \int_{\mathcal{X}} \exp \frac{r(x,y)}{\lambda_y} dx - \log g(y) = (\frac{r_0}{\lambda_y} - \nu_y) - \log g_0(y). \end{aligned} \tag{17}$$

[26] Dupuy and Galichon (2014) show that the competitive equilibrium maximizes the social welfare given by the sum of the total surplus and the entropy term:

$$\mathcal{W} = \max_{\pi(x,y) \in \mathcal{M}(f,g)} \left[E_\pi q(x,y) - \lambda E_\pi \log \pi(x,y) \right]$$

The equilibrium matching can also be derived from the first-order condition of this planner's problem.

Substituting Equation (17) into Equation (15),[27]

$$\lambda \log \pi(x,y) = \Phi xy + \Big(C - w_0 - r_0 + \lambda_x \nu_x + \lambda_y \nu_y\Big) + \lambda_x \log f_0(x) + \lambda_y \log g_0(y). \qquad (18)$$

Equation (18), together with the market clearing conditions $f_0(x) + \int_y \pi(x,y)dy = \overline{f}(x)$ and $g_0(y) + \int_x \pi(x,y)dx = \overline{g}(y)$, fully determines the matching distribution $\pi(x,y)$ and the unmatched distributions $f_0(x)$, $g_0(y)$.[28] As a result, taking as given other fundamental parameters, such as $(\Phi, \lambda_x, \lambda_y)$ and the endowment, $K \equiv (C - w_0 - r_0 + \lambda_x \nu_x + \lambda_y \nu_y)$ is the sufficient statistic for the determination of matching.[29]

The following propositions help with the understanding of the model structure and identification of the parameters: (1) A change in both w_0 and $\lambda_x \nu_x$ by the same amount would leave the entire equilibrium (matching distribution and the division of surplus) unchanged (and similarly for r_0 and $\lambda_y \nu_y$). (2) A change in both w_0 and r_0 by the same magnitude with opposite signs would leave the matching distribution unchanged, but the levels of equilibrium wage and profit would shift by the same amount. (3) If there is a simultaneous change in (C, w_0, r_0) such that $\Delta C = \Delta w_0 + \Delta r_0$, matching is not affected, and the extra surplus is divided according to $(\Delta w_0, \Delta r_0)$. (4) If K increases, there is increased participation or matching from both the workers and the firms, and vice versa.

4.2 Global Economy

In the global economy, we consider a North-South framework where only Home (North) finds offshoring a less expensive production alternative (Feenstra and Hanson, 1997; Grossman and Rossi-Hansberg, 2008).

[27] Similarly, substituting Equation (18) into Equation (14),

$$w(x,y) = \frac{\lambda_x}{\lambda}\Phi xy + \frac{\lambda_x}{\lambda}\Big(C - r_0\Big) + \frac{\lambda_y}{\lambda} w_0 - \frac{\lambda_x \lambda_y}{\lambda}\Big(\nu_x - \nu_y + \log \frac{f_0(x)}{g_0(y)}\Big)$$
$$r(x,y) = \frac{\lambda_y}{\lambda}\Phi xy + \frac{\lambda_y}{\lambda}\Big(C - w_0\Big) + \frac{\lambda_x}{\lambda} r_0 - \frac{\lambda_x \lambda_y}{\lambda}\Big(\nu_y - \nu_x + \log \frac{g_0(y)}{f_0(x)}\Big)$$

[28] Existence and uniqueness of the equilibrium follows from monotonicity. For example, for a given x, increase in $f_0(x)$ also increases $\pi(x,y)$ for all y (and thus $f(x)$) as a result of Equation (18). Thus, $f_0(x) + f(x|f_0(x))$ is increasing in $f_0(x)$, which is in equilibrium tied to the total endowment $\overline{f}(x)$.

[29] In the structural estimation, the parameters (C, ν_x, ν_y) are separately identified by using the levels of observed wages.

4.2.1 Model Environment in the Global Economy

We introduce Foreign (South) populated by a continuum of workers characterized by an N-dimensional observable vector of skills $x \in \mathcal{X} \subseteq \mathbb{R}^n$ with distribution $\overline{f^*}(x)$. For simplicity, only the traditional sector exists in Foreign, which is populated by self-employed workers who earn a constant income of w_0^*. The lack of manufacturing firms is the source of asymmetry between Home and Foreign, consistent with the empirical fact that Southern firms rarely offshore to the North.

The output of a domestic firm $y \in \mathcal{Y}$ when matched with a foreign worker $x \in \mathcal{X}$ is

$$q^*(x,y) = x'\Phi^* y + C^*, \tag{19}$$

where the parametric assumptions of the output function are symmetric to the domestic case in Equation (7). We assume that $\Phi^* = \Phi$ due to the limited availability of data for the identification of the parameters. By allowing C^* to be different from the domestic production function, the difference in output, $c_F \equiv C - C^*$, captures the *cost of offshoring*.

Again, the matching process requires forming acquaintances. A foreign worker faces a symmetric stochastic process in (y, e) with density $\exp(\nu_x^*) \cdot \exp(-e)\, de\, dy$. Each firm j, however, now has two independent sets of acquaintances: S^j (home workers) and S^{*j} (foreign workers). For tractability, we also assume $\lambda_x^* = \lambda_x$ and $\lambda_y^* = \lambda_y$.

The utility maximization problem of a foreign worker i^* follows the symmetric structure of the domestic worker's

$$U^{i*} = \max\left[w_0^* + \lambda_x \epsilon_0^{i*},\ \max_{y_k^{i*} \in S^{i*}} \left(w^*(x^{i*}, y_k^{i*}) + \lambda_x \epsilon_k^{i*}\right)\right] \tag{20}$$

where a foreign worker compares the utility of matching with a Northern firm from its acquaintance set that generates the highest utility and the utility of sorting into the traditional sector receiving a fixed payoff of w_0^*.

The profit maximization of a firm j with y^j which has access to workers from both countries can be described as

$$V^j = \max\left[r_0 + \lambda_y \epsilon_0^j,\ \max_{x_k^j \in S^j} \left(r(x_k^j, y^j) + \lambda_y \epsilon_k^j\right),\ \max_{x_k^{*j} \in S^{*j}} \left(r(x_k^{*j}, y^j) + \lambda_y \epsilon_k^{*j}\right)\right] \tag{21}$$

where a firm, in addition to the comparison in Equation (10), compares the utility of matching with a foreign worker from its acquaintance set that generates the highest profit.

Given endowments $\overline{f}(x), \overline{g}(y), \overline{f^*}(x)$, production technology $q(x,y), q^*(x,y)$, magnitudes of unobserved shocks λ_x, λ_y, outside options w_0, r_0, w_0^*, and matching intensities $\nu_x, \nu_y, \nu_x^*, \nu_y^*$, the equilibrium of the global economy is defined as the matching distributions $\pi(x,y), \pi^*(x,y)$, the distribution of the unmatched $f_0(x), g_0(y), f_0^*(x)$, and the wage and profit schedule $w(x,y), r(x,y), w^*(x,y), r^*(x,y)$ that satisfies the following three sets of conditions. First, domestic workers, foreign workers, and firms solve the optimization problems in Equations (8), (20), and (21), respectively, taking as given the equilibrium wages and profits $w(x,y), r(x,y), w^*(x,y), r^*(x,y)$. Second, the endowment conditions are satisfied—the overall supply of domestic workers with skill x is equal to the endowment $\overline{f}(x)$, $\forall x \in \mathcal{X}$, and similarly for the firms as well as foreign workers (i.e., $\overline{f^*}(x) = f_0^*(x) + f^*(x)$, $\forall x \in \mathcal{X}$). Third, the surplus is exhausted (i.e., $q^*(x,y) = w^*(x,y) + r^*(x,y)$ and $q(x,y) = w(x,y) + r(x,y)$ hold in equilibrium, $\forall (x,y) \in \mathcal{X} \times \mathcal{Y}$).

4.2.2 Characterization of the Equilibrium in the Global Economy

The global economy can be characterized in a way similar to the baseline economy described in the previous section.[30] Start by defining the auxiliary objects $a(x), b(y), a^*(x), b^*(y)$, where $a(x), b(y)$ are identical as before from Equation (13), and $a^*(x), b^*(y)$ are defined as

$$a^*(x) = \lambda_x \log \frac{\int_{\mathcal{Y}} \exp \frac{w^*(x,y)}{\lambda_x} dy}{f^*(x)}, \quad b^*(y) = \lambda_y \log \frac{\int_{\mathcal{X}} \exp \frac{r^*(x,y)}{\lambda_y} dx}{g^*(y)} \tag{22}$$

The equilibrium wage and profit in the global economy satisfies

$$\begin{aligned} w(x,y) &= a(x) + \lambda_x \log \pi(x,y), \quad & w^*(x,y) &= a^*(x) + \lambda_x \log \pi^*(x,y) \\ r(x,y) &= b(y) + \lambda_y \log \pi(x,y), \quad & r^*(x,y) &= b^*(y) + \lambda_y \log \pi^*(x,y) \end{aligned} \tag{23}$$

and the equilibrium matching in the global economy satisfies

$$\log \pi(x,y) = \frac{q(x,y) - a(x) - b(y)}{\lambda}, \quad \log \pi^*(x,y) = \frac{q^*(x,y) - a^*(x) - b^*(y)}{\lambda} \tag{24}$$

The set of equations related to the unmatched distribution is similar.

$$\begin{aligned} \frac{a(x)}{\lambda_x} &= (\frac{w_0}{\lambda_x} - \nu_x) - \log f_0(x), \quad & \frac{a^*(x)}{\lambda_x} &= (\frac{w_0^*}{\lambda_x} - \nu_x^*) - \log f_0^*(x) \\ \frac{b(y)}{\lambda_y} &= (\frac{r_0}{\lambda_y} - \nu_y) - \log g_0(y), \quad & \frac{b^*(y)}{\lambda_y} &= (\frac{r_0}{\lambda_y} - \nu_y^*) - \log g_0(y) \end{aligned} \tag{25}$$

[30] Equations (11) and (12) that describe $\pi(y|x), f_0(x), f(x)$ for the domestic workers in the baseline economy continue to hold in the global economy. In addition, similar Equations (A25) and (A21) for the Foreign workers regarding $\pi^*(y|x), f_0^*(x), f^*(x)$, as well as the modified Equations (A24), (A26), and (A22) for the firms regarding $\pi(x|y), \pi^*(x|y), g_0(y), g(y), g^*(y)$ hold.

Similar to the domestic economy, substituting Equation (25) into Equation (24), the equations analogous to Equation (18) are obtained, and we can see that $K \equiv (C - w_0 - r_0 + \lambda_x \nu_x + \lambda_y \nu_y)$ and $K^* \equiv (C^* - w_0^* - r_0 + \lambda_x \nu_x^* + \lambda_y \nu_y^*)$, or equivalently, K and $\widetilde{K} \equiv K^* - K$, are sufficient statistics for the determination of matching in the global economy.

In the global economy, the equilibrium matching between domestic and foreign workers has the following property:

$$\begin{aligned} \lambda \log \frac{\pi^*(x,y)}{\pi(x,y)} &= \Big(q^*(x,y) - a^*(x) - b^*(y)\Big) - \Big(q(x,y) - a(x) - b(y)\Big) \\ &= -c_F - \left(\widetilde{w}_0 - \lambda_x \widetilde{\nu}_x - \lambda_x \log \frac{f_0^*(x)}{f_0(x)}\right) + \lambda_y \widetilde{\nu}_y \end{aligned} \tag{26}$$

where tildes denote the difference between Foreign and Home: $\widetilde{X} \equiv X^* - X$.[31] This result shows that offshoring or matching with foreign relative to domestic workers increases when (i) the cost of offshoring (c_F) falls or (ii) the relative matching intensities between Foreign and Home matching, $(\widetilde{\nu}_x,\ \widetilde{\nu}_y)$, increase. A reduction in c_F can be associated with aggregate changes in technology, which lowers the cost of performing tasks outside the boundaries of the firm and country, while an increase in $(\widetilde{\nu}_x,\ \widetilde{\nu}_y)$ can capture institutional changes related to reducing barriers in foreign workers' access to domestic firms' job ads as well as the costs domestic firms incur when screening foreign workers' job applications. Given that K and K^* are sufficient statistics, an increase in C^* has the same impact as an increase in $\lambda_x \nu_x^* + \lambda_y \nu_y^*$ by the same amount on the matching distribution in both Home and Foreign (and thus on offshoring), holding K constant.

