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Offshoring and Segregation by Skill: Theory and Evidence*

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Abstract

This paper examines the labor market consequences of offshoring. We use the Danish employer-employee matched data together with the newly constructed skill measures to evaluate the effect of offshoring on wages and reallocation of workers within offshorable occupations. Offshoring reduces domestic worker wages; and increases the probability of reallocation away from the high-productivity firms to the low-productivity ones. The least skilled workers further face a greater risk of switching out to a less competitive sector. On the firm-side, offshoring improves the average skill of in-house workers at a lower cost. By estimating a worker-firm matching model, we examine the mechanisms of how offshoring affects labor market inequality and further assess the quantitative importance of various competing hypotheses such as technological change and the expansion of higher education, in addition to offshoring. We find substantially different effects: technology mainly increases the inequality between firms in terms of worker skill quality and average wages, while offshoring mitigates this rising trend.

Keywords: offshoring, skill, matching, segregation by skill, between-firm inequality
JEL Codes: F15, F16, F23, J21, J24, J31

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1 Introduction

The last two decades ushered in 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, which is the essence of what is generally referred to as "offshoring." In response to changes in the nature of production, firms make adjustments, re-optimizing the mix of occupations and the skill-type of workers to keep in-house.

In this paper, we study the labor market consequences of offshoring, with a particular focus on worker-firm matching and wage inequality. We use the Danish employer-employee matched data and the Danish international trade registers to examine the effects of offshoring on wages and reallocation of workers in the occupations with tasks that are highly offshorable.[1] Since examining the effects of offshoring at the within-occupation-worker level requires having a detailed measure of worker's skill, we construct a novel measure of skill using rich information on individual education and job training records. Armed with the measure of worker's skill, we empirically examine predictions derived from the model, and further establish a causal effect of offshoring using an instrumental variable in the reduced-form analysis. The predictions are based on a simple matching model between workers and firms where offshoring affects labor market outcomes by changing the effective supply of workers. Finally, we quantify the equilibrium effects of offshoring by estimating the matching model extended with unobserved heterogeneity in preferences.

A key prerequisite for an empirical investigation of matching and sorting is a measure of the characteristics by which agents are sorted. In the context of worker-firm matching, measures of worker's skill and firm's productivity are required. An important contribution of this paper is in the construction of worker's skill, using the rich information in the occupation and education contained in the Danish administrative data. More specifically, we extract the skill components in various dimensions (e.g. cognitive, manual, interpersonal) from the education and occupation records by linking the raw textual descriptions to the O*NET scores using techniques in textual analysis.[2]

To illustrate the mechanism, we build a matching model in the spirit of Becker (1973) and Sattinger (1993) where for each occupation, workers and firms with heterogeneous

[1] Offshorable occupations are generally associated with routine tasks that are easily codifiable (e.g., Autor et al., 2003; Oldenski, 2012). The work performance in these jobs, in general, does not require direct physical contact; or geographic proximity (e.g., Blinder, 2009; Blinder and Krueger, 2013; Goos et al., 2014).

[2] There is an increasing number of recent studies that conduct empirical analysis using data based on textual information processed through machine learning techniques: Atalay et al. (2018), Gentzkow et al. (2018) Hoberg and Phillips (2016), Michaels et al. (2016), Gentzkow and Shapiro (2010), etc.

attributes competitively find matches to produce occupation-specific outputs. Due to the complementarity in the production function, there is positive assortative matching between workers and firms in equilibrium, and the jointly produced output is shared as wages and profits. In a global economy, firms have the option to match with foreign workers upon paying a fixed cost of offshoring in each occupation.[3] We focus on the North-South framework of offshoring (e.g., Feenstra and Hanson, 1997; Grossman and Rossi-Hansberg, 2008), where only the North finds offshoring a less expensive alternative for production (one-way offshoring).[4]

The model yields several intuitive predictions. First, with additional supply of workers from abroad, domestic workers in offshorable occupations would experience a reduction in wages and face a greater reallocation risk. The flip side of this prediction is that firms are better off as they are able to hire better quality workers at a lower cost. Second, the variance of the worker's wage within offshorable occupations would decrease. While the model mechanism operates within each occupation, since different occupations have different degrees of offshorability, the model also generates predictions across occupations — each of these predictions would be more pronounced in occupations with higher offshorability.

Consistent with the model predictions, we confirm in the Danish data that workers with low cognitive skills are hurt relatively more in terms of reallocation risks compared to high-cognitive workers. Firms improve the average cognitive skill of their in-house workers in response to offshoring, and the extent to which firms improve their quality of workers is greater for low-productivity firms relative to high-productivity firms. We also confirm at the industry level that offshoring increases occupational segregation, which is measured as the variance in the share of offshorable occupations at the firm-level in the Danish data.[5] In order to address the simultaneity concerns, we also use instrumental variables based on the China's export supply to the world excluding Denmark.

A key departure from the offshoring models using a matching framework is the unobservable preference shocks introduced in the matching problem where we follow the marriage market literature (Choo and Siow, 2006; Dupuy and Galichon, 2014) in the assumptions. The main purpose of this extension is to estimate the model and perform counterfactual exercises, which allows to assess the quantitative impact of offshoring relative to other competing concurrent channels, such as technological change (e.g., Acemoglu

[3]The notion of offshoring is similar to Antràs et al. (2006) and Kremer and Maskin (2006) in the sense that it effectively changes the aggregate supply of workers in offshorable occupations.

[4]Burstein and Vogel (2010) and Grossman and Rossi-Hansberg (2012) explore a North-North framework where offshoring occurs between similar countries.

[5]Changes in between-firm inequality requires jointly examining both the within-occupation and between-occupation channels. As the model cannot incorporate any interactions across different occupation types due to properties of matching models, we consider this to be beyond the scope of this paper.

and Autor, 2011; Lindenlaub, 2017) and the expansion of higher education (Kremer and Maskin, 1996), on worker-firm matching and between-firm wage inequality.[6] Using the joint distribution of workers and firms in the Danish data, we estimate the matching model by a moment-matching procedure. The main challenge in the identification lies in the number of offshored matches, which is essentially not observed in the data. To recover the number of offshored matches that are unobserved in the data, we assume that the value-added per domestic worker is the same as the value of offshoring per foreign worker composites. The counterfactual experiments show that technology mainly drives firms to become more different in terms of worker quality and average wages, while offshoring offsets these differences between firms.

This study is related to a small yet growing trade literature that uses matching models[7] to study the distributional effects of globalization: heterogeneous effects of international trade within sector, firm, occupation etc. (e.g., Kremer and Maskin, 2006; Costinot and Vogel, 2010; Grossman et al., 2017). However, these matching models are seldom estimated, particularly in the context of offshoring. In this paper, by introducing unobserved preference shocks à la Dupuy and Galichon (2014), we are able to bring the matching framework to data. To the best of our knowledge, this is the first paper to estimate a worker-firm matching model with offshoring.

Next, this study contributes to the trade literature examining the labor market effects of offshoring. Previous studies (e.g., Feenstra and Hanson, 1997; Hsieh and Woo, 2005; Biscourp and Kramarz, 2007) have focused on changes in wage and employment outcomes in response to offshoring, comparing across broad categories: occupations, education groups etc. More recently, the focus has shifted to further examine the impact of offshoring at a more disaggregate level using administrative data on firms and workers (e.g., Baumgarten et al., 2013; Becker et al., 2013; Hummels et al., 2014). The novelty of our findings is based on the high-quality Danish data together with a full characterization of worker skill, which enable us to examine the distributional effects of offshoring on workers within offshorable occupations and further study changes in the skill composition at the firm-level.

Finally, this project also 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.[8] The potential

[6] Several papers aim to disentangle the impact of technological change and globalization on labor market outcomes (Autor et al., 2015; Bahar Baziki et al., 2015; Hakanson et al., 2015).

[7] Grossman and Maggi (2000) employ a matching model to study the type of production technology determining the pattern of specialization.

[8] e.g., United States (Song et al., 2019), United Kingdoms (Faggio et al., 2007), Germany (Card et al., 2013), France (Abowd et al., 1999), Sweden (Bahar Baziki et al., 2015; Hakanson et al., 2015), Denmark (Bagger et al., 2013; Bagger and Lentz, 2018)

mechanisms proposed in the literature include: technological change (e.g., Autor et al., 2003; Acemoglu and Autor, 2011), outsourcing (e.g., Abraham and Taylor, 1996; Goldschmidt and Schmieder, 2017), international trade (e.g., Helpman et al., 2010; Davidson et al., 2014)[9], and rising skill dispersion (e.g., Kremer and Maskin, 1996; Acemoglu, 1999). We propose offshoring as an important channel that affects between-firm inequality through the occupation composition as well as the worker mix within occupations.

The remainder of the paper proceeds as follows. Section 2 introduces the worker-firm matching model with a fixed cost of offshoring. Section 3 provides data descriptions with details on the skill construction and other measures. Section 4 presents the estimation strategy and results of the reduced-form analysis. Section 5 presents the structural estimation of the matching model and the results of the counterfactual experiments. The last section concludes.

2 Model

2.1 Baseline Economy

We build a Becker-type matching model (Becker, 1973) where for each occupation, workers and firms with heterogeneous attributes competitively find matches to produce occupation-specific outputs. In a global economy, firms have the option to form international teams upon paying a fixed cost of offshoring in each occupation. The notion of offshoring is similar to Antràs et al. (2006) and Kremer and Maskin (2006) where offshoring effectively changes the aggregate supply of workers in offshorable occupations. For estimation purposes, we introduce random preference shocks in the matching problem following Choo and Siow (2006) and Dupuy and Galichon (2014).