4.2.3 Illustration of Model Implications in the Global Economy

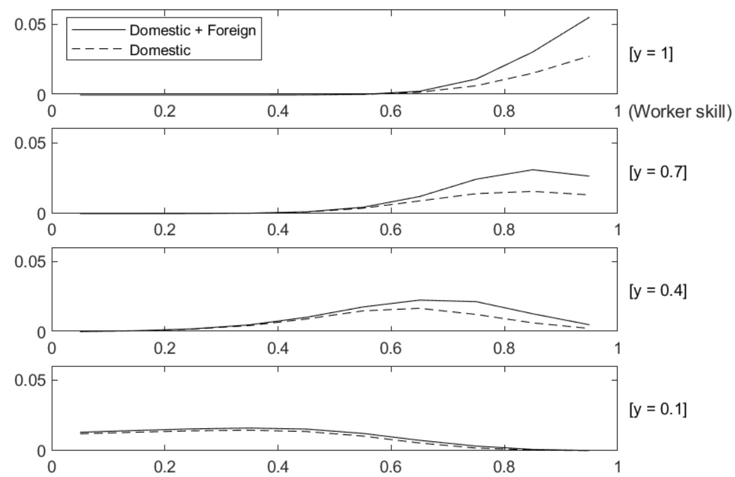
Next, we simulate the model and show how equilibrium matching probabilities, matched qualities, and wages/profits change with offshoring and discuss model implications. Specifically, we assume $q(x,y) = xy$, $c_F = 0.10$, $f(x) \sim U[0,1]$, $f^*(x) \sim U[0,1]$, $g(y) \sim U[0,1]$, $\lambda = 0.04$, and $\nu_x = \nu_x^* = \nu_y = 0$. We further impose $w_0 = w_0^* = r_0 = 0$.[32]

Figure 4 shows the probability mass of matched workers across the distribution of worker skill x for different levels of firm productivity $y = 0.1, 0.4, 0.7, 1$. The probability mass of offshored matches is captured in the area between the solid (domestic and foreign matches) and dashed lines (domestic matches). Two important patterns emerge. First, due

[31] $\widetilde{a}(x) = \widetilde{w}_0 - \lambda_x \widetilde{\nu}_x - \lambda_x \log \frac{f_0^*(x)}{f_0(x)}$ follows from the top two equations in Equation (25), and $\widetilde{b}(y) = -\lambda_y \widetilde{\nu}_y$ from the bottom two equations in Equation (25).

[32] Given the equivalence in the effect of offshoring through c_F and $(\widetilde{\nu}_x, \widetilde{\nu}_x)$, we present these simulation exercises focusing on one offshoring channel, namely c_F.

Figure 4: Probability Mass of Matched Domestic and Foreign Workers



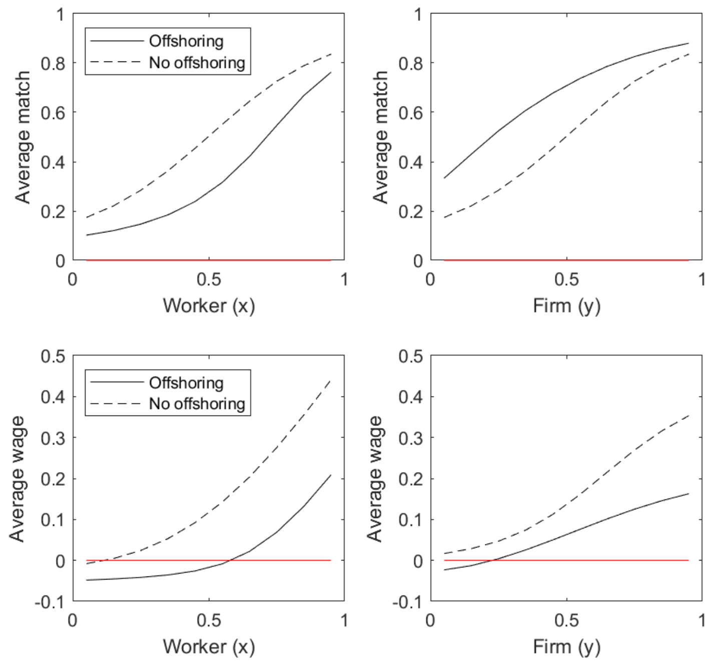
Notes: This figure shows the probability mass of matched workers across the distribution of worker skill x for different levels of firm productivity $y = 0.1, 0.4, 0.7, 1$. The probability mass of offshored matches is captured in the area between the solid (domestic and foreign matches) and dashed lines (domestic matches). We assume $q(x,y) = xy$, $c_F = 0.10$, $\overline{f}(x) \sim U[0,1]$, $\overline{f^*}(x) \sim U[0,1]$, $\overline{g}(y) \sim U[0,1]$, $\lambda = 0.04$, and $\nu_x = \nu_y = \nu_x^* = \nu_y^* = 0$. We further impose $w_0 = r_0 = w_0^* = 0$.

to the complementarity in the production technology $q(x,y) = xy$, it is more likely for high-skill workers to match with high-productivity firms, and vice versa; however, deviations from positive assortative matching occur due to the role of idiosyncratic preferences ($\lambda > 0$). Second, the probability mass of offshored matches is greater for high-productivity firms than for low-productivity firms, which is consistent with empirical patterns in the data, where firms that are larger in size, more capital-intensive, and more productive engage in offshoring (Hummels et al., 2014).

Figure 5 shows the average quality of matches and average wages. The top panel shows the average quality of matches by worker skill (left) and firm productivity (right) for cases with (solid lines) and without offshoring (dashed lines). With offshoring, while workers undergo a downward transition in match quality, firms improve the quality of their domestic worker match. That is, offshoring decreases the demand for domestic workers in offshoring-exposed jobs, which consequently drives out the least productive workers at the bottom end of the worker distribution to become unmatched. Firms, in contrast, can hire better domestic workers than before. And the types of workers they hire become more similar across the distribution of firms—a decrease in segregation by skill within these jobs exposed to foreign competition.

Similarly, the bottom panel describes the average wage by worker skill (left) and firm

Figure 5: Average Quality of Matches and Wages



Notes: This figure shows the average quality of matches and average wages. The top panel shows the average quality of matches by worker skill (left) and firm productivity (right) for cases with (solid lines) and without offshoring (dashed lines). The bottom panel presents the average wage by worker skill (left) and firm productivity (right) for cases with (solid lines) and without offshoring (dashed lines). We assume $q(x,y) = xy$, $c_F = 0.10$, $\overline{f}(x) \sim U[0,1]$, $\overline{f^*}(x) \sim U[0,1]$, $\overline{g}(y) \sim U[0,1]$, $\lambda = 0.04$, and $\nu_x = \nu_y = \nu_x^* = \nu_y^* = 0$. We further impose $w_0 = r_0 = w_0^* = 0$.

productivity (right) for cases with (solid lines) and without offshoring (dashed lines). Offshoring puts downward pressure on wages workers receive and firms pay—the labor supply effect identified in Grossman and Rossi-Hansberg (2008) where "factor prices respond to factor supplies."[33] Similar to the matched skill quality, the average wage firms pay also becomes similar across—the wage dispersion decreases.[34]

[33]Firms, on the other hand, gain from greater exposure to offshoring as they are able to not only hire better quality workers at a lower cost but also increase profits (Figure B.1)

[34]With offshoring, high-type firms become more homogeneous in their occupation mix by replacing offshorable occupations, whereas low-type firms keep both offshorable and non-offshorable occupations in-house. Figure B.2 presents the simulated results for the average share of occupations by offshorability using our illustrative example.

5 Structural Estimation

In this section, we structurally estimate the matching model to quantify the magnitude of offshoring on matched quality and wages. Consistent with the reduced-form exercises, we focus our analysis on worker-firm matching based on workers' skills and firms' productivity proxied using value-added per worker. Unlike the reduced-form exercises, which identify the effect of industry-level offshoring exposures on firm outcomes by leveraging within-firm variation over time, the structural estimation of the static matching model naturally focuses on each snapshot year to estimate the structural parameters and perform counterfactual exercises. Thus, the analysis in this section considers the full distribution of manufacturing firms in a given year of interest and workers hired in these firms.

5.1 Estimation Strategy

Our strategy to estimate the set of model parameters, $\Phi, C, C^*, \lambda, \nu_x, \nu_y, \nu_x^*, \nu_y^*$, involves exploiting the equilibrium properties of the model. To bring our worker-firm matching model to the data, which essentially assumes one-to-one matching, we treat each firm observed in the data as an aggregation of their vacancies, with a size equal to the number of employed workers, and examine matches at the worker-vacancy level.

Before proceeding with the estimation, we process the data as follows. First, we winsorize the top and bottom 1 percent of the distributions of workers (skills) and firms (value-added per worker) and normalize values so that the distribution ranges between 0 and 1. Second, we assign workers and firm vacancies into deciles of skills and productivity distributions, respectively. Third, we assign the value of each grid by taking the average value of skills or productivity measures in each bin. Finally, we construct a 10-by-10 joint distribution of workers and firm vacancies.

There are two sets of inputs to this estimation. The first set includes the matching distribution $\pi(x,y)$, the distribution of domestic firms that match with foreign workers $g^*(y)$, and the wage profile $w(x,y)$—all are obtained from our sample. The second set includes model parameters we calibrate using aggregate statistics from both external and internal data sources (Table 3) since we do not directly observe the corresponding information in our sample: outside options for domestic firms and workers r_0, w_0; the average wage of the agricultural sector (which corresponds to the traditional sector in our model) in China w_0^*; the average wage of the manufacturing sector in China $E(w^*)$; domestic aggregate share of wage-bill in value-added $\mathbb{W}/\mathbb{Y}$; domestic unemployment rate $|f_0|/|\overline{f}|$; mass of potential matches to Danish firms in China $|\overline{f^*}|$; rate of offshoring $|f^*|/|f|$; total mass of domestic workers $|\overline{f}|$; and total mass of domestic firms $|\overline{g}|$, where $|\cdot|$ indicates the L^1 norm (mass).[35] All of the monetary values are CPI-adjusted to 1995 in Denmark.

Table 3: Calibrated Parameters

Parameters	1996	2006	Note
r_0	0	0	outside option for domestic firms, authors' assumption
w_0	40.538	45.276	unemployment insurance benefit (hourly in DKK), Statistics Denmark
w_0^*	17.945	25.825	average wage of the agricultural sector in China (hourly in DKK), (Feenstra and Hong, 2007)
$E(w^*)$	28.672	56.513	average wage of the manufacturing sector in China (hourly in DKK), Feenstra and Hong (2007)
$\mathbb{W}/\mathbb{Y}$	0.5371	0.6786	aggregate share of wage-bill in value-added, author's calculation using Danish data
$\lvert f_0\rvert/\lvert\overline{f}\rvert$	0.0633	0.0391	unemployment rate, IMF International Financial Statistics (IFS)
$\lvert\overline{f^*}\rvert$	0.6325	0.6325	mass of potential matches to Danish firms in China (ILO, Fu and Wu (2013), Danish data)
$\lvert f^*\rvert/\lvert f\rvert$	0.0005	0.0155	rate of offshoring, author's calculation using Danish data
$\lvert\overline{f}\rvert$	1	1	total mass of domestic workers, normalization
$\lvert\overline{g}\rvert$	$\lvert\overline{f}\rvert(1+\frac{\lvert f^*\rvert}{\lvert f\rvert})$	$\lvert\overline{f}\rvert(1+\frac{\lvert f^*\rvert}{\lvert f\rvert})$	total mass of domestic firms

Notes: This table presents the set of calibrated parameters for the years 1996 and 2006. w_0, w_0^*, and $E(w^*)$ are calculated as hourly rates in DKK. For w_0, we use the monthly unemployment insurance benefits in Denmark for the 25th percentile of the distribution (9,000 DKK and 9,500 DKK), which we convert to hourly rates by multiplying by 12 and dividing by 2,000 annual work hours. For w_0^* and $E(w^*)$, we use the average wage of the agricultural and manufacturing sector calculated from Feenstra and Hong (2007) (Table 5A.4), extrapolate over the sample period, and adjust to hourly rates in DKK. We further adjust the calibrated wages w_0^* and $E(w^*)$ by the productivity differential between China and Denmark, proxied using the per capita GDP normalized by the hours worked as a proxy for the efficiency unit of labor obtained from the World Penn Table (Feenstra et al., 2015). All of these monetary values are CPI-adjusted to 1995. For $|\overline{f^*}|$, we use information on the employment share of manufacturing exporters $|f^*|/|\overline{f^*}|$ (ILO and Fu and Wu (2013)), the rate of offshoring $|f^*|/|f|$ (Danish data), and employment rate $|f|/|\overline{f}|$ (IMF IFS). The values are fixed at the level of 2004 for $|f^*|/|\overline{f^*}|$ and $|f|/|\overline{f}|$ due to data limitation on employment share of exporting firms in China. Note that $|\cdot|$ indicate the L^1 norm (mass).

There are three points related to the calibration that are worth discussing. First, to be consistent with how foreign labor is defined in efficiency units (Section 5.1.2), we adjust the calibrated foreign wages w_0^* and $E(w^*)$ by the productivity differential between China and Denmark—using the per capita GDP normalized by the hours worked obtained from the World Penn Table (Feenstra et al., 2015)—so that they represent wage per efficiency unit. Second, we calibrate the mass of potential matches to Danish firms in China

[35] As a natural starting point to think about the mass of vacancies and that of workers in the domestic case, one can assume equal masses, $|\overline{g}| = |\overline{f}|$. Then, in the global case, where we consider additional foreign matches, one can assume that the total mass of vacancies is equal to $|\overline{f}| + |\overline{f}|\frac{|f^*|}{|f|}$.