Economic Environment There are two sectors (manufacturing and traditional) and multiple occupations in the economy. The manufacturing sector is endowed with a continuum of heterogeneous firms with productivity y, which is a realization of $Y \subseteq \mathbb{R}_+$ with p.d.f. of $\overline{g}(y)$. In each occupational category ($o \in O$), there exists a continuum of inelastically supplied[10] heterogeneous workers characterized by their skills x that contribute to the production process: a realization of $X \subseteq \mathbb{R}_+$, denoted by x with p.d.f of $\overline{f}(x)$. Workers can either partici-

[9] 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.

[10] While interesting analysis arises with matching in relation to workers' choice of occupation, we consider this to be beyond the scope of this paper, as in many previous studies including Grossman et al. (2017).

pate in the manufacturing sector where they match with a firm to produce a task output and earn wages; or sort into the traditional sector where they are offered a constant wage $\underline{w}$ regardless of their skills. Firms may also choose not to operate in the manufacturing sector, which allows them a constant outside option of zero. The distributions of those who take the outside option are denoted as $f_0(x)$ and $g_0(y)$; and those of workers and firms in the manufacturing sector, $f(x)$ and $g(y)$ respectively. By construction, $f_0(x) + f(x) = \overline{f}(x)$, $g_0(y) + g(y) = \overline{g}(y)$.

Production Technology Production in the traditional sector requires workers only; however, in the manufacturing sector, it requires output from each occupation which is generated through matching between a firm and a worker.

$$q(x,y) = xy \tag{1}$$

Occupation-specific outputs are required to produce a final good and there is no complementarity between different occupations in production.[11] The functional form of the task output is a simplified version of a bilinear production technology $\mathbf{x}'\Gamma\mathbf{y}$ where $\mathbf{x} = [x_1, x_2, ...x_n]'$ and $\mathbf{y} = [y_1, y_2, ..., y_m]'$ provide characteristics of workers and firms respectively combined through a production technology Γ, an n-by-m matrix that captures the complementarity between workers and firms across different characteristics. In this section, we use the one-dimensional matching model for simplicity; however, when we structurally estimate the model in Section 5, we use the fully developed multidimensional matching model with unobservable preferences.[12]

Unobserved Preferences In order to allow deviations from pure positive assortative matching[13] that is rarely observed in the real world, unobserved components are introduced closely following Dupuy and Galichon (2014).[14] A worker with skill x maximizes his or her utility, which includes wages and unobserved preferences.

$$\max \ [\underline{w} + \varepsilon_1^o, \ \{\max_y \ w(x,y) + \varepsilon_1(y)\}] \tag{2}$$

[11]Such abstraction is necessary to ensure "existence and tractability" of matching models (Eeckhout and Kircher, 2018).

[12]Note that it is also possible to include worker or firm-specific effects, capturing the extent to which workers or firms contribute to the output independent of the matches. These components can even take nonlinear functions (Dupuy and Galichon, 2014).

[13]Pure matching denotes the case where each x is matched with a unique y, and vice versa. In this case, for each given x or y, there is only one value of y or x for which $\pi(x,y)$ is nonzero, and there exists a one-to-one matching function $\mu : X \rightarrow Y$ and $\mu^{-1} : Y \rightarrow X$.

[14]Their study is a continuous generalization of Choo and Siow (2006) which introduced standard multinomial logit over discrete types into the matching problem.

$\varepsilon_1(y)$ is the unobserved, idiosyncratic preference of the worker for each firm of productivity y; and ε_1^o is the utility the worker gets by sorting into the traditional sector. Analogously, a firm with productivity y maximizes its surplus, which includes profits and unobserved preferences.

$$\max\ [\varepsilon_2^o,\ \{\max_x\ r(x,y)+\varepsilon_2(x)\}] \tag{3}$$

$\varepsilon_2(x)$ is the unobserved, idiosyncratic preference of the firm for each worker of skill x, and ε_2^o is the utility the firm receives by exiting the manufacturing sector. Random preference shocks $\varepsilon_1(y)$, ε_1^o and $\varepsilon_2(x)$, ε_2^o are assumed to follow an extreme value stochastic process with scale parameters λ_x, λ_y capturing the extent to which unobserved heterogeneity plays a role.[15] Each worker with observed skill x has a set composed of random realization of "acquaintances," which follows a Poisson point process on $Y \times R$ of intensity $\exp(-\varepsilon_1)d\varepsilon_1 dy$. As a consequence of the Poisson point process assumption, each individual has an infinite but countable number of acquaintances. Note that a competitive equilibrium requires $w(x,y)+r(x,y)=q(x,y)$.

Equilibrium Matching and Wages Using properties of generalized extreme value distributions, the equilibrium matching between workers and firms as well as equilibrium wages are given as follows,[16]

$$\pi(x,y) = \hat{a}(x)\hat{b}(y)\exp(\frac{q(x,y)}{\lambda}) \tag{4}$$

$$w(x,y) = \frac{\lambda_x(q(x,y)-b(y))+\lambda_y a(x)}{\lambda} \tag{5}$$

where $\lambda_x+\lambda_y=\lambda$; $\hat{a}(x)=\exp(-\frac{a(x)}{\lambda})$; and $\hat{b}(y)=\exp(-\frac{b(y)}{\lambda})$.[17] Note that the wage depends not only on x but also on y due to the unobserved heterogeneity components.[18] Greater values of λ generate a matching that is closer to a random match whereas small λ implies a matching that primarily relies on observed characteristics. Also, $a(x)$ and $b(y)$ correspond to Lagrange multipliers on the scarcity constraint $f(x)=\int \pi(x,y)dy$ and $g(y)=\int \pi(x,y)dx$. Therefore, higher values of $a(x)$ indicate scarcity in workers with observed characteristics x which results in greater extraction of the produced task output while a large $b(y)$ would benefit

[15] In order to maintain the analytical tractability of the standard logit problem with discrete choice, the same scale parameter σ_x is used for both the outside option and for each of the matching options y. See Appendix C for further details on the random shock process.

[16] See Appendix B for derivation of equilibrium matching and wages.

[17] $a(x)=\lambda_x \log\frac{\int \exp(\frac{w(x,y)}{\lambda_x})dy}{f(x)}$; $b(y)=\lambda_y \log\frac{\int \exp(\frac{r(x,y)}{\lambda_y})dx}{g(y)}$;

[18] As this unobserved heterogeneity converges to zero, $w(x,y)\to w(x)$ and $r(x,y)\to r(y)$.

firms' profits. See Appendix C for the details on the characterization of the exogenously given marginal distributions and also on how we solve the model equilibrium.[19]

2.2 Global Economy Equilibrium

With globalization, domestic firms have the option to match with foreign workers upon paying an occupation-specific fixed cost of offshoring. Similar to Antràs et al. (2006), we refer to improvements in the information communication technology (ICT), or economic reforms in China or Eastern European countries followed by increased participation in global economic activities as forces of *globalization* that reduce the cost of offshoring.

Global Economic Environment Foreign is endowed with workers with observed skill x_F a realization of X_F with p.d.f of $\overline{h}(x_F)$ in each occupation o. For simplicity, only the traditional sector exists in Foreign, which is populated with self-employed workers that earn a constant income of $\underline{w}_F$. The marginal distributions of agents in a global economy are denoted as follows: $\overline{f}(x) = f_0(x) + f(x)$, $\overline{h}(x_F) = h_0(x_F) + h(x_F)$, and $\overline{g}(y) = g_0(y) + g(y) + g_F(y)$ where those with a subscript zero denote agents who are not in the manufacturing sector.[20]

Production with Offshoring The output when matched with a Foreign worker, $q_F(x_F, y)$, is as follows:

$$q_F(x_F, y) = q(x_F, y) - C = x_F y - C \tag{6}$$

Here, we assume that the firm's productivity level y does not change with respect to the location of operation while the model can incorporate a more general form of technology.[21] A simple way would be to allow for the coefficient on $x_F y$ to be different from 1. We maintain this simple form to understand the mechanism in this section; however, when we do a structural estimation in Section 5, we estimate the value of coefficients using data.

In the global economy, firms have the option to match with foreign workers upon paying a fixed cost of offshoring in each occupation where the cost is associated with managing production processes of each intermediate good overseas that often involves a significant level of organizational complexity as it limits the opportunities for monitoring

[19] There is a straightforward iterative algorithm proposed in Bojilov and Galichon (2016); referred as the "Iterated Proportional Fitting Procedure (IPFP)" or "Sinkhorn's algorithm." to recover all other endogenous objects, including the matching function $\pi(x, y)$ as well as wages $w(x, y)$ and profits $r(x, y)$.

[20] In addition, $\int f(x)dx = \int g(y)dy = \int\int \pi(x, y)dxdy$, and $\int h(x_F)dx_F = \int g_F(y)dy = \int\int \pi_F(x_F, y)dx_F dy$, where $\pi(x, y)$ and $\pi_F(x_F, y)$ are the density functions that describe the realized pattern of matching with Home and Foreign workers, respectively.

[21] Ramondo and Rodríguez-Clare (2013) examine multinational firm activities and how the firm's technology potentially differs depending on the location of operation .

and coordinating workers (Grossman and Rossi-Hansberg, 2008). The per-match aspect of the cost reflects the model mechanism where offshoring firms seek to match with the best possible foreign workers[22] in the global economy (Alchian and Allen, 1983).[23]

Each firm's decision to offshore depends on the benefit of matching with foreign workers and the cost associated with hiring them. Conditional on the cost of offshoring, which decreases with globalization, firms would only find offshoring profitable when foreign workers demonstrate competitive skill-levels to their domestic workers. However, it is difficult to define a skill measure that is comparable across countries nor is it available in the data. So instead, we focus on the notion of worker composites from Foreign that can be comparable to one Danish worker that the firm hires.