$|\overline{f^*}|$ by combining information on (i) the employment share of manufacturing exporters $|f^*|/|\overline{f^*}|$ using data from the International Labor Organization (ILO) and Fu and Wu (2013) (Table 1),[36] (ii) the rate of offshoring $|f^*|/|f|$ from the Danish trade registers, and (iii) the employment rate $|f|/|\overline{f}|$ from the International Monetary Fund's (IMF) International Financial Statistics (IFS).[37] Finally, we note that the calibration of masses and outside options are immaterial to the core of the matching model (i.e., Φ and λ), but is key to the identification of ν_x, ν_y, ν_x^*, and ν_y^*.

These two sets of inputs produce the model-imputed information for the following elements, which are unobserved in the data: matching distribution with foreign workers $\pi^*(x,y)$, the firm's profit from domestic $r(x,y)$, the firm's profit from foreign matches $r^*(x,y)$, and the wage profile of foreign workers matched with domestic firms $w^*(x,y)$. The following sections describe the detailed steps of the estimation process for domestic matching, followed by foreign matching.

5.1.1 Domestic Matching

In this section, we estimate the key model parameters Φ, λ, C, ν_x, and ν_y. We begin with Equation (15), which shows that the log of matching distribution is proportional to the level of output, and take the exponential transformation as follows,[38]

$$\pi(x,y) = \exp\left(\frac{q(x,y) - a(x) - b(y)}{\lambda}\right) + \epsilon^{\pi}(x,y). \tag{27}$$

Note that the matched surplus from Equation (7), focusing on 1-dimensional characteristics on both ends, gives $q(x,y) = \Phi xy + C$. We regress $\log \pi(x,y)$ on xy and dummy variables for each discretized value of x, y using Poisson regression to obtain estimates for $\frac{\Phi}{\lambda}$, and $\frac{a(x)}{\lambda}$, $\frac{b(y)}{\lambda}$ (up to levels only). We use the fitted value of $\pi(x,y)$ henceforth to ensure that the matching distribution is consistent with the model prediction.

Next, we use the wage equation from Equation (14) to identify $\lambda = \lambda_x + \lambda_y$. Again, taking the exponential transformation, we obtain

$$w(x,y) = \lambda\left(\frac{a(x)}{\lambda}\right) + \lambda_x \log \pi(x,y) + \epsilon^{w}(x,y). \tag{28}$$

[36] The employment share of manufacturing exporters is obtained by multiplying the share of manufacturing employment (0.127, ILO) and (0.130, Fu and Wu (2013)). Due to data limitations, we are not able to provide time-varying measures.

[37] Due to data limitation on the employment share of exporting firms in China, the values are fixed at the level of 2004 for $|f^*|/|\overline{f^*}|$ and $|f|/|\overline{f}|$.

[38] Imposing an additive mean-zero error in $\pi(x,y)$ preserves the total matching between the data and the fitted values: $\int \widehat{\pi}(x,y)dxdy = \int \pi(x,y)dxdy$, which is a desirable property. In contrast, an additive mean-zero error in $\log \pi(x,y)$ would result in a discrepancy that would require ad hoc adjustments when using $\widehat{\pi}(x,y)$.

Note that $\pi(x, y)$ and $w(x, y)$ are obtained from the data, $\frac{a(x)}{\lambda}$ is estimated from the first step described above, and there is no constant term in this regression. We further assume $\lambda_x = \lambda_y = \frac{1}{2}\lambda$, which attributes an equal size of the contribution of the unobserved heterogeneity between workers and firms. This is due to data limitation where we do not have firm-side profit data at the vacancy level, which would help separately identify λ_x and λ_y. In this step, both $a(x)$ and λ are identified.

We then use the profit equation from Equation (14), applying a similar exponential transformation to identify $b(y)$. We match the aggregate wage-to-profit ratio from the aggregate data to pin down the level of $r(x, y)$—due to lack of firm-side profit data at the vacancy level—which, in turn, pins down the level of $b(y)$. With the levels of both $a(x)$ and $b(y)$ identified, we back out the constant term C using Equation (7) and Equation (15), which characterize the matched surplus and equilibrium matching, respectively.

Finally, with the calibrated values for w_0 and $|f_0| = \frac{|f_0|}{|\overline{f}|} \cdot |\overline{f}|$ and the estimated $a(x)$ and λ_x, we use the first line of Equation (17) to identify $f_0(x)$ and ν_x. Since all other terms are constant, variation in $a(x)$ would identify the variation in $f_0(x)$. Combined with the calibrated $|f_0|$, $f_0(x)$ is fully identified, which in turn identifies ν_x, the only remaining parameter on the worker side.[39] With the calibrated r_0 and $|g_0|$,[40] and the estimated $b(y)$ and λ_y, $g_0(y)$ and ν_y are similarly identified using the second line of Equation (17).

5.1.2 Foreign Matching

Next, we discuss our strategy for foreign matching and estimate parameters, C^*, ν_x^*, and ν_y^*. The key challenge in estimating the global economy is that we do not observe the supply of foreign workers nor the skill characteristics of foreign workers in the data.

To make progress, we make the following assumption building on our interpretation of the measure of offshoring—firm-level purchases of intermediate and final goods used in the production process—as the value-added form of foreign workers' human capital:

$$\frac{\text{Purchases Abroad}}{\text{Value Added}} = \frac{\text{Number of Offshored Workers}}{\text{Number of Domestic Workers}} = \frac{g^*(y)}{g(y)}. \tag{29}$$

That is, we normalize the hypothetical number of foreign workers in terms of the unit of labor that would generate the same value added as a domestic worker. For example, if a firm with 100 workers had a value added of 10,000 DKK per hour and also spent 3,000

[39] From $\frac{w_0}{\lambda_x} - \nu_x = \frac{a(x)}{\lambda_x} + \log f_0(x)$, we derive $\nu_x = \log \frac{\int \exp \frac{w_0 - a(x)}{\lambda_x} dx}{|f_0|}$. Identification relies on the assumption that both w_0 and ν_x are constant.

[40] Note that $|g_0| = |\overline{g}| - |g| - |g^*|$, where $|g| = |f|$ and $|g^*| = |f^*|$ due to one-to-one matching, and $|f| = |\overline{f}| - |f_0|$, $|f^*| = \frac{|f^*|}{|f|} \cdot |f|$ hold.

DKK per hour for purchases abroad, we would infer that the firm is implicitly matched with 30 Foreign workers in addition to the 100 domestic workers. We take into account the general productivity difference between the domestic and foreign workers as measured by the GDP per capita per hours worked. If home workers are k times more productive, we assume that one unit of foreign labor is composed of k workers, and thus foreign wage will correspond to the amount paid per k workers. This is consistent with the calibration of foreign wages shown in Table 3.

Offshoring is inherently a firm-level variable, as described in Equation (29). The equilibrium condition related to this object is Equation (26), in the form of $\frac{\pi^*(x,y)}{\pi(x,y)}$; however, in that equation we showed how $\frac{\pi^*(x,y)}{\pi(x,y)}$ depends only on x. To be consistent with the model prediction, we distribute the firm-level offshoring across different worker skill x. The problem boils down to determining $h(x) \equiv \frac{\pi^*(x,y)}{\pi(x,y)}$ that satisfies

$$g^*(y) = \int_{\mathcal{X}} \pi^*(x,y)dx = \int_{\mathcal{X}} h(x)\pi(x,y)dx = g(y) \cdot \int_{\mathcal{X}} h(x)\pi(x|y)dx \tag{30}$$

where $g^*(y)$ and $\pi(x,y)$ are given. We further divide both sides by $g(y)$ and take a quadratic approximation of $h(x) = h_0 + h_1 x + h_2 x^2$ to obtain[41]

$$\frac{g^*(y)}{g(y)} = \int_{\mathcal{X}} h(x)\pi(x|y)dx = h_0 + h_1 E[x|y] + h_2 E[x^2|y] \tag{31}$$

We next regress $\frac{g^*(y)}{g(y)}$ on $E[x|y]$, $E[x^2|y]$ to identify $h(x)$. With the predicted $h(x)$, the distribution of matching with foreign workers $\pi^*(x,y) = \pi(x,y)h(x)$ is estimated. For internal consistency, we use the fitted value of $\pi^*(x,y)$ and the corresponding $g^*(y)$ henceforth.

In the next step, we identify $a^*(x)$. Here, we revisit Equation (26). With $a(x)$ obtained from Section 5.1.1 and $h(x)$ estimated above, we identify $a^*(x)$ up to level. Subsequently, using the wage equation for foreign workers from Equation (23), we obtain $w^*(x,y)$ up to level. We further calibrate the level of $w^*(x,y)$ using the average wage in the exporting sector in China, which then allows us to obtain the level of $a^*(x)$.

Similar to the domestic matching case, with the calibrated value for w_0^* and $|f_0^*| = |\overline{f^*}| - |f^*|$, we use Equation (25) to identify $f_0^*(x)$ and ν_x^*.[42] Further determining ν_y^*, or equivalently the level of $b^*(y)$,[43] requires information on the level of $r^*(x,y)$. We take

[41] Note that the nonparametric inversion approach ($H = \Pi^{-1}G^*$) is not recommended since $h(x) < 0$ would be easily possible for some x.

[42] Specifically, we use $\frac{w_0^*}{\lambda_x} - \nu_x^* = \frac{a^*(x)}{\lambda_x} + \log f_0^*(x)$, which is the same equation for domestic matching was derived in Footnote 39.

[43] Recall that $b^*(y) - b(y) = -\lambda_y(\nu_y^* - \nu_y)$; $b(y)$ and ν_y are already obtained from the domestic matching.

a natural assumption that the average profit from matching with the foreign worker is the same as that with the domestic worker ($E_{\pi^*}[r^*(x,y)] = E_{\pi}[r(x,y)]$). This assumption is enough for identifying $b^*(y)$ using Equation (23). In turn, ν_y^* is identified using Equation (25). Finally, we use our estimates of λ, $h(x)$, C, $a(x)$, $a^*(x)$, $b(y)$, and $b^*(y)$ obtained in the previous steps to back out C^* using Equation (26).

5.1.3 Estimation Results

Table 4 presents the estimation results. We focus on the results for the years 1996 and 2006. The parameter estimates related to the production technology (Φ, C, C^*, λ) are adjusted in units of hourly rates in DKK. The matching intensity parameter estimates ($\nu_x, \nu_y, \nu_x^*, \nu_y^*$) after taking the exponential transformation indicate positive intensity rates. Bootstrapped 95 percent confidence intervals based on 200 draws are included in parentheses.[44]

Table 4: Parameter Estimates

Parameter		1996	2006
Φ	matching technology	75.38 (69.16, 79.58)	75.55 (70.37, 79.07)
λ	variance of idiosyncratic preferences ($\lambda_x + \lambda_y$)	108.78 (80.49, 170.42)	37.56 (33.55, 41.69)
C	constant term in the matched surplus for domestic matches	240.66 (240.01, 241.30)	207.90 (207.35, 208.71)
C^*	constant term in the matched surplus for foreign matches	138.73 (137.75, 139.46)	119.94 (119.38, 120.62)
ν_x	matching intensity for domestic workers towards domestic firms	-1.32 (-1.92, -.7)	-4.51 (-5.15, -3.98)
ν_y	matching intensity for domestic firms towards domestic workers	-1.73 (-2.47, -.96)	-2.79 (-3.23, -2.43)
ν_x^*	matching intensity for foreign workers towards domestic firms	-9.56 (-9.70, -9.43)	-7.57 (-7.78, -7.37)
ν_y^*	matching intensity for domestic firms towards foreign workers	-9.22 (-10.00, -8.44)	-6.99 (-7.44, -6.59)

Notes: This table reports the estimation results for the parameters using data from the years 1996 and 2006. Parameter estimates related to the production technology (Φ, C, C^*, λ) are adjusted in units of hourly rates in DKK. The matching intensity parameter estimates ($\nu_x, \nu_y, \nu_x^*, \nu_y^*$) indicate positive intensities after taking the exponential transformation. Note that $C^* - C$ captures the cost of offshoring (c_F). Bootstrapped 95 percent confidence intervals based on 200 draws are included.

[44] Table A.8 presents results combining all occupations.

There are three aspects of the results that merit discussion. First, the estimated production technology reveals positive assortative matching ($\Phi > 0$) for both years. The magnitude of the estimated complementarity Φ is smaller than the estimates of λ in 1996; however, this relationship reverses in 2006, with the estimate of Φ becoming twice as large as that of λ. That is, the importance of the observable characteristics relative to the unobservables, or Φ/λ, in explaining the worker-firm matches increases over time (0.6930 to 2.011). Consistent with this result, the correlation between worker skill and firm productivity is initially 0.022 and becomes three times larger in 2006 (Table A.7).

Second, the estimated cost of offshoring ($c_F = C - C^*$) decreases from 101.93 to 87.96 (DKK per hour) over time. In terms of magnitudes, this cost is roughly twice the hourly rate of unemployment insurance benefits (40.54 and 45.28 DKK per hour), which is the outside option parameter w_0 we calibrate using aggregate statistics from Statistics Denmark (Table 3). Due to positive assortative matching, greater values of x and y produce greater values of matched surplus. As we normalize the skill and productivity distributions to range from 0 to 1, our estimates of C and C^* indicate the lower bounds of our matched surpluses, while $\Phi + C$ and $\Phi + C^*$ are the upper bounds for Home and Foreign, respectively.

Third, the estimated matching intensities are higher for domestic matching (ν_x, ν_y) compared to foreign matching (ν_x^*, ν_y^*); the differences in matching rates ($\nu_x - \nu_x^*$, $\nu_y - \nu_y^*$) decrease over time. The estimates—after taking the exponential transformation—which then reveal intensity rates, are 0.267 and 0.177 for domestic matching and 7.049×10^{-5} and 9.904×10^{-5} for foreign matching in 1996; and 0.011 and 0.061 for domestic matching and 5.157×10^{-4} and 9.210×10^{-4} for foreign matching in 2006. We find that foreign matching intensities improved over the decade, both in terms of foreign workers' access to firms' job ads as well as firms' costs in screening foreign workers' job applications.

5.2 Counterfactual Analysis

In this section, we use these estimated parameters to simulate a counterfactual economy by changing the structural parameters on offshoring cost (c_F), the skill complementarity in the production technology (Φ), and the matching intensities (ν_x, ν_y, ν_x^*, ν_y^*).

We first assess the offshoring channel by simulating a counterfactual economy with no offshoring cost (i.e., $c_F = 0$). Figure 6 presents results for the baseline (in blue bars) and the offshoring-related counterfactual scenario (in red bars). Compared to the baseline economy, increased offshoring effectively puts downward pressure on wages (top left) and produces a greater share of unmatched workers at Home, where the magnitude of these shares is greater for workers with lower skill levels (top right). A similar conclusion holds when computing the average wages firms pay their domestic workers (bottom left). The overall skill quality of workers firms hire increases with offshoring (bottom right).

Increasing the matching intensities with foreign matching—either through greater values of ν_x^* or ν_y^*—produces qualitatively similar results (yellow bars) compared to counterfactual outcomes with no offshoring cost (red bars). The graph shows results by increasing the matching intensity of home firms toward foreign workers (i.e., $\nu_y^* + 1$). Figure B.3 presents results that include increasing the matching intensity of foreign workers toward home firms (i.e., $\nu_x^* + 1$), which provide quantitatively similar findings.

Figure 6: Counterfactual Outcomes Compared to Baseline (2006)

Notes: The graphs present the baseline results (2006) in blue bars and counterfactual results for: (i) increasing offshoring or removing offshoring cost ($c_F = 0$) in red bars, (ii) doubling skill complementarity ($\Phi \times 2$) in green bars, and (iii) increasing the matching intensity of firms toward workers by 1 ($\nu_y^* + 1$) in yellow bars. The top graphs plot the average wage (left) and share of unmatched (right) across the distribution of worker skills. The bottom graphs plot the average wage of matched workers (left) and the average matched worker quality (right) across the distribution of firm productivity. Wages (in levels, DKK) are CPI-adjusted to 1995.

Greater values of matching intensities with domestic matching, on the other hand, produce important differences (Figure B.4). An increase in ν_x induces a greater probability of home workers choosing to match with home firms instead of remaining unmatched, which in essence, increases labor supply and bids down wages. Similarly, an increase in ν_y makes matching attractive; however, due to greater labor demand, wages are bid up. In both cases, firms end up matching with workers with lower quality of skill compared to the baseline due to workers with lower x joining the labor force.

Increasing skill complementarity, where we double the skill complementarity parameter (i.e., $\Phi \times 2$), thereby generating greater degrees of positive assortative matching on the observables, produces counterfactual outcomes (green bars) that sharply contrast with the increased offshoring case (red bars). A production technology that increasingly complements workers' skills leads to an increase in the average wage of workers with larger gains for those with higher skill levels. Additionally, the share of unmatched workers decreases. Due to increased sorting, the average skill quality of matched workers rises for firms at the top of the productivity distribution but declines for those at the bottom.

Table 5: Counterfactuals: Wage Inequality

	Baseline (2006)	Counterfactuals					
		$c_F = 0$	$\Phi \uparrow$	$\nu_x \uparrow$	$\nu_y \uparrow$	$\nu_x^* \uparrow$	$\nu_y^* \uparrow$
$E(wage)$	147.42	130.81	151.72	139.18	157.96	145.46	145.46
$SD(wage)$	4.63	4.47	9.58	4.67	4.67	4.61	4.61
$E(wage \vert y)_{10-90}$	1.33	1.01	5.95	1.11	1.11	1.27	1.27
$E(wage \vert x)_{10-90}$	15.73	15.03	32.51	15.90	15.90	15.66	15.66

Notes: This table presents the baseline (2006) and counterfactual results for: (i) increasing offshoring ($c_F = 0$); (ii) doubling skill complementarity ($\Phi \times 2$); (iii) increasing matching intensities of home workers facing home firms by 1 ($\nu_x + 1$); (iv) increasing matching intensities of home firms facing home workers by 1 ($\nu_y + 1$); (v) increasing matching intensities of foreign workers facing home firms by 1 ($\nu_x^* + 1$); and (vi) increasing matching intensities of home firms facing foreign workers by 1 ($\nu_y^* + 1$). $E(wage)$ is the average wages; $SD(wage)$ is the standard deviation of wages; $E(wage|y)_{10-90}$ is the difference between average wages of top and bottom deciles of firms; $E(wage|x)_{10-90}$ is the difference between average wages of top and bottom deciles of workers. Wages (in levels, DKK) are CPI-adjusted to 1995.

Our counterfactual results highlight the contrasting effects of offshoring and production technology. Table 5 underscores their implications related to wage inequality. We show that wage inequality measured using the standard deviation of wages $SD(wage)$ and the difference between average wages of top and bottom deciles of workers $E(wage|x)_{10-90}$ decreases by 3.5 percent and 4.5 percent, respectively, in a counterfactual economy with no additional cost associated with foreign matching, compared to the baseline. The results are qualitatively similar when we examine the difference between average wages of top and bottom deciles of firms $E(wage|y)_{10-90}$, which decreases by 24 percent with greater exposure to offshoring. However, these measures of wage inequality increase with greater skill complementarity in the production technology: $SD(wage)$, $E(wage|x)_{10-90}$, and $E(wage|y)_{10-90}$ rise by 107 percent, 347 percent, and 107 percent, respectively.

While our main results focus on high-offshorable occupations, we also perform supplementary exercises to estimate the model combining all occupations. Table A.9 presents the results.[45] We find a qualitatively similar conclusion: increased sorting in the economy drives an increase in both aggregate inequality as well as between-firm wage inequality, whereas offshoring operates in a way that mitigates this rise.

Table 6: Contribution of Offshoring on Wage Inequality (1996-2006)

	Baseline		Counterfactual			Percent Changes relative to 1996			
	1996	2006	c_F	ν_x, ν_y	c_F, $\widetilde{\nu}_x$, $\widetilde{\nu}_y$	Actual	c_F	$\widetilde{\nu}_x$, $\widetilde{\nu}_y$	c_F, $\widetilde{\nu}_x$, $\widetilde{\nu}_y$
$E(wage)$	134.01	147.42	148.44	150.88	150.90	0.10	0.11	0.13	0.13
$SD(wage)$	4.05	4.63	4.64	4.66	4.66	0.14	0.14	0.15	0.15
$E(wage|y)_{10-90}$	0.36	1.33	1.36	1.45	1.45	2.71	2.80	3.05	3.05
$E(wage|x)_{10-90}$	14.08	15.73	15.76	15.83	15.84	0.12	0.12	0.12	0.12

Notes: This table presents the baseline results for the years 1996 and 2006 and the counterfactual results for the year 2006 using the offshoring-related structural parameter estimates of 1996. Offshoring cost (c_F) is the difference between C and C^*. Matching intensity differentials ($\widetilde{\nu}_x$ and $\widetilde{\nu}_y$) are the differences between ν_x and ν_x^* as well as ν_y and ν_y^*, respectively. $E(wage)$ is the average wages; $SD(wage)$ is the standard deviation of wages; $E(wage|y)_{10-90}$ is the difference between average wages of top and bottom deciles of firms; $E(wage|x)_{10-90}$ is the difference between average wages of top and bottom deciles of workers. Wages (in levels, DKK) are CPI-adjusted to 1995.

As our final exercise, we examine the contribution of offshoring in explaining changes in wage inequality between 1996 and 2006 by comparing the baseline results of 2006 with counterfactual results derived using parameter estimates obtained from 1996. Table 6 presents results. The average wage increased by 10 percent over the decade but would have risen by 11 percent if offshoring levels had remained at their 1996 levels. When further accounting for the foreign matching intensity rates channel, an additional counterfactual increase of 2 percentage points would have been observed by 2006. We find a similar overall change in wage dispersion, measured by the standard deviations of wages. The actual increase in between-firm inequality, measured by the difference in average wages between the top and bottom deciles of firms, increased by more than 200 percent over the

[45] See Table A.8 for parameter estimates.

decade, which would have exceeded 300 percent counterfactually, with 1996 offshoring levels.

Our findings in the reduced-form analysis highlight the role of worker-firm matching in firm-level adjustments to offshoring, which results in distributional effects where low-productivity firms (compared to high-productivity ones) benefit from hiring better-skilled workers within these high-offshorable jobs. Consistent with these results, our counterfactual exercises underscore the significant role of offshoring in reducing the dispersion across firms in terms of the skills hired and wages paid in occupations facing foreign competition. As technological advancements continue to reshape the task space and more occupations become offshorable, our findings suggest that, with globalization intensifying competition in jobs, the type of workers hired (and therefore wages paid) within these jobs becomes less significant in differentiating one firm from another.

6 Conclusions

This paper examines how offshoring affects worker skill demands and studies its implications for wage inequality. Using rich administrative data from Denmark, our analysis combines reduced-form and structural modeling approaches to empirically assess offshoring-induced adjustments, theoretically illustrate mechanisms, and quantify the impact of offshoring on domestic labor market outcomes.

The first part of our analysis identifies a causal effect of offshoring on firm-level demands for worker skills using a shift-share instrumental variable research design. We find a positive impact of offshoring on the average skills of workers employed in high-offshorable occupations. This increase pertains only to firms classified as low-productivity firms, which indicates distributional effects across firms. In addition, our results are driven by firms replacing low-skilled workers with high-skilled ones rather than workers improving skills through training. Thus, our findings collectively suggest that significant offshoring-induced adjustments take place through changes in worker-firm matching.

The second part of the analysis constructs a Becker-type matching model, which extends Dupuy and Galichon (2014) to a worker-firm matching context in a global economy setting. Our counterfactual exercises shed light on the importance of competing hypotheses, namely technological change versus globalization, in explaining changes in between-firm inequality, which has been shown to importantly drive aggregate labor market inequality (Song et al., 2019). We show that increased offshoring results in firms becoming more similar in both skill and wage levels in these jobs. Such between-firm inequality, in contrast, significantly increases under a production technology with greater skill complementarity.

The key mechanisms of our model and the corresponding consequences on labor market inequality demonstrated in our results have broader implications for workers in other occupations with low offshorability due to existing institutional constraints (e.g., occupational licensing) or the current state of offshoring technology. This is particularly relevant in light of the rapid changes in technology and globalization, which continue to reshape the nature of tasks, including the degree of foreign competition workers face through their jobs.

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Appendix

FOR ONLINE PUBLICATION

Offshoring, Matching, and Wage Inequality: Theory and Evidence

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Appendices

Appendix A Additional Tables

Table A.1: Occupational Offshorability by 1-digit ISCO codes

1-digit ISCO	Occupation Description	Offshorability
1	Management at the highest level in companies, organizations and the public sector	-0.985
2	Work that requires the highest level of skills	-0.373
3	Work requiring intermediate skills	-0.693
4	Office work	0.076
5	Sales, service and care work	-0.915
6	Work in agriculture, horticulture, forestry, hunting and fishing that requires basic skills	-2.000
7	Craftsmanship	0.356
8	Process and machine operator work; transport and construction work	0.235
9	Other work	-1.155
10	Military work	NA

Notes: This table lists the 1-digit ISCO codes and the corresponding offshorability index from Blinder and Krueger (2013). Higher values indicate high offshorability. Given our focus on manufacturing firms, we classify ISCO codes 7 and 8, which are (i) Craftsmanship and (ii) Process and Machine Operators; Transport and Construction Work, as high-offshorable occupations.