Firms solve the profit maximization problem by optimally choosing the best possible worker from each country and comparing profits.

$$\max\ [\varepsilon_2^o,\ \max_x\{r(x,y)+\varepsilon_2(x)\},\ \max_{x_F}\{r_F(x_F,y)+\varepsilon_{F2}(x_F)\}] \tag{7}$$

$\varepsilon_2(x)$, $\varepsilon_{F2}(x_F)$, and ε_2^o are the unobserved, idiosyncratic random shocks of the firm for a Home worker x, a Foreign worker x_F, and exiting the sector, respectively. Analogously, each worker from Home and Foreign maximizes his or her utility, which includes wages and preferences as follows.

$$\begin{aligned} \max\ [\underline{w}+\varepsilon_1^o,\ \max_y\{w(x,y)+\varepsilon_1(y)\}] \\ \max\ [\underline{w}_F+\varepsilon_{F1}^o,\ \max_y\{w_F(x_F,y)+\varepsilon_{F1}(y)\}] \end{aligned} \tag{8}$$

$\varepsilon_1(y)$ and ε_1^o ($\varepsilon_{F1}(y)$ and ε_{F1}^o) denote the unobserved, idiosyncratic random shocks of the Home (Foreign) worker for firm y and sorting into the traditional sector respectively. Note that $w(x,y)$, $w_F(x_F,y)$, $r(x,y)$, $r_F(x_F,y)$ are endogenous objects to be determined in equilibrium. Again, a competitive equilibrium requires $q(x,y) = w(x,y) + r(x,y)$ and $q_F(x_F,y) = w_F(x_F,y) + r_F(x_F,y)$.

While features of globalization lower costs related to transportation and communication or even institutional factors such as tariffs, the extent to which the cost C decreases is occupation-specific, which depends on the nature of the task. That is, a decline in C would be trivial for occupations that perform nonroutine tasks that require direct physical contact and geographic proximity, i.e. *non-offshorable* occupations. Even for occupations that

[22]Note that the foreign worker endowment should be interpreted as worker composites whose skills are comparable to domestic ones in a one-to-one manner. Therefore, the notion of "quality" of foreign workers is in efficiency units of labor, which consistently applies to firms hiring foreign labor in greater quantities taking advantage of the low cost.

[23]The Alchian-Allen effect demonstrates how in the presence of a per unit cost consumption shifts towards high quality goods, and in the context of international trade,"shipping the good apples out."

demonstrate high offshorability, there exists a cost component that remains high for firms to operationalize offshoring: the inherent cost associated with managing production processes of each intermediate goods overseas, which involves a significant level of organizational complexity. In fact, it is often observed to be mainly concentrated in firms that are more productive, larger, older, and capital-intensive (Hummels et al., 2014; Monarch et al., 2017). The implied cost may be even higher if countries where offshoring is performed do not have the institutions that effectively enforce intellectual property rights (IPR) on firm-specific innovations embodied in the production process. To reflect these empirical regularities, we further assume the following.

Assumption 1 The cost of offshoring is greater than the traditional sector's wage gap: $C > \underline{w} - \underline{w}_F$.

It is worth mentioning that, it may not be sensible to make one-to-one comparisons of workers' talent across countries, especially in a North-South framework that we intend to bring to data, in the context of offshoring. For example, the fact that a Danish firm chooses to hire workers from low wage countries through offshoring should not have the interpretation that workers from low wage countries are more skilled than Danish ones. Thus, in order to model offshoring in a way that indicates the possibility of substituting home workers, we characterize the foreign worker endowment as *worker composites* whose skills are comparable to the domestic ones at a fixed ratio that we exogenously impose.[24] The value of the ratio does not affect the analysis as the final quality of skill provided through a match is what counts, whether it is a single worker or a bundle of workers.[25]

Global Economy Equilibrium Matching and Wages Again, using properties of generalized extreme value distributions, the equilibrium matching between workers and firms as well as equilibrium wages and profits are given as follows,[26]

$$\pi(x,y) = \hat{a}(x)\hat{b}(y)\exp(\frac{q(x,y)}{\lambda}) \quad \text{and} \quad \pi_F(x_F,y) = \hat{c}(x_F)\hat{b}_F(y)\exp(\frac{q_F(x_F,y)}{\lambda_F}) \tag{9}$$

$$w(x,y) = \frac{\lambda_x(q(x,y) - b(y)) + \lambda_y a(x)}{\lambda} \quad \text{and} \quad w_F(x_F,y) = \frac{\lambda_{x_F}(q(x_F,y) - b_F(y)) + \lambda_y c(x_F)}{\lambda_F} \tag{10}$$

[24]In a fully developed model, the ratio would depend on the wage differences between two different locations.

[25]The same framework can be applied to examining changes in worker-firm matching when firms gain opportunities to adopt automation technology. See Appendix C for further analysis on the worker-firm matching problem when, instead of foreign workers, there is a machine that replaces a subset of workers with certain level of skills.

[26]See Appendix C for the derivation of equilibrium matching and wages.

where $\lambda \equiv \lambda_x + \lambda_y$, $\lambda_F \equiv \lambda_{x_F} + \lambda_y$, $\hat{a}(x) \equiv \exp(-\frac{a(x)}{\lambda})$, $\hat{b}(y) \equiv \exp(-\frac{b(y)}{\lambda})$, $\hat{c}(x_F) \equiv \exp(-\frac{c(x_F)}{\lambda_F})$, $\hat{b}_F(y) \equiv \exp(-\frac{b_F(y)}{\lambda_F})$. We show in Appendix C that $\hat{b}_F(y) = \hat{b}(y)^{\frac{\lambda}{\lambda_F}}$ must hold, which allows for a simple characterization of the equilibrium under offshoring.[27]

Numerical Exercise Here, we examine the model implications derived using an example setting the parameter values as $\lambda = 1$ and $\sigma = 1$. For simplicity, we additionally assume uniform distributions $X \sim U[0,1]$, $X_F \sim U[0,1]$, and $Y \sim U[0,1]$; and further impose $\underline{w} = \underline{w}_F$.

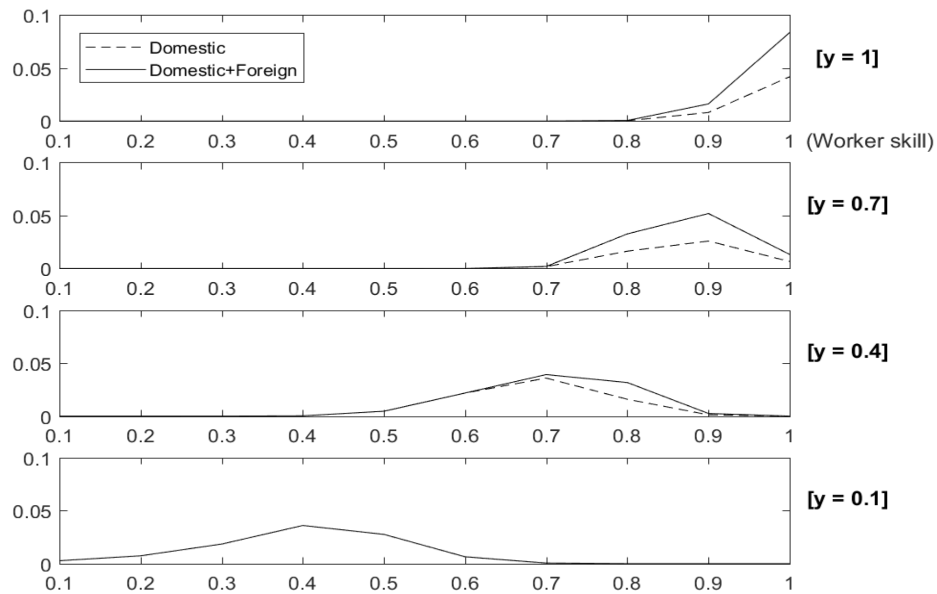

Figure 1: Equilibrium Matching of Workers for Each Firm-type

Each panel shows the probability mass of workers for each firm-type y under closed economy and global economy. The share of foreign workers is captured in the area between the dashed and the solid lines.

First, due to the fixed cost associated with offshoring, firms with higher values of y face a greater probability of matching with foreign workers (Figure 1). Note that in the special case of the model where $\lambda = 0$ and the upper bound of the Foreign endowment is greater compared to that of Home, the model predictions regarding "who offshores" are consistent with Helpman et al. (2004): high-productivity firms strictly prefers to offshore. In particular, if the wage differences between home and foreign are large, allowing domestic firms to hire foreign workers in greater quantities, it is possible that the skill output of these foreign worker composites is high enough that there are no home workers to compete with the corresponding level of skill output.

[27] See Appendix C for full derivation of the equilibrium.

Next, firms improve upon the quality of their domestic worker match while workers undergo a downward transition in the match quality (Figure 2). Due to the formation of international teams in offshorable occupations, the demand for domestic workers within these jobs decreases, which consequently drives out the least productive workers at the bottom end of the worker distribution to the traditional sector. Thus, within occupations that are highly exposed to offshoring, the less skilled workers face a greater risk of reallocation with globalization.

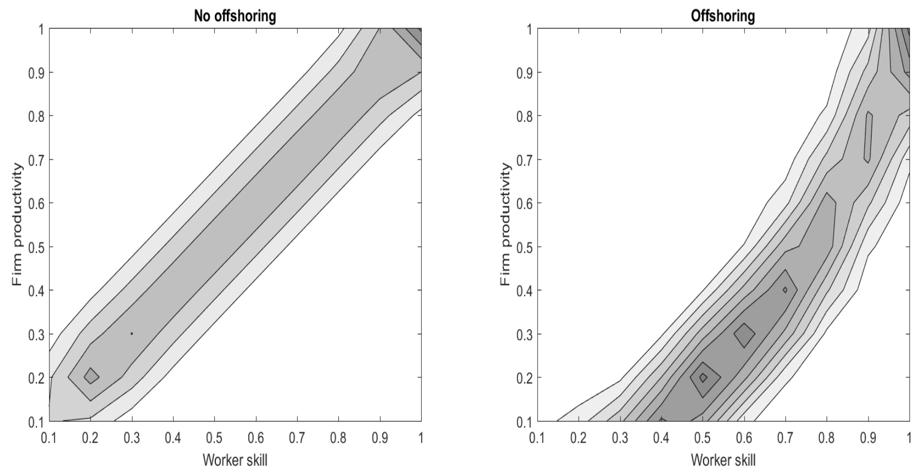

Figure 2: Equilibrium Matching between Firms and Domestic Workers

Finally, as workers in offshorable occupations become less expensive with a decline in the cost C, the overall wage-level falls for these workers domestically. Note that when the cost of offshoring becomes negligible ($C \to 0$), which indicates a convergence to a perfectly integrated world economy, the wage profile does not differ between workers from home and foreign within these jobs.[28] This is the labor supply effect identified in Grossman and Rossi-Hansberg (2008) where "factor prices respond to factor supplies." Further, comparing across occupations that differ in their offshorability,[29] offshoring facilitated by features of globalization magnifies inequality in wages, which resonates with the wage inequality results in Feenstra and Hanson (1996), Zhu and Trefler (2005), and Costinot and Vogel (2010).[30]

[28] See Appendix C for analysis with the economy setting $\lambda = 0$.

[29] If firms increase their demand for non-offshorable occupations as a result of an expansion in size, this would increase the wage for non-offshorable occupations, which would amplify the wage inequality between offshorable and non-offshorable occupations.

[30] 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. See Appendix A for changes in profits in the simulation exercise.

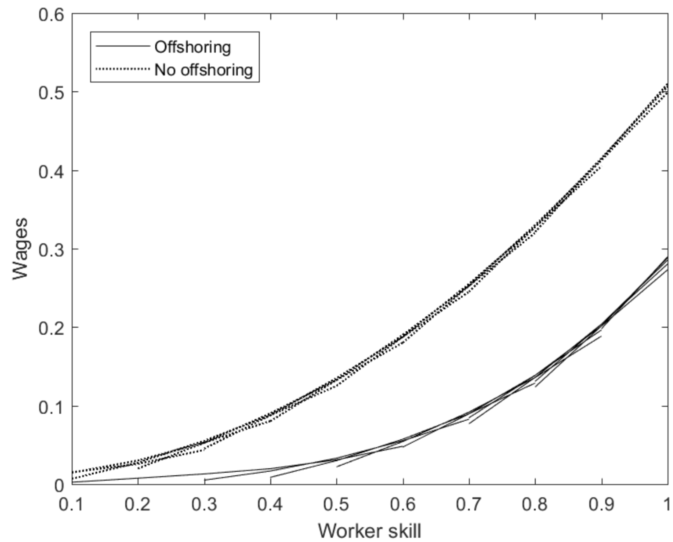

Figure 3: Equilibrium Wage Profile

2.3 Between-Firm Inequality in a Global Economy

So far, we have examined how offshoring by high-productivity firms, facilitated by globalization, increases competition from foreign workers in offshorable occupations domestically. As a result, within offshorable jobs: (i) domestic workers undergo a wage loss, (ii) switch down their firm matches, and (iii) the least skilled workers reallocate to the traditional sector. What implications does the model provide in terms of between-firm inequality? We discuss the extent to which firms diverge or converge in their occupational composition, their worker composition within occupations, and the average wages they pay.

Occupational Segregation With globalization, firms become increasingly different in their occupation composition. That is, occupational segregation across firms increases with offshoring. As noted earlier, channels of globalization only affect the cost of offshoring by lowering the transactional component (Fort, 2017; Benfratello et al., 2015). As a result, high productivity firms that are both technologically and managerially better equipped to produce outside the boundaries of the firm can engage in offshoring activities and replace their in-house workers while those that are not keep their offshorable occupations. In a sense, offshoring technology functions as one of the key mechanisms that drives firms to differentiate themselves in their demand for occupations, causing higher degrees of occupational segregation across firms.[31]

[31]As examined in previous studies such as Goldschmidt and Schmieder (2017) and Handwerker (2015), domestic outsourcing is one of the other important channels through which occupational segregation increases in the economy.[32] However, there are important distinctions between the two in terms of *how* the distribution

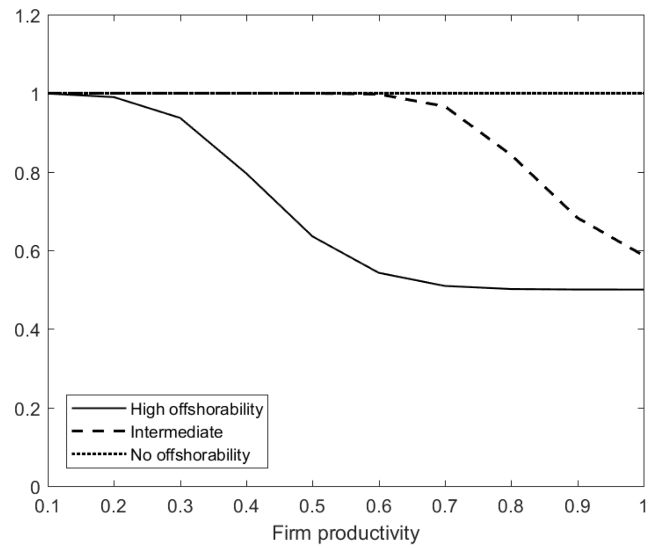

Figure 4: Occupation Composition across Firms under Global Economy

We show, for each firm-type y, the probability of keeping different occupation categories in-house, which vary in offshorability.

The model also generates predictions on the between-occupation channel (Figure 4). High-productivity firms replace their in-house workers in offshorable occupations whereas low-productivity firms that cannot afford offshoring have no choice but to keep all occupation types within their firm boundaries. Thus, with offshoring possibilities, high-productivity firms become more homogeneous in their occupation mix by replacing the offshorable occupations whereas low-productivity firms keep both offshorable and non-offshorable occupations in-house.

Within-Occupation Segregation by Skill With greater exposure to offshoring, firms are able to hire better domestic workers within offshorable jobs in terms of skill levels than before; and the type of workers they hire become more similar across the distribution of firms. In other words, within offshorable jobs, there is a decrease in segregation by skill, in addition to skill upgrading. As shown in the results earlier, domestic workers within offshorable jobs that are exposed to competition from foreign workers switch down their

of occupations across firms is affected. In comparison to outsourcing, offshoring involves a higher cost due to monitoring and managing production overseas in addition coordinating differences in institutions that affect economic activities, etc. As a result, a firm's decision to participate in offshoring hinges on the firm's productivity, which subsequently affects its occupational demand differentially even among firms that have the same core competency. Domestic outsourcing, however, mainly shapes occupational segregation in a way that results in an economy with firms specialized in what they identify as the core of their production.

firm matches, and the least skilled ones reallocate to the traditional sector. As a result, firms face a pool of domestic workers that are better in their overall quality and that demonstrate increased homogeneity. The implications are reminiscent of Melitz (2003) where increased forces of competition driving out the least productive firms.

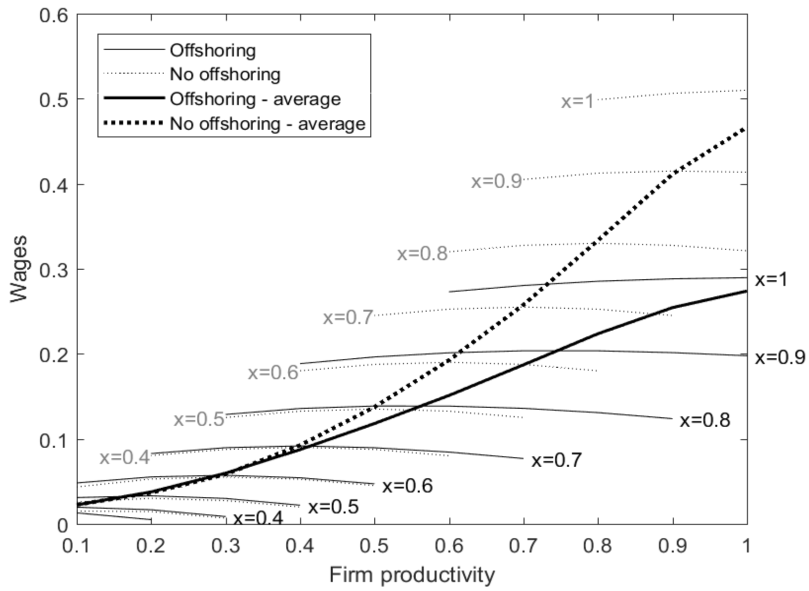

Figure 5: Equilibrium Wages

Between-Firm Wage Inequality For domestic workers with occupations that are vulnerable to foreign competition under the global economy, the average wage firms pay also becomes similar across. As mentioned earlier, workers within offshorable jobs undergo a wage loss, with high-skill workers that face direct foreign worker competition losing more. That is, the wage dispersion within offshorable jobs decreases. Note that the overall between-firm wage inequality combining across occupations should depend on the magnitude of within-occupation versus between-occupation channel. While the within-occupation channel operates in the direction of making firms become more similar in their average wages to workers in offshorable occupations, the between-occupation channel potentially amplifies the differences across firms. That is, as high-productivity firms trim down their offshorable occupations in-house, the average wage for their domestic workers increasingly depend on workers in non-offshorable jobs. Low-productivity firms, on the other hand, keep both the non-offshorable jobs and offshorable jobs in-house, and therefore, the average wage they pay reflects the overall wage loss workers with offshorable occupations have undergone with globalization taking place.[33] In the following section, we use the Danish matched

[33] Although the model does not explicitly feature across-occupation interactions that would allow us to

employer-employee data to empirically test the predictions of the model.