Table A.2: Summary Statistics (Firm-level)

Variables	Definition	Mean	Sd
Panel A: **Skill variables**			
Average Skill	average skills constructed using education and training at the firm-level in a given year	49.24	5.42
Average Skill (ISCO 1-2)	average skills for low-offshorable occupations at the firm-level in a given year	56.74	10.19
Average Skill (ISCO 3-5)	average skills for low-offshorable occupations at the firm-level in a given year	53.81	7.81
Average Skill (ISCO 7-8)	average skills for high-offshorable jobs at the firm-level in a given year	46.83	5.41
Panel B: **Offshoring variables**			
Offshoring (CN)	log of offshoring values at the industry-level from China	2.93	6.98
Offshoring (CN-IV)	predicted log of offshoring values at the industry-level from China	6.79	7.11
Offshoring (LW)	log of offshoring values at the industry-level from low wage countries	3.22	7.24
Offshoring (LW-IV)	predicted log of offshoring values at the industry-level from low wage countries	7.03	7.14
Export	log of export values at the industry-level	18.35	4.25
Panel C: **Firm variables**			
High productivity	1, if the firm sales per employee above median of the sample distribution	0.50	0.50
Sales	log of sales	16.71	1.55
Size	number of employees	54.54	186.83
Importer	1, if the firm imports	0.53	0.49
Exporter	1, if the firm exports	0.54	0.49
Number of Observations		35,998	
Number of firms		3,329	

Notes: All descriptive statistics are calculated as averages over the period 1996-2006. All the skill variables are multiplied by 100. All monetary figures are CPI-adjusted to the level of 1995. 1 Danish krone (DKK) is approximately 0.15 US Dollars.

Table A.3: Summary Statistics (Worker-level)

Variables	Definition	Mean	Sd
Panel A: **Sociodemographic variables**			
Age	age (years)	41.52	10.62
Female	1, if female	0.27	0.44
Education	Years of Education	12.02	2.01
Panel B: **Work-related variables**			
Wages	log of hourly wages	4.99	0.33
Work experience	work experience (years)	15.10	6.21
Panel C: **Skill variables**			
Cognitive	Index of cognitive skills (O*NET)	50.53	11.92
Number of observations		1,393,598	
Number of workers		309,697	

Notes: All descriptive statistics are calculated as averages over the period 1996-2006. All the skill variables are multiplied by 100. All monetary figures are CPI-adjusted to the level of 1995. 1 Danish krone (DKK) is approximately 0.15 US Dollars.

Additional tests on the instrument We follow Borusyak et al. (2022) in assessing the assumption that the number of shocks (the shifters) in our instrumental variable must be large, and none of them is large enough to drive the results. Table A.4 reports summary statistics for the number of offshoring products h by time t included in our instrumental variable computed with importance weights $s_h = \sum_k \frac{Import_{kh0}}{Import_{k0}}$ and characterizes these weights. The number of shocks is clearly large, as is the number of products. The standard deviation and interquartile range are large, suggesting a lot of variation. These statistics remain sizable when considering within-period variation. The inverse of the Herfindahl index (HHI), $1/\sum_{h,t} s_h^2$, corresponds to the effective sample size in a product-level regression. This number is large when considering all periods, but gets smaller when considering products within the same period. The group with the largest product share in 1995 is Electrical machines (12%), followed by plastic products (10%) and garments and accessories for garments (9%).

Table A.4: Summary statistics for Shifters

	(1)	(2)
	Raw	**Year FE**
Mean	1.408	0.0
Standard deviation	18.228	18.226
Interquartile range	0.429	0.761
Effective sample size (1/HHI) of s_d		
across products and periods	318.056	
across products	1.857	
Largest share s_d		
across products and periods	0.015	
across products	0.121	
No. of shocks	1500	
No. of products	135	
No. of periods	11	

Notes: The table summarizes the distribution of the imports of product d from China in period t. 1/HHI is the inverse of the Herfindahl–Hirschman index.

Table A.5: Average Skills and Offshoring

	OLS (Dependent Variable: Average Cognitive Skills × 100)			
	All	By Occupational Offshorability		
		Low (H-Skill)	**Low (M/L-Skill)**	**High**
	(1)	**(2)**	**(3)**	**(4)**
Offshoring (China)	-0.0074	0.0062	0.0122	0.0049
	(0.0115)	(0.0154)	(0.0147)	(0.0150)
Sector by Year FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Mean Y	49.24	56.77	53.83	46.83
N	35,998	22,988	28,679	34,162
	IV (Dependent Variable: Average Cognitive Skills × 100)			
	All	By Occupational Offshorability		
		Low (H-Skill)	**Low (M/L-Skill)**	**High**
	(5)	**(6)**	**(7)**	**(8)**
Offshoring (China)	0.0945*	0.3678***	0.1242	0.1365**
	(0.0494)	(0.0858)	(0.0762)	(0.0569)
Sector by Year FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Mean Y	49.24	56.77	53.83	46.83
F-stat	849.39	548.53	762.03	820.89
AR-stat	4.28	23.01	3.18	6.77
N	35,998	22,988	28,679	34,162

Notes: This table reports results examining Equation (6). The dependent variable is the firm-level average skills in a given year. All skill variables are multiplied by 100. Columns (1) and (5) considers all workers; Columns (2)-(4) and (6)-(8) focus on workers by occupation groups: low-offshorable-high-skill occupations (1-digit ISCO 1 and 2) in Columns (2) and (6); low-offshorable-medium/low-skill occupations (1-digit ISCO 3 to 5) in Columns (3) and (7); and high-offshorable occupations (1-digit ISCO 7 and 8) in Columns (4) and (8). Offshoring$_{kt}$ is the offshoring exposure measured at 6-digit industries. We include firm fixed effects and 4-digit industry-by-year fixed effects We also add 6-digit industry-level exports. The top panel reports OLS results; the bottom reports IV results. Robust standard errors clustered at the industry level in parentheses. AR First Stage F-stat on Instrument refers to the identification-robust Anderson-Rubin Wald test. Significance levels: ***1%, **5%, *10%.

Table A.6: Average Skills and Offshoring: Robustness Checks

	IV (Dependent Variable: Average Cognitive Skills × 100, High-offshorable)							
	Sales per K		**TFP**		**Offshoring (Alternate)**		**Employment-Weighted**	
	Low	**High**	**Low**	**High**	**Low**	**High**	**Low**	**High**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Offshoring (China)	0.27370***	-0.26391	0.21736**	-0.02198			0.20060***	-0.14762
	(0.06453)	(0.14491)	(0.09089)	(0.11207)			(0.05821)	(0.11160)
Offshoring (Low)					0.17940***	-0.09907		
					(0.05765)	(0.08115)		
Sector by Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Mean Y	46.42	47.23	46.69	47.28	46.42	47.23	46.42	47.23
First Stage F-stat	663.74	125.47	308.44	232.97	822.66	400.28	675.09	159.56
AR First Stage F-stat	22.12	4.19	7.06	0.04	11.72	1.83	14.45	2.17
N	15,871	17,844	15,871	16,874	16,856	16,882	16,856	16,882

	IV (Dependent Variable: Average Cognitive Skills × 100, High-offshorable)								
	Exclude Copenhagen		**Firm Controls**		**L-Intensive**		**K-Intensive**	**IV Export**	
	Low	**High**	**Low**	**High**	**Low**	**High**	**All**	**Low**	**High**
	(9)	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**	**(16)**	**(17)**
Offshoring (China)	0.24881***	-0.26258*	0.27355***	-0.26308*	0.27788*	-0.03773	0.31495	0.27369***	-0.26619
	(0.06457)	(0.14530)	(0.0628)	(0.1349)	(0.16552)	(0.48388)	(0.21480)	(0.06391)	(0.16252)
Sector by Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean Y	46.43	47.24	46.42	47.23	46.12	46.79	47.94	46.40	47.22
First Stage F-stat	634.83	122.01	665.23	124.75	84.49	7.16	112.27	335.71	48.72
AR First Stage F-stat	17.90	4.03	22.08	4.14	3.48	0.01	2.77	23.61	3.45
N	16,076	16,386	16,856	16,882	14,559	13,585	8,110	16,660	16,637

Notes: This table reports results examining Equation (6) by firm type: we classify firms as having low (high)-productivity if their average sales per employee in 1995 is below (above) the median of the distribution. The dependent variable is the average skills for high-offshorable jobs at the firm level. All skill variables are multiplied by 100. For Columns (1) through (14), the odd columns include results for low-type firms and the even columns for high-type firms. Column (15) combines all observations. Columns (16) and (17) include results for low-type and high-type firms, respectively. Offshoring$_{kt}$ is the offshoring exposure measured at 6-digit industries. We include firm fixed effects and 4-digit industry-by-year fixed effects We also add 6-digit industry-level exports. Robust standard errors clustered at the industry level in parentheses. AR First Stage F-stat on Instrument refers to the identification-robust Anderson-Rubin Wald test. Significance levels: ***1%, **5%, *10%.

Table A.7: Summary Statistics (Model Predicted)

	Share of Matched and Unmatched					Mean, Standard Deviations, and Correlations						
	Matched (x)	Matched (x^*)	Unmatched (x)	Unmatched (x^*)	Unmatched (y)	E(x)	SD(x)	E(y)	SD(y)	Corr(x, y)	E(w)	SD(w)
Offshorable Occupations												
1996	0.94	0.00	0.06	0.63	0.06	0.37	0.16	0.31	0.19	0.02	134.01	4.05
2006	0.96	0.01	0.04	0.62	0.04	0.39	0.18	0.31	0.18	0.07	147.42	4.63
All Occupations												
1996	0.94	0.00	0.06	0.63	0.06	0.42	0.21	0.33	0.20	0.13	151.45	20.24
2006	0.96	0.02	0.04	0.62	0.04	0.42	0.21	0.32	0.20	0.19	167.55	21.39

Notes: This table provides the summary statistics using the model-generated data for the years 1996 and 2006. The top panel reports statistics focusing on offshorable occupations; the bottom panel combines all occupations. Matched (x) and Matched (x^*) are the share of matched domestic and foreign workers, respectively. Unmatched (x), Unmatched (x^*), and Unmatched (y) are the share of unmatched domestic and foreign workers, and domestic firms, respectively. The mean and standard deviations of domestic worker skill (normalized), domestic firm productivity (normalized), and domestic worker wage (levels, DKK) are: E(x), SD(x), E(y), SD(y), E(w), and SD(w). The correlations between our normalized measures of worker skill and firm productivity are Corr(x, y).

Table A.8: Parameter Estimates (All Occupations)

	Parameter	1996	2006
Φ	matching technology	264.41 (259.47, 270.1)	288.85 (281.73, 295.24)
λ	variance of idiosyncratic preferences ($\lambda_x + \lambda_y$)	89.18 (85.99, 93.17)	65.08 (62.51, 67.47)
C	constant term in the matched surplus for domestic matches	244.00 (243.29, 244.76)	205.83 (205.1, 206.82)
C^*	constant term in the matched surplus for foreign matches	130.16 (125.78, 133.58)	110.02 (108.11, 111.66)
ν_x	matching intensity for domestic workers towards domestic firms	-2.01 (-2.1, -1.91)	-2.68 (-2.83, -2.57)
ν_y	matching intensity for domestic firms towards domestic workers	-2.42 (-2.52, -2.3)	-1.32 (-1.41, -1.25)
ν_x^*	matching intensity for foreign workers towards domestic firms	-9.36 (-9.45, -9.28)	-6.60 (-6.68, -6.53)
ν_y^*	matching intensity for domestic firms towards foreign workers	-9.89 (-10.01, -9.75)	-5.57 (-5.67, -5.49)

Notes: This table reports the estimation results (combining all occupations) for the parameters using data from the years 1996 and 2006. Parameter estimates related to the production technology (Φ, C, C^*, λ) are adjusted in units of hourly rates in DKK. The matching intensity parameter estimates ($\nu_x, \nu_y, \nu_x^*, \nu_y^*$) indicate positive intensities after taking the exponential transformation. Note that $C^* - C$ captures the cost of offshoring (c_F). Bootstrapped 95 percent confidence intervals based on 200 draws are included.

Table A.9: Counterfactuals: Wage Inequality (All Occupations)

	Baseline (2006)	Counterfactuals					
		$c_F = 0$	$\Phi \uparrow$	$\nu_x \uparrow$	$\nu_y \uparrow$	$\nu_x^* \uparrow$	$\nu_y^* \uparrow$
$E(wage)$	167.55	152.42	186.91	153.33	185.87	163.87	163.87
$SD(wage)$	21.39	21.04	44.14	21.47	21.47	21.31	21.31
$E(wage\|y)_{10-90}$	16.33	15.59	63.12	15.62	15.62	16.11	16.11
$E(wage\|x)_{10-90}$	66.62	65.24	140.24	67.09	67.09	66.30	66.30

Notes: The table presents the baseline (2006) and counterfactual results (combining all occupations) for: (i) increasing offshoring ($c_F = 0$); (ii) doubling skill complementarity ($\Phi \times 2$); (iii) increasing matching intensities of home workers facing home firms by 1 ($\nu_x + 1$); (iv) increasing matching intensities of home firms facing home workers by 1 ($\nu_y + 1$); (v) increasing matching intensities of foreign workers facing home firms by 1 ($\nu_x^* + 1$); and (vi) increasing matching intensities of home firms facing foreign workers by 1 ($\nu_y^* + 1$). $E(wage)$ is the average wages; $SD(wage)$ is the standard deviation of wages; $E(wage|y)_{10-90}$ is the difference between average wages of top and bottom deciles of firms; $E(wage|x)_{10-90}$ is the difference between average wages of top and bottom deciles of workers. Wages (in levels, DKK) are CPI-adjusted to 1995.