Offshoring by high-productivity firms, facilitated by globalization, generates distributional effects in the labor market:
1. Occupational segregation across firms increases.
2. Within offshorable occupations, firms improve upon their worker matches, thereby decreasing between-firm inequality in average worker quality and average wages.

3 Data

Denmark is a small open economy, which is part of the European Union (EU), and has limited power in affecting trade policies according to its domestic economic environment. Thus, changes in the economic environment faced by Danish firms due to China's entry to WTO and subsequent changes in the quota policies on Chinese products or the enlargement of the EU to include Eastern European countries are exogenous variations that affect Danish firms' incentives to offshore their production. The labor market impact of these shocks facilitated by globalization is more prominent when the labor market demonstrates flexibility compared to a centralized market where collective bargaining prevails (Hummels et al., 2014).

Since the major labor market decentralization in 1989, Denmark has been shifting away from centralized collective bargaining to a decentralized system: between the years 1995 and 2004, firm-level wage bargaining grew from a coverage of 11% to 22%. The decentralization process was initiated by the firm side to negotiate wage contracts at the worker-firm level as they found the standard-rate system[34] not flexible enough to incorporate changes led by forces of globalization or technological change (Dahl et al., 2013). In fact, the Danish labor market currently exhibits great flexibility with average tenure comparable to Anglo-Saxon countries; and these high turnover rates are accompanied by a well-designed social security system which provides generous unemployment benefits yet incentivizes the unemployed to search for jobs actively.[35] Hence, Denmark is a good candidate country to examine labor market responses to changes in the global economic environment in the past two decades.

quantitatively evaluate the magnitudes of each channel, it is still useful to think about how the two channels qualitatively operate in different directions in terms of between-firm wage inequality.

[34]The wage bargaining occurred at the industry level.

[35]It is characterized by a "flexicurity model," which comprises three components: (i) considerable flexibility for firms right to hire and fire employees; (ii) an extensive social safety net in case of unemployment; and (iii) active labour market policies where the entitlement to compensation in the event of unemployment is countered by the obligation to actively seek a job and to participate in job-related activities (Kristofferson, 2016).

3.1 Data Source and Baseline Sample

We use the Danish register-based Matched Employer-Employee panel (1995-2011), which provides the universe of private firms and the population of individuals matched through their unique identifiers. The database includes variables on standard individual socioeconomic characteristics and detailed firm characteristics. Data on international trade comes from UHDI that records from Denmark's customs in addition to firm-level reports to Statistics Denmark regarding any trade activities (1993-2013) (Keller and Utar, 2016). It contains firm-level international transactions of goods (weight and value) observed at a triplet of year-country-product (8-digit product classifications according to the Combined Nomenclature (CN) system). We further utilize the U.S. Department of Labor Occupational Characteristics Database (O*NET), the successor of the Dictionary of Occupation Titles (DOT), to obtain factor descriptions of occupation-specific skill and task requirements in the skill construction. More specifically, O*NET provides information on key features of occupation-specific requirement for knowledge, skills, and abilities in standardized measures on almost 1,000 occupations covering the entire U.S. economy. The data is collected by surveying job incumbents or occupation experts, and updated frequently to keep up with changes in the occupation structure over time.

The empirical analysis uses the Matched Employer-Employee panel as the baseline panel focusing on the period 1995-2004, with the unit of observation as an individual each year. We trim the data in the following way: we drop observations with missing identification codes for individual, firm or industry. We also disregard individuals with age below 20 and above 65 and those with missing occupation codes or military-related occupations. We focus on the manufacturing sector only, leaving out retail, service and public sectors. we follow (Bagger et al., 2013) and further trim the top and bottom 1% of each education and experience subgroup. Merging the trade register, with observations provided at the product-level transaction for each firm-year, to the baseline sample, we work with 5,305,975 observations with the unit of observation as an individual each year that include 28,276 firms through 1995-2004. Wages are CPI-adjusted to the level of 1995.

3.2 Construction of Measures

Skill Supply We construct a vector of skills (cognitive, manual and interpersonal skills) for each individual using (i) the highest obtained education (*hfaudd*), and (ii) the highest completed professional training (*erhaudd*)[36] together with one's occupation tracked through-

[36]Vocational education in Denmark tends to be between 2.5 to 5 years long which includes periods of formal schooling and apprenticeships (Keller and Utar, 2016). For example, vocational training for a blacksmith involves 2.5 to 5 years of education depending on the specialization choice. And the baseline training period

out 1995-2004.[37] There are 2449 different types of education and job training records in the Danish data described in detailed textual information (e.g. B.A. in Engineering, Jewelry Designing, etc.). The strength of this measure lies in the great heterogeneity of worker skill, reflecting rich information on both education and occupation, which allows us to examine the quality of worker skills at the firm-level within different occupation categories. It is particularly useful investigating the skill quality of workers between firms since, unlike wages, the measure is independent of the firm component.

In order to construct quantifiable measures of skill, we proceed in the following three steps. First, we create a mapping between the education records and the most relevant occupation, assuming that an individual's educational attainment or job training reflects his or her ability to perform tasks required in a particular occupation. The mapping is

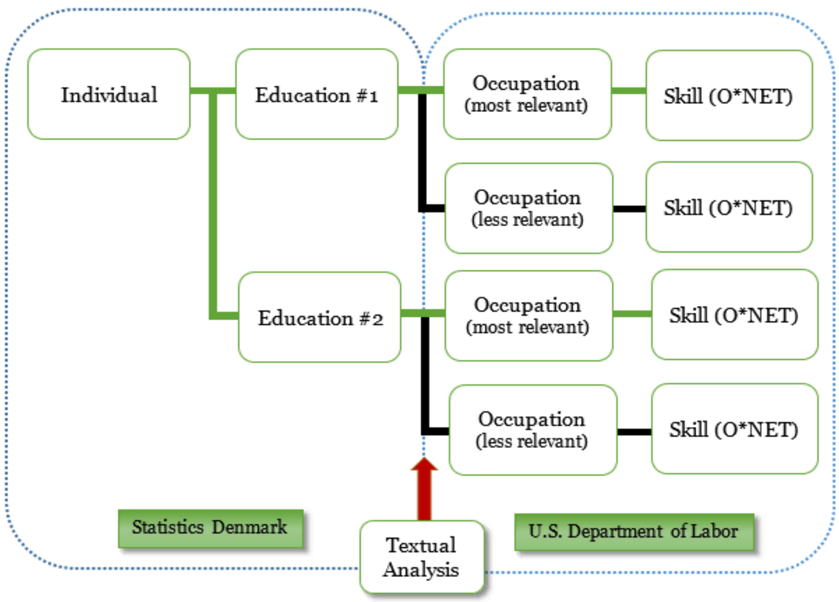

Figure 6: Mapping Education to Skill

generated employing the Continuous Bag of Words (CBOW) Model, which examines the similarity of the context in which education records and occupations appear in Wikipedia.[38] We further do a robustness check of the data construction using the *O*NET code connector*

is followed by formal schooling which includes blocks of internships providing opportunities to practice in actual workplaces (`https://www.ug.dk`).

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

[38] The algorithm employed in the skill construction can be utilized in different data sets with rich textual information. Note that there is an increasing number of recent empirical studies that use textual data processed through machine learning techniques: Atalay et al. (2018), Gentzkow et al. (2018), Hoberg and Phillips (2016), Michaels et al. (2016), Gentzkow and Shapiro (2010), etc.

where we feed in keywords collected from education and job training records and obtain the most relevant occupation. See Appendix A for further details.

Second, we use the O*NET data to obtain occupation-specific factor descriptions. There is no Danish version of O*NET data that we can utilize, hence, we assume that the occupation-specific task and skill requirements measured in the U.S. are similar to those in Denmark. Then, we reduce down the dimensionality of the data on occupation-specific standardized descriptors to cognitive, manual, and interpersonal skills, using principal component analysis. More specifically, we collect standardized descriptors in the following categories, in importance scales, reported at the O*NET-SOC-level: "cognitive abilities" in O*NET Abilities (1.A.1.a.1 - 1.A.1.g.2), "psychomotor and physical abilities" in O*NET Abilities (1.A.2.a.1 - 1.A.3.c.4), and "social skills" in O*NET Skills (2.B.1.a - 2.B.1.f). Then, we perform principal component analysis in each category and reduce the dimensions by taking the first principal component.[39]

So far, we have explained how we obtain a vector of cognitive, manual, and interpersonal skills using individuals' records in education attainment and professional training. In the final steps of skill assignment in the data, we incorporate the occupation-specific skills obtained using information on one's occupation choice at the 2 digit-level. For each point in time t, we add the two skill vectors to impute the individual skill scores:

$$s_{it} = \alpha s^o_{it} + (1-\alpha)s^e_{it} \quad \text{where} \quad \alpha > 0, \quad s^o_{it} = [c^o, m^o, p^o], \;\; s^e_{it} = [c^e, m^e, p^e] \tag{11}$$

Due to occupation switching or additional training, the skill values under the current construction may vary over time. Assuming that each experience through a job or institutional training provides value-added in one's skill accumulation, we compare the skill vector in time t (s_{it}) with that in time $t+1$ (s_{it+1}) and take the maximum of each skill component and replace the skill vector in time $t+1(s'_{it+1})$.