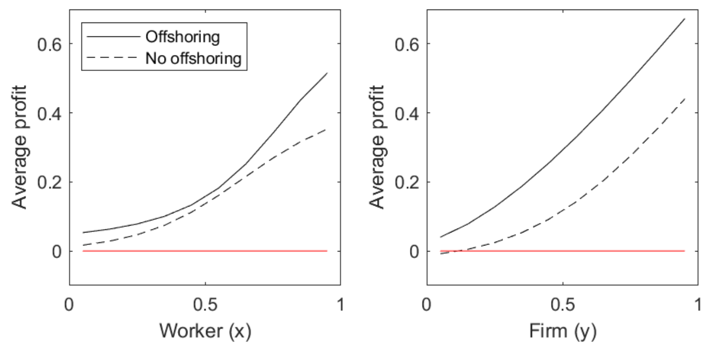
Table A.10: Contribution of Offshoring on Wage Inequality (1996-2006, All Occupations)

	Baseline		Counterfactual			Percent Changes relative to 1996			
	1996	2006	c_F	ν_x, ν_y	$c_F, \widetilde{\nu}_x, \widetilde{\nu}_y$	Actual	c_F	$\widetilde{\nu}_x, \widetilde{\nu}_y$	$c_F, \widetilde{\nu}_x, \widetilde{\nu}_y$
$E(wage)$	151.45	167.55	169.06	174.11	174.17	0.11	0.12	0.15	0.15
$SD(wage)$	20.24	21.39	21.42	21.54	21.54	0.06	0.06	0.06	0.06
$E(wage\|y)_{10-90}$	10.65	16.33	16.43	16.81	16.81	0.53	0.54	0.58	0.58
$E(wage\|x)_{10-90}$	64.23	66.62	66.75	67.18	67.19	0.04	0.04	0.05	0.05

Notes: The table presents the baseline results (combining all occupations) for the years 1996 and 2006 and the counterfactual results for the year 2006 using the offshoring-related structural parameter estimates of 1996. Offshoring cost (c_F) is the difference between C and C^*. Matching intensity differentials ($\widetilde{\nu}_x$ and $\widetilde{\nu}_y$) are the differences between ν_x and ν_x^* as well as ν_y and ν_y^*, respectively. $E(wage)$ is the average wages; $SD(wage)$ is the standard deviation of wages; $E(wage|y)_{10-90}$ is the difference between average wages of top and bottom deciles of firms; $E(wage|x)_{10-90}$ is the difference between average wages of top and bottom deciles of workers. Wages (in levels, DKK) are CPI-adjusted to 1995.

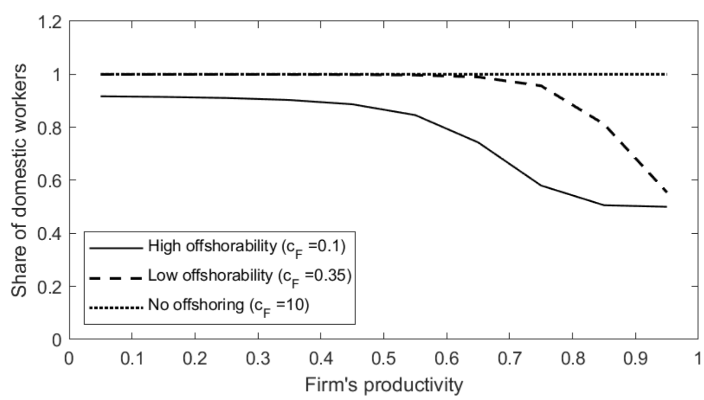
Appendix B Additional Figures

Figure B.1: Average Profits



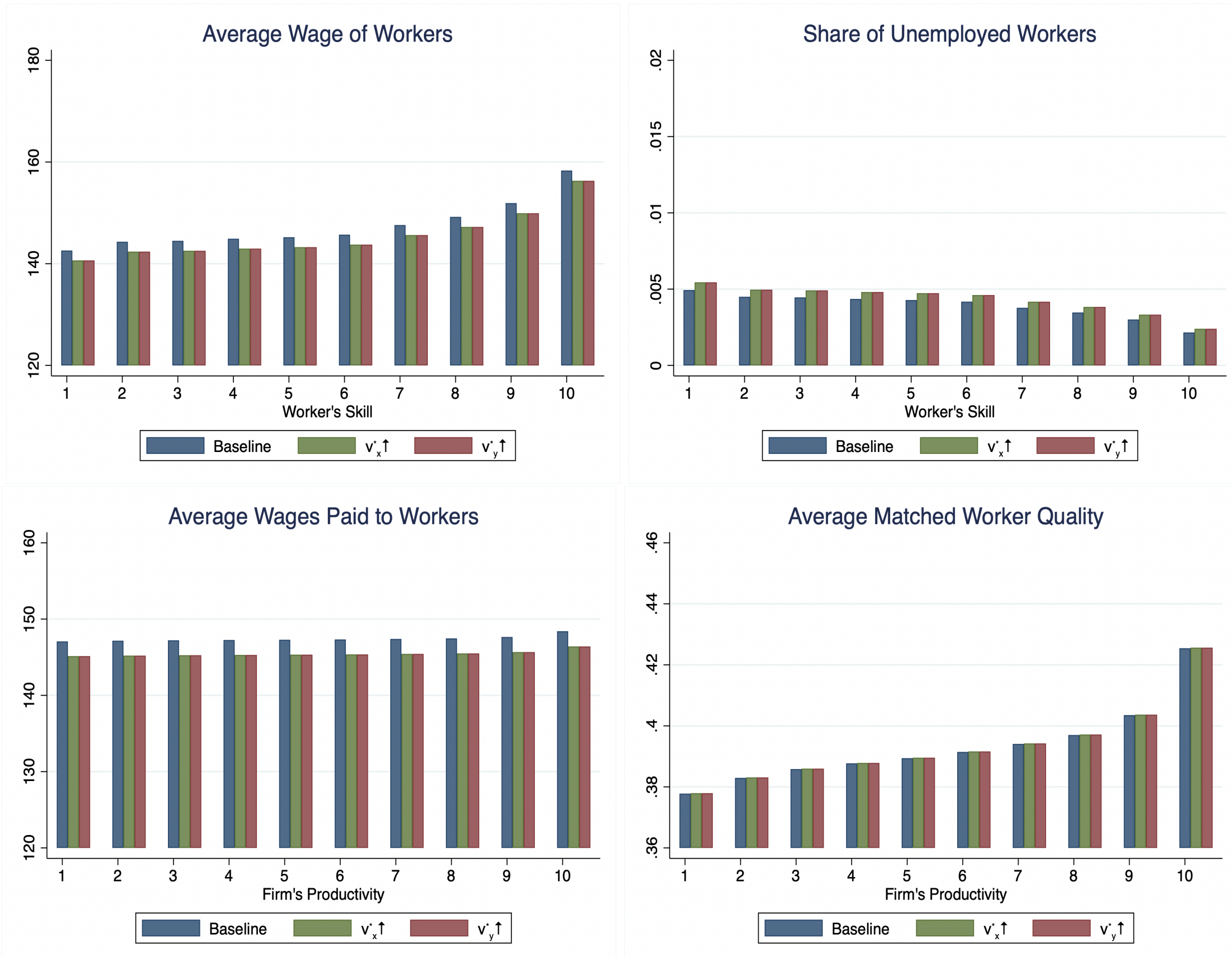
Notes: This figure presents the average profits by worker skill (left) and firm productivity (right) for cases with (solid lines) and without offshoring (dashed lines). We assume $q(x,y) = xy$, $c_F = 0.10$, $\overline{f}(x) \sim U[0,1]$, $\overline{f^*}(x) \sim U[0,1]$, $\overline{g}(y) \sim U[0,1]$, $\lambda = 0.04$, and $\nu_x = \nu_y = \nu_x^* = \nu_y^* = 0$. We further impose $w_0 = r_0 = w_0^* = 0$.

Figure B.2: Share of Domestic Workers in Firms by Offshorability



Notes: This figure shows the share of domestic workers hired across the distribution of firm productivity for different occupation categories, which vary in offshorability. We assume $q(x,y) = xy$, $c_F = 0.10$, $\overline{f}(x) \sim U[0,1]$, $\overline{f^*}(x) \sim U[0,1]$, $\overline{g}(y) \sim U[0,1]$, $\lambda = 0.04$, and $\nu_x = \nu_y = \nu_x^* = \nu_y^* = 0$. We further impose $w_0 = r_0 = w_0^* = 0$. Different degrees of offshorability are captured using different levels of offshoring cost c_F: 0.1, 0.35, and 10.

Figure B.3: Counterfactual Outcomes Compared to Baseline (2006): Matching Intensities (Foreign)



Notes: The graphs present the baseline results (2006) in blue bars and counterfactual results for: (i) increasing matching intensities of foreign workers facing home firms by 1 ($\nu_x^* + 1$) in green bars and (ii) increasing matching intensities of home firms facing foreign workers by 1 ($\nu_y^* + 1$) in red bars. The top graphs plot the average wage (left) and share of unmatched (right) across the distribution of home worker skills. The bottom graphs plot the average wage of matched home workers (left) and the average matched home worker quality (right) across the distribution of firm productivity. Wages (in levels, DKK) are CPI-adjusted to 1995.

Figure B.4: Counterfactual Outcomes Compared to Baseline (2006): Matching Intensities (Home)

Notes: The graphs present the baseline results (2006) in blue bars and counterfactual results for: (i) increasing matching intensities of home workers facing home firms by 1 ($\nu_x + 1$) in green bars and (ii) increasing matching intensities of home firms facing home workers by 1 ($\nu_y + 1$) in red bars. The top graphs plot the average wage (left) and share of unmatched (right) across the distribution of worker skills. The bottom graphs plot the average wage of matched workers (left) and the average matched worker quality (right) across the distribution of firm productivity. Wages (in levels, DKK) are CPI-adjusted to 1995.

Appendix C Theory and Proofs

C.1 Unobserved Preferences

We closely follow Dupuy and Galichon (2014) in the assumptions for unobserved heterogeneity. Each worker with observable skill x has a set composed of random realization of "acquaintances," which follows a Poisson point process on $\mathcal{Y} \times \mathbb{R}$ with intensity $\lambda(y,e) = \exp(-e + \nu_x)$ where ν_x is a given constant. If a point (y,e) is in the acquaintance set, this implies that the individual's unobserved preference for a firm with productivity y is equal to e.[46] As a consequence of the Poisson point process assumption, each individual has infinite but countable number of acquaintances. For all values of y that are not in the acquaintance set, negative infinity is assigned to the preference shock, which is a natural assumption in the current context, implying that they can never be optimally chosen. In sum,

$$e_x(y) = \begin{cases} \max_k e_k & \text{if } y_k \in \text{acquaintance set} \\ -\infty & \text{otherwise} \end{cases}$$

Fix a worker with skill x, and consider a set $S \subseteq \mathcal{Y}$. Define the random variable $Z(S,x)$ as

$$Z(S,x) = \max_{y_k \in S} \Big\{ w(x,y_k) + \lambda_x e_k \Big\}$$

which is the maximized utility for this worker within the set $S \subseteq \mathcal{Y}$. The cdf of this random variable is[47]

$$\begin{aligned}
P\Big(Z(S,x) \le c\Big) &= P\Big(w(x,y_k) + \lambda_x e_k \le c,\ \forall k\Big) \\
&= P\Big(e_k \le \frac{c - w(x,y_k)}{\lambda_x},\ \forall k\Big) \\
&= P\Big(\text{No points in the region } e > \frac{c - w(x,y)}{\lambda_x},\ \forall y \in S\Big) \\
&= \exp\Big(-\int_S \int_{\frac{c-w(x,y)}{\lambda_x}}^{\infty} \exp(\nu_x - e)\, de\, dy\Big) \\
&= \exp\Big[-\int_S \exp\Big(\nu_x - \frac{c - w(x,y)}{\lambda_x}\Big) dy\Big] \\
&= \exp\Big[-\exp\Big(-\frac{c}{\lambda_x} + \nu_x + \log \int_S \exp \frac{w(x,y)}{\lambda_x} dy\Big)\Big]
\end{aligned}$$

[46] When there are multiple e's that coincide with the same y, the maximum of these e's are taken. However, since such events occur with probability zero, this consideration is, in fact, immaterial.

[47] Note that the 4th equality uses a general property of the Poisson process that $P(X = k) = \frac{\Lambda^k}{k!} e^{-\Lambda}$, with $k = 0$ and $\Lambda = \int\int \lambda(y,e)\, de\, dy$.