Firm Productivity We proxy firms using various measures: size, value-added, capital-intensity, and total factor productivity in the initial year of operation, which we obtain using methods in Olley and Pakes (1996). See Appendix A for details on the construction of measures.

Offshoring The measure of offshoring in this study is constructed using the value of firm-level imported intermediate and final goods from abroad that are utilized in the production

[39]The methodology we follow is adopted from existing studies such as Postel-Vinay and Lise (2015) and Goos et al. (2014), etc. that utilize the O*NET database in constructing multidimensional skill or task measures. To provide robustness on how the skill construction does not rely on the *a priori* skill categorization assigned in O*NET, we take all the descriptors and perform PCA obtaining the principal components, which demonstrate high correlation with the cognitive, manual, and interpersonal skills constructed above.

process and potentially substitute in-house workers, as in Hummels et al. (2014). In doing so, we exclude imports of raw materials[40] and only consider transactions that are in the same industry category as the firm's final good production: *narrow offshoring* (Feenstra and Hanson, 1999). Furthermore, focusing on the manufacturing sector in the case of Denmark ensures that the purpose of these purchases is not reselling for direct consumption (Hummels et al., 2014).[41] We also note that this measure of offshoring 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.

The measure of offshoring in the reduced-form analysis is the industry-level offshoring exposure from low wage countries (Bernard et al., 2006). Following the literature (Feenstra and Hanson, 1999), we define and identify offshoring using firm-level data on intermediate and final good purchases from abroad in the Danish trade registers.[42] In particular, we utilize purchases that are used as inputs in the final good production and also serve as potential substitutes for in-house workers (Hummels et al., 2014). We aggregate these firm-level offshoring at the industry-level.

We focus on the North-South framework of offshoring (Feenstra and Hanson, 1997; Grossman and Rossi-Hansberg, 2008) where only the North finds offshoring a less expensive production alternative (one-way offshoring), and look into the intermediate and final goods purchases from low wage and eastern European countries (henceforth, simply 'South'). Low wage countries are defined as those with less than 5% GDP per capita relative to the U.S. during 1972-2001 (Bernard et al., 2006). The eastern European countries of interest are those that were included in the European Union through the Eastern Enlargement: Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia, Slovenia, Malta, and Cyprus. Separately looking into offshoring from low wage countries provides substantive importance in thinking about changes in the feasible worker-firm matches. Due to recent institutional changes that integrate these countries into the global economy (e.g. China's accession to WTO (December 11th, 2001) and the Eastern Enlargement of EU (May 1st, 2004)),

[40] To identify raw materials, we follow Eurostat and use the definitions of goods according to the fourth revision of Standard International Trade Classification (SITC rev. 4) section 2 (crude materials, inedible, except fuels) and section 4 (animal and vegetable oils, fats and waxes).

[41] There are challenges faced by empirical studies examining offshoring as they lack data sources that comprehensively cover offshoring activities. Looking into offshoring through imported intermediate and final goods, for example, fails to capture any offshoring activities through multinational activities of firms or the final assembly offshoring (Park, 2018).

[42] Offshoring in this paper means that the firm chooses to match with foreign workers instead of home workers. In bringing this notion to data, we use firm-level purchases of intermediate and final goods, which are interpreted as the embodiment of foreign workers' human capital and value-added. For example, if Danish firms purchase industrial robots from South Korea, this can be interpreted as Danish firms matching with South Korean workers whose value-added is captured in the form of robots.

labor endowments that demonstrate clear differences in terms of skill composition, skill abundance, etc. have become easily accessible and further expanded economic activities worldwide.[43] In our sample, the share of offshoring from low wage and eastern European countries more than doubled, from 1.8% to 4.1%, and from 4% to 10% each. As for low wage countries, the share of offshoring from China increased from 47% to 82%.

Occupational Offshorability We mainly follow Blinder and Krueger (2013) to measure occupational offshorability at the ISCO two-digit level and to categorize occupations as offshoreable or non-offshoreable. Blinder and Krueger (2013) utilizes household survey measurements of job offshorability.[44] 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). Also, offshorable 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). However, as the focus of this paper is on offshoring activities in the manufacturing sector, we classify the following occupations as offshorable: stationary plant and related operators; other craft and related trades workers; precision, handicraft, craft printing and related trades workers; machine operators and assemblers.

4 Empirical Evidence

Here, we examine how greater exposure to offshoring from the South affects changes in the distribution of occupations across firms at the industry level, the employment composition at the firm level, and reallocations at the worker level.

Identification Strategy for Offshoring In each of the analysis below, the exogenous variation is the over time reduction in the cost of offshoring (e.g. tariffs) at the industry or the product level due to institutional changes: China's accession to the WTO and the eastern enlargement of EU. However, lowering of tariffs through such institutional changes has also

[43]In particular, the rise of China constitutes perhaps one of the most important trade shocks from low wage countries to hit the northern economies (Keller and Utar, 2016). 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)

[44]The literature offers several different ways to capture the degree of offshorability at the occupation-level: Autor et al. (2003), Blinder (2009), Goos et al. (2014). To ensure that our results are not sensitive to the offshorability measure used to categorize occupations, we also try different measures following these existing studies. See Appendix A for details regarding comparisons between the measures.

increased trade flows at the final goods level and thereby affected labor market outcomes through the labor demand channel as well. We complement this strategy in the following two ways: First, we add time-varying and time-invariant controls to capture other factors at the industry level or firm level that potentially correlate with offshoring. Second, we employ an instrumental variable to address concerns regarding unobserved industry-level adjustments or industry-specific characteristics that change firms' incentives to offshore, re-ogranize the production process or the workforce, which also affect workers' reallocation risks. The instrument is similar to Hummels et al. (2014) and Baumgarten et al. (2013),

$$I_{kt} = \sum_{h} s_{hk0} \times \text{WES}_{ht} \tag{12}$$

where WES_{ht} is the export supply of product h from China to the world excluding Denmark in time t and $s_{hk0} = \frac{\text{Offshoring}_{hk0}}{\text{Offshoring}_{h0}} = \frac{\text{Offshoring}_{hk0}}{\sum_k \text{Offshoring}_{hk0}}$ is industry k's contribution to total offshored product h in the pre-sample period in Denmark where Offshoring_{hk0} is the value of offshoring in product h for industry k in the pre-sample period and aggregating this measure across all industries, $\sum_k \text{Offshoring}_{hk0}$ generates the total value of offshoring in product h in that year, which we denote as Offshoring_{h0}. In a nutshell, we combine the product-level export supply from China to the world excluding Denmark weighted by initial industry shares in offshoring of each product in Denmark. Note that we primarily focus on China as most of the change in offshoring from the South is driven by China. Therefore, the instrument, which has a product-time variation, is correlated with the value of Danish firms' purchases from low wage countries, but is external to the firm-level or worker-level labor market outcomes in Denmark. We further discuss how we address potential threats to the validity of the instrumental variable in each of the regressions below.

4.1 Occupational Segregation

Industry-level Analysis In order to examine the distributional effects of offshoring in terms of the degrees of occupational segregation by offshorability, we begin with the following industry-level regression.

$$\text{Segregation}_{kt} = \alpha_0 + \alpha_1 \text{Offshoring}_{kt} + \eta_k + \eta_t + \varepsilon_{kt} \tag{13}$$

Offshoring_{kt} is the share of narrow offshoring from low wage countries and eastern European countries in the aggregate value of offshoring in industry k. The dependent variable Segregation_{kt} captures the degrees of occupational segregation across firms in industry k using the segregation index (Kremer and Maskin, 1996), which is the ratio of the between-firm variance and the total variance.

$$\rho_{kt} = \frac{\text{Between-firm variance in industry } k \text{ in time } t}{\text{Total variance in industry } k \text{ in time } t} = \frac{\sum_{i,j}(\overline{x}_{jkt} - \overline{x}_{kt})^2}{\sum_{i,j}(x_{ijkt} - \overline{x}_{kt})^2} \tag{14}$$

We assign $x_{ijkt} = 1$ if worker i in firm j and industry k has an offshorable occupation according to the previously defined categories in time t. So $\overline{x}_{jkt}$ indicates the share of offshorable occupations in firm j that operates in industry k in time t, and $\overline{x}_{kt}$, the share of offshorable occupations in industry k in time t.[45] Thus, the segregation index captures the *variance in the share of offshorable occupations at the firm-level*, $\frac{\mathrm{Var}(\overline{x}_{jt})}{\overline{x}_t(1-\overline{x}_t)}$. In attempts to address concerns that certain industries that are inherently more segregated in their occupational structure potentially facing greater exposure to offshoring from the South, industry fixed effects (η_k) are included to control for time-invariant industry characteristics. We also add year fixed effects (η_t) to control for time-varying macroeconomic shocks such as the business cycle that potentially affect both offshoring intensity and the distribution of occupations. Thus, the coefficient α_1 captures the within-industry-over-time variation in the degree of matching due to changes in offshoring, net of aggregate time trends.

The degree of occupational segregation can be affected by time-varying industry components such as (i) the level of technology adoption (Acemoglu (1999), Albrecht and Vroman (2002)); (ii) other major global engagement activities such as exporting (Davidson et al., 2014); and (iii) domestic outsourcing (Goldschmidt and Schmieder, 2017). To disentangle the effect of offshoring from the effects of these channels, we further add technology intensity, export intensity, and domestic outsourcing intensity as controls. Technology intensity is constructed by taking the share of technical equipment and machinery in the capital stock. We use the sum of export value normalized by aggregate production for each industry to construct export intensities. Finally, we identify outsourcing activities[46] using the sum of variables on the cost of intermediate goods, the cost of subcontractors, and the cost of temporary employment agencies normalized by value-added.[47] To control for any time-varying industry-specific demand or technology shocks that demonstrate correlations with offshoring from the South, we employ the instrumental variables.

Baseline results (Table 2) show a positive and statistically significant correlation between the share of offshoring activities from low wage and eastern European countries in aggregate offshoring and the degree of occupational segregation across firms. We find qualitatively similar results for segregation by skill in response to the offshoring shock. That is, industries that are exposed to high offshoring from the South demonstrate a more segregated occu-

[45] As for segregation by skill in general, we denote worker i's skill as x_{ijkt}, so $\overline{x}_{jkt}$ indicates the average skill-level at firm j that operates in industry k in time t, and $\overline{x}_{kt}$, the average skill-level in industry k in time t.

[46] As an alternative way to control for outsourcing, we identify firms that perform outsourcing following Goldschmidt and Schmieder (2017) and exclude them from the sample and repeat the exercise above.

[47] We exactly follow Bagger et al. (2014) to construct value-added from the Danish data. See Appendix C for details.

pational structure, and a more sorted workforce. Quantitatively, one standard deviation increase in the share of offshoring from the South is associated with an increase of 0.143 standard deviations in occupational segregation, which corresponds to a 7.5% increase in the degree of segregation relative to the mean value of 0.24. This demonstrates economic significance in the association between changes in the distribution of occupations across firms and changes in offshoring shares from the South. Furthermore, the quantitative magnitude is greater employing the instrumental variable.

4.2 Within-Occupation Quality of Skill

We present within-occupation evidence using both firm-level and worker-level regressions on how offshoring exposure from the South affects the firm-level average skill quality and the reallocation of workers within these occupations across firms. Note that the regression is conducted for offshorable occupations. In order to avoid issues related to product-level import penetration that directly affects industry size, we focus on *export-oriented* industries where an industry is defined as *export-oriented* if (i) the change in the value of net exports is greater than zero and it has a positive net export value in 2004; or (ii) it continues to have positive net export values between the years 1995 and 2004. Otherwise, it is identified as an *import-oriented* sector.

Firm-level Analysis The following firm-level regression examines how the average skill of workers hired in-house responds to changes in industry-specific exposure to offshoring from low-wage and eastern European countries. Note that the interaction term captures additional information on the between-firm inequality in average skills.

$$\begin{aligned} \text{Average Skill}^{s}_{jkt} =& \alpha^{m}_{0} + \alpha^{m}_{1}\text{Offshoring}_{kt} + \alpha^{m}_{2}(\text{Offshoring}_{kt} \times \text{TFP}_{jk0}) + \alpha^{m}_{3}\text{TFP}_{jk0} \\ &+ \text{Firm}_{jkt} + \text{Industry}_{kt} + \eta^{m}_{k't} + \varepsilon^{m}_{jkt} \end{aligned} \tag{15}$$

Average Skill^{s}_{jkt} is the average skill s of workers in firm j and industry k in time t where $s =$ cognitive, manual, or interpersonal skills. TFP_{jk0} is the firm-specific total factor productivity in the initial year of operation obtained using Olley and Pakes (1996). Time-varying firm controls include size, share of high-skilled workers, share of female workers, capital intensity, outsourcing intensity, and exporting intensity. We also add time-varying industry controls, which include capital intensity, exporting intensity, and domestic outsourcing intensity. Note that adding the firm's size controls for any changes in average skills due to an expansion in employment size as a result of productivity gains from performing offshoring (Hummels et al., 2014). We further include sector-by-year fixed effects ($\eta_{k't}$) to control for any sector-specific time-varying exogenous demand or technology shocks. Therefore, the coefficient α_2^m for the interaction term together with α_1^m provides implications for changes in the average skill of firms and the magnitude of change based on the firm's initial productivity levels. For example, $\alpha_1^m > 0$ and $\alpha_2^m < 0$ indicates that with an increase in the offshoring shock from the South, the average quality of in-house workers improves and the extent to which firms improve the quality of worker skills is greater for low productivity firms compared to high productivity ones. the between-firm inequality across firms in their average workers' skills decreases. As the industry-level offshoring measure is constructed using the sum of firm-level offshoring, simultaneity concerns potentially arise in the presence of industries with a high concentration ratio. Again, we employ an instrument to address this concern.

Results (Table 3) show that, within offshorable occupations, exposure to offshoring from low wage and eastern European countries is positively associated with the average quality of workers' cognitive and interpersonal skills. In particular, the coefficient α_1^m maintains statistical significance for average cognitive skills of workers across different specifications. Note that the magnitude of improvement is greater in response to offshoring exposure from low wage countries only, compared to that of all countries in the South including eastern European countries. Also, we find evidence that the extent to which firms improve their average quality of worker skill is greater for the low-productivity firms compared to the high-productivity firms. That is, firms with an initial TFP below 5.85 (i.e. TFP $< \frac{0.123}{0.021} = 5.85$) would benefit from the offshoring shock in terms of average quality of workers' cognitive skills that they hire while those above would not.[48] We find a negative sign for α_2^m across all specifications for average cognitive skills while the statistical significance holds only for the fixed effect specification with low wage countries. This can be explained by how high-productivity firms offshore and find substitutes for their high-skilled workers allowing lower productivity firms to match with the next best workers that the offshoring firms release.

Worker-level Analysis If firms are improving in the average quality of workers' skills in export-oriented industries in response to offshoring from the South, does it mean that workers face a greater risk of undergoing downward transitions? Here, we examine whether workers are more likely to move down the firm ladder or switch out to a less competitive sector, in response to offshoring exposure from the South. We use the following worker-level regression to investigate these hypotheses, changing definitions of the dependent variable accordingly.

$$\begin{aligned} C_{ijkt} =& \alpha_0^c + \alpha_1^c \text{Offshoring}_{kt} + \alpha_2^c(\text{Offshoring}_{kt} \times \text{ Skill}_i^s) + \alpha_3^c \text{Skill}_i^s \\ &+ \text{Worker}_{ijkt} + \text{Firm}_{jkt} + \text{Industry}_{kt} + \eta_{k't}^c + \varepsilon_{ijkt}^c \end{aligned} \tag{16}$$

[48] The average firm with a TFP of 6.923 is expected to experience an increase in average cognitive skills by 0.002 standard deviations in response to an increase in offshoring from the South by 1 standard deviation.

C_{ijkt} is a dummy variable set equal to 1 if a worker experiences *downward transitions* between time t and $t+1$: (i) a worker is reallocated to a firm with lower TFP than his or her previously matched firm; (ii) a worker switches out to the import-oriented sector. Skill_i^s is the level of worker i's skill s where s = cognitive, manual, or interpersonal skills. In addition to the time-varying controls for firms and industries described in the previous regression exercise, we further include time-varying controls for workers: years of experience and years of education. Again, we control for sector-by-year fixed effects ($\eta_{k't}^c$). Therefore, the coefficient α_2^c for the interaction term together with α_1^c provides implications for changes in the probabilities workers face in terms of descending transitions with further information on the magnitude of change by worker skill-levels. For example, $\alpha_1^c > 0$ and $\alpha_2^c < 0$ indicate that workers with lower skill levels are more likely to switch down their firm or sector in response to an increase in the offshoring shock from the South. Simultaneity or reverse causality is less of an issue in worker-level regressions as it is unlikely to have individual workers affect industry level offshoring (Ebenstein et al., 2014; Baumgarten et al., 2013). However, if high-skilled workers in Danish manufacturing sort into industries with high offshoring activities from the South, this may not be a negligible issue. Again, we employ the instrumental variable in this analysis to address this concern.

In terms of the qualitative implications of the results (Table 4), an increase in offshoring from the South increases the probability that workers in offshorable occupations undergo a descending transition in workplace as well as sectors where those with low cognitive skills face a relatively greater risk. Again, the magnitude of the coefficients is greater when employing the instrumental variable. Quantitatively, the average worker with cognitive skills of 0.38 faces a greater probability of experiencing a transition in sector by 0.006 standard deviations in response to an increase in offshoring from the South by one standard deviation while for workers in the bottom quartile on average, by 0.023 standard deviations. As for reallocation across firms, workers with cognitive skills below 0.44 face a positive probability of moving down to a firm with lower TFP in response to an offshoring shock. Comparing the magnitudes across workers by their cognitive skills, those in the top quartile on average face a greater probability of switching down by 0.069 standard deviations in response to an increase in offshoring from the South by one standard deviation, whereas for those in the bottom quartile on average, by 0.104 standard deviations.

With high-productivity firms performing offshoring, high-skilled workers hired in these firms face direct competition from foreign workers, which effectively alters worker-firm matching at the top of the distributions for both workers and firms. This impact of foreign labor supply subsequently spills over down the distributions, eventually affecting even those who are not directly exposed to offshoring from the South. In other words, offshoring causes workers in offshorable occupations to move down the firm ladder, and ultimately the least productive workers are reallocated to the less competitive sector. As in Hummels et al. (2014), a potential threat to the instrumental variable in the analyses above is whether domestic demand shocks from Denmark affect the world export supply from China. In the industry-level analysis, it is unlikely that the industry-level demand shocks in Danish manufacturing affect the world export supply as Denmark is a small open economy. In the firm-level and worker-level analyses, this threat is less of a concern as it is unlikely that firm-level or worker-level demand meaningfully affects the aggregate world export supply from China.