Thus the distribution of $Z(S,x)$ is Gumbel with $E[Z] = \lambda_x \cdot \Big(\nu_x + \log \int_S \exp \frac{w(x,y)}{\lambda_x} dy + \gamma\Big)$, and $V[Z] = \frac{\pi^2}{6}\lambda_x^2$, where $\gamma \approx 0.577$ is the Euler–Mascheroni constant. Note that the scalar for the matching intensity ν_x acts to shift up this random variable by $\lambda_x \nu_x$.

Now, consider a small interval $dy \subset \mathcal{Y}$. Similarly, it can be shown that

$$P\Big(Z(dy,x) \le c\Big) = \exp\Big[-\exp\Big(-\frac{c}{\lambda_x} + \nu_x + \frac{w(x,y)}{\lambda_x} + \log dy\Big)\Big]$$

and thus $Z(dy,x)$ is Gumbel with mean $\lambda_x \cdot \Big(\nu_x + \frac{w(x,y)}{\lambda_x} + \log dy + \gamma\Big)$ and variance $\frac{\pi^2}{6}\lambda_x^2$.

Probability that the best match $y^*(x)$ is found within dy is

$$\begin{aligned}
P(y^*(x) \in dy) &= P\Big(\max_{y_k \in dy} w(x,y_k) + e_k \ge \max_{y_k \in \mathcal{Y}\setminus dy} w(x,y_k) + e_k\Big) \\
&= P\Big(E[Z(dy,x)] + \lambda_x \epsilon_1 \ge E[Z(\mathcal{Y}\setminus dy,x)] + \lambda_x \epsilon_2\Big) \\
&= P\Big(\epsilon_2 \le \epsilon_1 + \frac{E[Z(dy,x)] - E[Z(\mathcal{Y}\setminus dy,x)]}{\lambda_x}\Big) \\
&= \frac{1}{1 + \exp\Big(-\frac{1}{\lambda_x}(E[Z(dy,x)] - E[Z(\mathcal{Y}\setminus dy,x)])\Big)} \\
&= \frac{\exp \frac{w(x,y)}{\lambda_x} dy}{\exp \frac{w(x,y)}{\lambda_x} dy + \int_{\mathcal{Y}\setminus dy} \exp \frac{w(x,y)}{\lambda_x} dy} = \frac{\exp \frac{w(x,y)}{\lambda_x} dy}{\int_{\mathcal{Y}} \exp \frac{w(x,y)}{\lambda_x} dy}
\end{aligned}$$

where (ϵ_1, ϵ_2) are independent draws from the baseline Gumbel distribution with mean γ and variance $\frac{\pi^2}{6}$.

The worker also has an outside option, which gives the utility of $w_0 + \lambda_x \epsilon_0$ where ϵ_0 is also drawn from the same Gumbel distribution. The overall maximization problem, including this outside option is

$$U = \max\Big[w_0 + \lambda_x \epsilon_0,\ \Big(\lambda_x \log \int_{\mathcal{Y}} \exp \frac{w(x,y)}{\lambda_x} dy + \lambda_x \nu_x\Big) + \lambda_x \epsilon_1\Big] \tag{A1}$$

Thus the probability of choosing the outside option is

$$\frac{f_0(x)}{\overline{f}(x)} = \frac{\exp(\frac{w_0}{\lambda_x} - \nu_x)}{\exp(\frac{w_0}{\lambda_x} - \nu_x) + \int \exp(\frac{w(x,y)}{\lambda_x}) dy} \tag{A2}$$

and the probability of matching with a firm is

$$\frac{f(x)}{\overline{f}(x)} = \frac{\int \exp(\frac{w(x,y)}{\lambda_x})dy}{\exp(\frac{w_0}{\lambda_x} - \nu_x) + \int \exp(\frac{w(x,y)}{\lambda_x})dy} \tag{A3}$$

The masses of unmatched and matched workers with skill x are thus

$$f_0(x) = \frac{\exp\frac{w_0-\nu_x}{\lambda_x}}{\exp\frac{w_0-\nu_x}{\lambda_x} + \int_{\mathcal{Y}} \exp\frac{w(x,y)}{\lambda_x}dy}\overline{f}(x), \quad f(x) = \int_{\mathcal{Y}} \pi(x,y)dy = \overline{f}(x) - f_0(x) \tag{A4}$$

Since all the idiosyncratic shocks are independent of one another, this extensive margin does not affect the matching distribution conditional on matching. From $P(y^*(x) \in dy)$ derived above, the pdf conditional on matching can be obtained as

$$\pi(y|x) = \frac{\pi(x,y)}{f(x)} = \frac{P(y^*(x) \in dy)}{dy} = \frac{\exp\frac{w(x,y)}{\lambda_x}}{\int_{\mathcal{Y}} \exp\frac{w(x,y)}{\lambda_x}dy} \tag{A5}$$

Similarly, on the firm side, the probability of choosing the outside option is

$$\frac{g_0(y)}{\overline{g}(y)} = \frac{\exp(\frac{r_0}{\lambda_y} - \nu_y)}{\exp(\frac{r_0}{\lambda_y} - \nu_y) + \int \exp(\frac{r(x,y)}{\lambda_y})dx} \tag{A6}$$

and the probability of matching with a worker is

$$\frac{g(y)}{\overline{g}(y)} = \frac{\int \exp(\frac{r(x,y)}{\lambda_y})dx}{\exp(\frac{r_0}{\lambda_y} - \nu_y) + \int \exp(\frac{r(x,y)}{\lambda_y})dx} \tag{A7}$$

The masses of unmatched and matched firms with characteristic y are thus

$$g_0(x) = \frac{\exp\frac{r_0-\nu_y}{\lambda_y}}{\exp\frac{r_0-\nu_y}{\lambda_y} + \int_{\mathcal{X}} \exp\frac{r(x,y)}{\lambda_y}dx}\overline{g}(y), \quad g(y) = \int_{\mathcal{X}} \pi(x,y)dx = \overline{g}(y) - g_0(y) \tag{A8}$$

The pdf conditional on matching is

$$\pi(x|y) = \frac{\pi(x,y)}{g(y)} = \frac{\exp\frac{r(x,y)}{\lambda_y}}{\int_{\mathcal{X}} \exp\frac{r(x,y)}{\lambda_y}dx} \tag{A9}$$

C.2 Solving the Baseline Economy Equilibrium

Taking logs on both sides and rearranging, collecting terms independent of y,

$$\log \pi(x,y) = \frac{w(x,y)}{\lambda_x} - \log \frac{\int \exp(\frac{w(x,y)}{\lambda_x})dy}{f(x)} = \frac{w(x,y) - a(x)}{\lambda_x} \tag{A10}$$

where $a(x) \equiv \lambda_x \log \frac{\int \exp(\frac{w(x,y)}{\lambda_x})dy}{f(x)}$. Similarly, on the firm's side,

$$\pi(x|y) = \frac{\pi(x,y)}{g(y)} = \frac{\exp(\frac{r(x,y)}{\lambda_y})}{\int \exp(\frac{r(x,y)}{\lambda_y})dx} \tag{A11}$$

$$\log \pi(x,y) = \frac{r(x,y)}{\lambda_y} - \log \frac{\int \exp(\frac{r(x,y)}{\lambda_y})dx}{g(y)} = \frac{r(x,y) - b(y)}{\lambda_y} \tag{A12}$$

and $b(y) \equiv \lambda_y \log \frac{\int \exp(\frac{r(x,y)}{\lambda_y})dx}{g(y)}$. Combining the above two equations and using $q(x,y) = w(x,y) + r(x,y)$, the endogenous objects $w(x,y)$ and $r(x,y)$ can be canceled out to yield $(\lambda_x + \lambda_y)\log \pi(x,y) = q(x,y) - a(x) - b(y)$. Denoting $\lambda \equiv \lambda_x + \lambda_y$,

$$\pi(x,y) = \exp(-\frac{a(x)}{\lambda})\exp(-\frac{b(y)}{\lambda})\exp(\frac{q(x,y)}{\lambda}) = \hat{a}(x)\hat{b}(y)\exp(\frac{q(x,y)}{\lambda}) \tag{A13}$$

where $\hat{a}(x) \equiv \exp(-\frac{a(x)}{\lambda})$ and $\hat{b}(y) \equiv \exp(-\frac{b(y)}{\lambda})$ are defined for convenience. In addition,

$$\exp(-\frac{a(x)}{\lambda_x}) = \frac{f(x)}{\int \exp(\frac{w(x,y)}{\lambda_x})dy} = \frac{\overline{f}(x)}{\exp(\frac{w_0}{\lambda_x} - \nu_x) + \int \exp(\frac{w(x,y)}{\lambda_x})dy} = \hat{a}(x)^{\frac{\lambda}{\lambda_x}} \tag{A14}$$

$$\exp(-\frac{b(y)}{\lambda_y}) = \frac{g(y)}{\int \exp(\frac{r(x,y)}{\lambda_y})dx} = \frac{\overline{g}(y)}{\exp(\frac{r_0}{\lambda_y} - \nu_y) + \int \exp(\frac{r(x,y)}{\lambda_y})dx} = \hat{b}(y)^{\frac{\lambda}{\lambda_y}} \tag{A15}$$

From these equations, it immediately follows that

$$f_0(x) = \frac{\exp(\frac{w_0}{\lambda_x} - \nu_x)\overline{f}(x)}{\exp(\frac{w_0}{\lambda_x} - \nu_x) + \int \exp(\frac{w(x,y)}{\lambda_x})dy} = \hat{a}(x)^{\frac{\lambda}{\lambda_x}} \exp(\frac{w_0}{\lambda_x} - \nu_x) \tag{A16}$$

$$g_0(y) = \frac{\exp(\frac{r_0}{\lambda_y} - \nu_y)\overline{g}(y)}{\exp(\frac{r_0}{\lambda_y} - \nu_y) + \int \exp(\frac{r(x,y)}{\lambda_y})dx} = \hat{b}(y)^{\frac{\lambda}{\lambda_y}} \exp(\frac{r_0}{\lambda_y} - \nu_y) \tag{A17}$$

Now the exogenously given marginal distributions can be expressed as

$$\overline{f}(x) = \hat{a}(x)^{\frac{\lambda}{\lambda_x}} \exp(\frac{w_0}{\lambda_x} - \nu_x) + \hat{a}(x) \int \hat{b}(y) \exp(\frac{q(x,y)}{\lambda}) dy \tag{A18}$$

$$\overline{g}(y) = \hat{b}(y)^{\frac{\lambda}{\lambda_y}} \exp(\frac{r_0}{\lambda_y} - \nu_y) + \hat{b}(y) \int \hat{a}(x) \exp(\frac{q(x,y)}{\lambda}) dx \tag{A19}$$

where $f(x) = \int \pi(x,y)dy$ and $g(y) = \int \pi(x,y)dx$ have been used.

This last set of equations is crucial for solving the equilibrium. The endogenous objects $\hat{a}(x), \hat{b}(y)$ need to be solved, taking as given: marginal distributions $\overline{f}(x), \overline{g}(y)$, production function $q(x,y)$, and the degrees of unobserved heterogeneity λ_x, λ_y. There is a straightforward iterative algorithm to solve for $\hat{a}(x), \hat{b}(y)$: start with an initial $\hat{b}(y)$, plug in to (1) to obtain $\hat{a}(x)$, then plug in to (2) to obtain $\hat{b}(y)$, and repeat until convergence.[48] Once $\hat{a}(x), \hat{b}(y)$ are found, it is straightforward to recover all other endogenous objects, including the matching function $\pi(x,y)$ as well as wages and profits $w(x,y), r(x,y)$.

C.3 Solving the Global Economy Equilibrium

Home worker with skill x maximizes his utility: $max(w + \lambda_x e, max_y\{w(x,y) + \lambda_x e(y)\})$. Likewise, foreign worker with skill z maximizes his utility: $max(w^* + \lambda_x e, max_y\{w^*(x,y) + \lambda_x e(y)\})$. The utility shocks are defined in the same way as before. Foreign workers may have different outside wage option of w^*, different wage $w^*(x,y)$, and different degree of heterogeneity λ_x. A (home) firm with productivity y maximizes its utility as before, but now it has a third option: to offshore by matching with a foreign worker. The problem thus becomes: $max(\lambda_y e, max_x\{r(x,y) + \lambda_y e(x)\}, max_z\{r^*(x,y) + \lambda_y e(x)\})$. As before, competitive equilibrium implies $w^*(x,y) + r^*(x,y) = q^*(x,y)$. The conditional distributions of choices for home and foreign workers are the same as before:

$$\frac{f_0(x)}{\overline{f}(x)} = \frac{\exp(\frac{w_0}{\lambda_x} - \nu_x)}{\exp(\frac{w_0}{\lambda_x} - \nu_x) + \int \exp(\frac{w(x,y)}{\lambda_x}) dy}, \quad \frac{f(x)}{\overline{f}(x)} = \frac{\int \exp(\frac{w(x,y)}{\lambda_x}) dy}{\exp(\frac{w_0}{\lambda_x} - \nu_x) + \int \exp(\frac{w(x,y)}{\lambda_x}) dy} \tag{A20}$$

$$\frac{f_0^*(x)}{\overline{f}^*(x)} = \frac{\exp(\frac{w_0^*}{\lambda_x} - \nu_x^*)}{\exp(\frac{w_0^*}{\lambda_x} - \nu_x^*) + \int \exp(\frac{w^*(x,y)}{\lambda_x}) dy}, \quad \frac{f^*(x)}{\overline{f}^*(x)} = \frac{\int \exp(\frac{w^*(x,y)}{\lambda_x}) dy}{\exp(\frac{w_0^*}{\lambda_x} - \nu_x^*) + \int \exp(\frac{w^*(x,y)}{\lambda_x}) dy} \tag{A21}$$

The distributions for the firms must be modified to incorporate the newly available

[48] This algorithm is proposed in Bojilov and Galichon (2016), which they refer to as "Iterated Proportional Fitting Procedure (IPFP)" or "Sinkhorn's algorithm."

choice of offshoring:

$$\frac{g_0(y)}{\overline{g}(y)} = \frac{\exp(\frac{r_0}{\lambda_y})}{D}, \quad \frac{g(y)}{\overline{g}(y)} = \frac{\int \exp(\frac{r(x,y)}{\lambda_y} + \nu_y)dx}{D}, \quad \frac{g^*(y)}{\overline{g}(y)} = \frac{\int \exp(\frac{r^*(x,y)}{\lambda_y} + \nu_y^*)dx}{D} \tag{A22}$$

where $D \equiv \exp(\frac{r_0}{\lambda_y}) + \int \exp(\frac{r(x,y)}{\lambda_y} + \nu_y)dx + \int \exp(\frac{r^*(x,y)}{\lambda_y} + \nu_y^*)dx$. The conditional probabilities for those who form matches are:

$$\pi(y|x) = \frac{\pi(x,y)}{f(x)} = \frac{\exp(\frac{w(x,y)}{\lambda_x})}{\int \exp(\frac{w(x,y)}{\lambda_x})dy} \tag{A23}$$

$$\pi(x|y) = \frac{\pi(x,y)}{g(y)} = \frac{\exp(\frac{r(x,y)}{\lambda_y})}{\int \exp(\frac{r(x,y)}{\lambda_y})dx} \tag{A24}$$

$$\pi^*(y|x) = \frac{\pi^*(x,y)}{f^*(x)} = \frac{\exp(\frac{w^*(x,y)}{\lambda_x})}{\int \exp(\frac{w^*(x,y)}{\lambda_x})dy} \tag{A25}$$

$$\pi^*(x|y) = \frac{\pi^*(x,y)}{g^*(y)} = \frac{\exp(\frac{r^*(x,y)}{\lambda_y})}{\int \exp(\frac{r^*(x,y)}{\lambda_y})dx} \tag{A26}$$

Taking logs on both sides and rearranging,

$$\begin{aligned}
\log \pi(x,y) &= \frac{w(x,y)}{\lambda_x} - \log \frac{\int \exp(\frac{w(x,y)}{\lambda_x})dy}{f(x)} = \frac{w(x,y) - a(x)}{\lambda_x} \\
\log \pi(x,y) &= \frac{r(x,y)}{\lambda_y} - \log \frac{\int \exp(\frac{r(x,y)}{\lambda_y})dx}{g(y)} = \frac{r(x,y) - b(y)}{\lambda_y} \\
\log \pi^*(x,y) &= \frac{w^*(x,y)}{\lambda_x} - \log \frac{\int \exp(\frac{w^*(x,y)}{\lambda_x})dy}{f^*(x)} = \frac{w^*(x,y) - a^*(x)}{\lambda_x} \\
\log \pi^*(x,y) &= \frac{r^*(x,y)}{\lambda_y} - \log \frac{\int \exp(\frac{r^*(x,y)}{\lambda_y})dx}{g^*(y)} = \frac{r^*(x,y) - b^*(y)}{\lambda_y}
\end{aligned} \tag{A27}$$

where $a(x) \equiv \lambda_x \log \frac{\int \exp(\frac{w(x,y)}{\lambda_x})dy}{f(x)}$, $b(y) \equiv \lambda_y \log \frac{\int \exp(\frac{r(x,y)}{\lambda_y})dx}{g(y)}$, $a^*(x) \equiv \lambda_x \log \frac{\int \exp(\frac{w^*(x,y)}{\lambda_x})dy}{h(x)}$, $b^*(y) \equiv \lambda_y \log \frac{\int \exp(\frac{r^*(x,y)}{\lambda_y})dx}{g(y)}$. Again, it is straightforward to obtain $\lambda \log \pi(x,y) = q(x,y) - a(x) - b(y)$

and $\lambda \log \pi^*(x,y) = q^*(x,y) - a^*(x) - b^*(y)$, and thus,

$$\pi(x,y) = \exp(-\frac{a(x)}{\lambda})\exp(-\frac{b(y)}{\lambda})\exp(\frac{q(x,y)}{\lambda}) = \hat{a}(x)\hat{b}(y)\exp(\frac{q(x,y)}{\lambda}) \tag{A28}$$

$$\pi^*(x,y) = \exp(-\frac{a^*(x)}{\lambda})\exp(-\frac{b^*(y)}{\lambda})\exp(\frac{q^*(x,y)}{\lambda}) = \hat{a}^*(x)\hat{b}^*(y)\exp(\frac{q^*(x,y)}{\lambda}) \tag{A29}$$

where $\lambda \equiv \lambda_x + \lambda_y$, $\hat{a}(x) \equiv \exp(-\frac{a(x)}{\lambda})$, $\hat{b}(y) \equiv \exp(-\frac{b(y)}{\lambda})$, $\hat{a}^*(x) \equiv \exp(-\frac{c(x)}{\lambda})$, $\hat{b}^*(y) \equiv \exp(-\frac{b^*(y)}{\lambda})$. Note that following equations hold, as before:

$$\begin{aligned}
\exp(-\frac{a(x)}{\lambda_x}) &= \frac{f(x)}{\int \exp(\frac{w(x,y)}{\lambda_x})dy} = \frac{\overline{f}(x)}{\exp(\frac{w_0}{\lambda_x} - \nu_x) + \int \exp(\frac{w(x,y)}{\lambda_x})dy} = \hat{a}(x)^{\frac{\lambda}{\lambda_x}} \\
\exp(-\frac{a^*(x)}{\lambda_x}) &= \frac{f^*(x)}{\int \exp(\frac{w^*(x,y)}{\lambda_x})dy} = \frac{\overline{f}^*(x)}{\exp(\frac{w_0^*}{\lambda_x} - \nu_x^*) + \int \exp(\frac{w^*(x,y)}{\lambda_x})dy} = \hat{a}^*(x)^{\frac{\lambda}{\lambda_x}} \\
\exp(-\frac{b(y)}{\lambda_y}) &= \frac{g(y)}{\int \exp(\frac{r(x,y)}{\lambda_y})dx} = \frac{\exp(\nu_y)\cdot\overline{g}(y)}{\exp(\frac{r_0}{\lambda_y}) + \int \exp(\frac{r(x,y)}{\lambda_y} + \nu_y)dx + \int \exp(\frac{r^*(x,y)}{\lambda_y} + \nu_y^*)dx} = \hat{b}(y)^{\frac{\lambda}{\lambda_y}} \\
\exp(-\frac{b^*(y)}{\lambda_y}) &= \frac{g^*(y)}{\int \exp(\frac{r^*(x,y)}{\lambda_y})dx} = \frac{\exp(\nu_y^*)\cdot\overline{g}(y)}{\exp(\frac{r_0}{\lambda_y}) + \int \exp(\frac{r(x,y)}{\lambda_y} + \nu_y)dx + \int \exp(\frac{r^*(x,y)}{\lambda_y} + \nu_y^*)dx} = \hat{b}^*(y)^{\frac{\lambda}{\lambda_y}}
\end{aligned} \tag{A30}$$

As already shown in the main text, $b^*(y) - b(y) = -\lambda_y(\nu_y^* - \nu_y)$ holds, or equivalently, $\hat{b}^*(y) = \hat{b}(y)\cdot\exp(\frac{\lambda_y}{\lambda}(\nu_y^* - \nu_y))$. Combining these results, the exogenously given marginal distributions can be expressed as,

$$\begin{aligned}
\overline{f}(x) &= \hat{a}(x)^{\frac{\lambda}{\lambda_x}}\exp(\frac{w_0}{\lambda_x} - \nu_x) + \hat{a}(x)\int \hat{b}(y)\exp(\frac{q(x,y)}{\lambda})dy \\
\overline{f}^*(x) &= \hat{a}^*(x)^{\frac{\lambda}{\lambda_x}}\exp(\frac{w_0^*}{\lambda_x} - \nu_x^*) + \hat{a}^*(x)\int \hat{b}(y)\exp(\frac{q^*(x,y)}{\lambda})\exp\Big(\frac{\lambda_y}{\lambda}(\nu_y^* - \nu_y)\Big)dy \\
\overline{g}(y) &= \hat{b}(y)^{\frac{\lambda}{\lambda_y}}\exp(\frac{r_0}{\lambda_y} - \nu_y) + \hat{b}(y)\Big[\int \hat{a}(x)\exp(\frac{q(x,y)}{\lambda})dx + \int \hat{a}^*(x)\exp(\frac{q^*(x,y)}{\lambda})\exp\Big(\frac{\lambda_y}{\lambda}(\nu_y^* - \nu_y)\Big)dx\Big]
\end{aligned} \tag{A31}$$

Similar to the previous section, the equilibrium boils down to solving for the endogenous objects $\hat{a}(x), \hat{a}^*(x), \hat{b}(y)$, taking as given: marginal distributions $\overline{f}(x), \overline{f}^*(x), \overline{g}(y)$, production functions $q(x,y), q^*(x,y)$, and the degree of unobserved heterogeneity λ_x, λ_y. The previously described algorithm can still be used – this time, start with an initial $\hat{b}(y)$, plug in to (1) and (2) to obtain $\hat{a}(x), \hat{a}^*(x)$, then plug in to (3) to obtain $\hat{b}(y)$, and repeat until convergence.

Again, once $\hat{a}(x), \hat{a}^*(x), \hat{b}(y)$ are found, it is straightforward to recover all other endogenous objects, including the matching function $\pi(x, y), \pi^*(x, y)$ as well as wages and profits $w(x, y), r(x, y), w^*(x, y), r^*(x, y)$.

Appendix D Institutional Background

The Danish System in a Global Economy

Denmark is a particularly fitting setting for our study for two main reasons. First, it features a flexible labor market characterized by a high level of labor mobility and generous social security schemes. The absence of severance pay reduces hiring and firing costs, facilitating firms' efforts to adjust the quality and size of their workforce in response to exogenous events. Although workers are not protected by stringent employment rules, they bear relatively low costs of changing employers and have easy access to unemployment or social assistance benefits. In fact, the share of a worker's previous earnings replaced by unemployment benefits in Denmark is among the most generous in the world, around 74%, whereas in most countries, it is around 50% (Botero et al., 2004).[49]

Second, it is a small open economy with limited power to shape trade policies according to its domestic economic performance. Thus, trade liberalization episodes, such as China's entry to the World Trade Organization (WTO) in 2001 or the eastern enlargement of the EU in 2004, can be considered exogenous events from the perspective of domestic firms (Hummels et al., 2014; Bernard et al., 2020). Flexible labor market conditions further facilitate domestic firms to respond promptly to the evolving market conditions of the global economy. Hence, Denmark is an ideal case to examine labor market responses to globalization.

Appendix E Data and Measures

Mapping of Education to Occupations

We scrape education and vocational training records from variables *hfaudd* and *erhaudd* respectively, where we obtain 2449 different types of records and clean the textual information: make all words lower-case, remove unnecessary abbreviations, replace punctuation characters with blank spaces, etc. Then, we translate the Danish words into English and manually examine words that are not directly translatable. We end up with 523 corresponding O*NET-SOC occupations that correspond to the educational information provided in the two variables. As the goal lies in identifying textual information in each education record that can be useful in relating the skill sets of an individual worker, we further use the education guide provided by the Ministry of Education in Denmark

[49] Wage contracts are negotiated at the firm level and are subject only to the lower bound on wages of the very inexperienced workers set at the industry level (Groes et al., 2015).

(https://www.ug.dk) to capture key words that characterize the task/skill content of academic education as well as vocational training records.

Next, we feed in the cleaned textual information of each education entry to the O*NET code connector (https://www.onetcodeconnector.org), which provides a list of relevant corresponding occupations. The criteria we use for finding a match are: (i) relevance scores higher than 90; (ii) the education keywords checked off with the occupation title, the lay title, the job description, the task content, and work activities. For education entries that fail these criteria, they go through a second set of algorithms, which requires (i) relevance scores higher than 90 and (ii) the education keywords checked off with the occupation title or the task content or work activities. Educational records that are too general and abstract are not included in the algorithm.