5 Structural Estimation

In this section, we use the Danish matched employer-employee data to estimate the key model parameters and examine the quantitative impact of the globalization channel on: (i) how worker-firm matching evolves, and (ii) how the between-firm inequality in wages is affected. The value-added in analyzing through the lens of a structural model lies in assessing the quantitative importance of offshoring in comparison to competing hypotheses and identifying the main channel that drives labor market inequality.

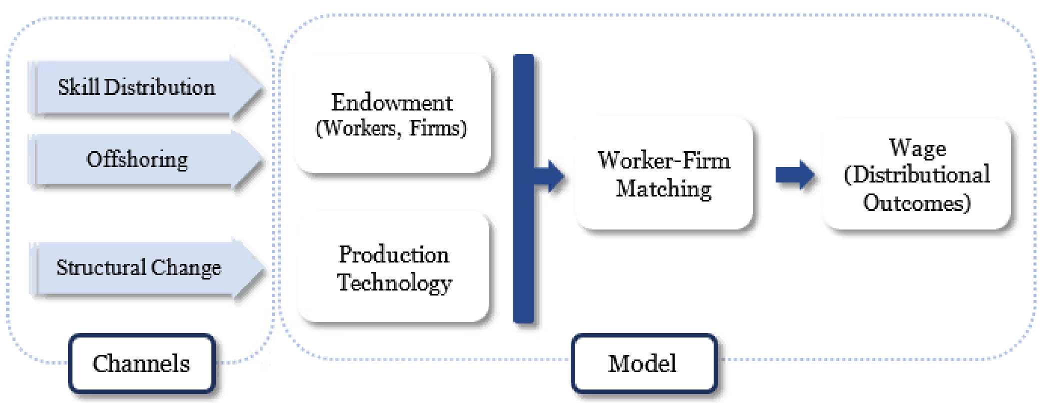

Figure 7: Changes in Worker-Firm Matching

Along with channels of globalization that lowers the cost of matching with foreign workers, there are important concurrent changes that potentially affect worker-firm matching and further distributional labor market outcomes: changes in the skill distribution of workers and that in the production technology. If the supply of workers' skills has evolved toward higher skill dispersion, then for a fixed production technology, worker-firm matching is affected in a way that increases segregation by skill (Kremer and Maskin, 1996). Additionally, structural changes in the production technology such as skill-biased technological change (Acemoglu and Autor, 2011; Lindenlaub, 2017) can alter worker-firm matching: cognitive skills relative to manual skills of workers become more important, and thus, the assortative matching between firms and workers is greater on worker's cognitive skills. In other words, firms' productivity becomes more *complementary* with the cognitive skill of workers, resulting in a greater degree of assortative matching on worker's cognitive skills.

Multidimensional Skills Introducing multidimensional skills, the bilinear production technology assumed in Section 3 extends as follows:

$$q(x_c, x_m, x_p, y) = (\gamma_c x_c + \gamma_m x_m + \gamma_p x_p)y + u_c(x_c) + u_m(x_m) + u_p(x_p) \tag{17}$$

The production technology parameters $\gamma_c, \gamma_m, \gamma_p$ represent the *strength of complementarities* between firms' productivities and different dimensions of workers' skills in each occupation, which indicates whether workers' cognitive, manual, or interpersonal skills are complements or substitutes to firms' productivity.[49] we also include skill-specific main effects, capturing the extent to which each skill component of the workers contributes to the task output independent of the firm's productivity.[50]

5.1 Estimation Strategy

We first identify the skill complementarity parameter $\Gamma = [\gamma_c, \gamma_m, \gamma_p]$ that would generate the same model moments as those observed in the data ($i = c, m, p$)[51]:

$$E_{\pi^{\Gamma}}[X_i Y] = E_{\pi^{\hat{\Gamma}}}[X_i Y] \tag{18}$$

More specifically, we derive the marginal densities $f(x)$ and $g(y)$ from the data and use the iterated proportional fitting procedure (IPFP) to recover the Lagrangian multipliers $a(x)$ and $b(y)$ for a particular assumed Γ, which simulates a corresponding worker-firm matching. Optimal $\hat{\Gamma}$ is obtained by a moment matching procedure where we iterate this process until the difference between the model moments and the data moments is minimized.[52] Using the estimated $\hat{\Gamma}$ together with data on workers' wages, we nonparametrically estimate the scale parameter λ_x capturing the extent to which workers' unobserved characteristics matter

[49] While it is possible to have multiple characteristics on both firms and workers to examine complementarity across different attributes, we keep the firm-side as unidimensional in order to maintain the focus on the worker-side attributes in explaining chages in matching. See Lindenlaub (2017) for a two-sided multidimensional matching models with analytical solutions.

[50] Note that the skill-specific main effect components can also take nonlinear functions (Dupuy and Galichon, 2014).

[51] Dupuy et al. (2017) proves that the log-likelihood function in MLE is equivalent to the moment matching estimator.

[52] For estimation purposes, we consider each job the firm holds as a unit of firm.

in the matching process, which subsequently determines λ_y, and the parameters for the worker's skill-specific main effects.

Results Recall that the parameters in the production technology represent the strength of complementarities between firms' productivity and different dimensions of workers' skill. Here, we highlight features of the estimated skill complementarities in the Danish data for the following ISCO 1-digit occupation category (Table 5). First, for most occupations, cognitive and interpersonal skills relative to manual skills demonstrate greater importance in worker-firm matching for both 1995 and 2004. As for workers in craft occupations, for example, increasing the workers' cognitive (interpersonal) skills and the firms' productivity by one standard deviation increases the task output by 0.134 (0.074) units in 1995 and 0.116 (0.115) units in 2004. However, increasing their manual skills and the firms' productivity by one standard deviation increases the task output by 0.084 units in 1995 and 0.072 units in 2004.

		Crafts	Elementary	Managers	Clerical	Machines	Professionals	Service, Sales	Associates
1995	Cognitive	0.134	0.045	0.045	-0.014	0.068	0.036	0.063	0.046
		(0.010)	(0.017)	(0.040)	(0.015)	(0.008)	(0.040)	(0.030)	(0.023)
	Manual	0.084	-0.015	0.007	-0.065	0.033	0.048	0.058	0.001
		(0.010)	(0.016)	(0.036)	(0.013)	(0.008)	(0.036)	(0.029)	(0.022)
	Interpersonal	0.074	0.000	-0.051	-0.010	0.023	0.059	0.077	-0.024
		(0.009)	(0.014)	(0.034)	(0.018)	(0.007)	(0.039)	(0.027)	(0.018)
2005	Cognitive	0.116	0.012	-0.041	-0.019	0.072	0.095	0.061	0.031
		(0.010)	(0.016)	(0.034)	(0.019)	(0.007)	(0.025)	(0.035)	(0.015)
	Manual	0.072	0.033	-0.025	-0.109	0.062	0.044	-0.021	0.012
		(0.009)	(0.016)	(0.034)	(0.017)	(0.007)	(0.025)	(0.034)	(0.016)
	Interpersonal	0.115	0.070	0.142	-0.011	0.017	0.062	0.008	0.060
		(0.011)	(0.015)	(0.034)	(0.030)	(0.007)	(0.027)	(0.040)	(0.016)

Bootstrapped standard errors in parentheses

Table 1: Estimated Complementarity By ISCO (1-digit)

Second, the manual skills of workers become more substitutable for managers, clerical workers, and those in sales and services while complementary for the rest. A negative value in the estimated coefficients indicates how an increase in the firm's productivity increases the task output of the matched pair whose workers are relatively less skilled in their manual ability. Consistent with what existing studies find (Autor et al., 2003; Autor and Dorn, 2013; Lindenlaub, 2017), how talented workers are in their physical or psychomotor ability became less important for the firms in hiring workers due to changes in the production technology (e.g.automation or mechanization).

Third, for most occupations, the importance of cognitive and interpersonal skills grew over time. Not only do cognitive and interpersonal skills remain important characteristics across time, but also their importance relative to manual skills increased. For example, for workers in professional occupations in 1995, increasing their cognitive skills and the firms' productivity by one standard deviation increased the task output by 0.036 units, and to achieve the equivalent increment in the task output, workers' manual skill and firms' productivity both had to increase by 0.87 ($=\sqrt{\frac{0.036}{0.048}}$) standard deviations. However, in 2004 the corresponding increment is 1.47 ($=\sqrt{\frac{0.095}{0.044}}$) standard deviations for both workers and firms, which indicates the rising importance of cognitive skills relative to manual skills in task output. Using a similar argument for workers in craft occupations, increasing their interpersonal skills and firms' productivity by one standard deviation raises output by 0.074, which takes an increase by 0.94 ($=\sqrt{\frac{0.074}{0.084}}$) standard deviations for workers' manual skills and the productivity of firms in 1995 to obtain the equivalent amount; however, it becomes 1.26 ($=\sqrt{\frac{0.115}{0.72}}$) standard deviations in 2004.

5.2 Estimation with Offshoring

In the estimation results so far, we assume that matches between workers and firms observed in the data capture the full population of firms and workers in Danish manufacturing; however, what we observe in the data are worker-firm pairs that chose to match domestically, which fails to capture the international matches. More specifically, the problem with the data associated with estimating the model with offshoring comprises two parts: for each occupational category, (i) firms that match with foreign workers are not observed in the data; and (ii) the skill characteristics of foreign workers are not provided. In the following, we elaborate on how we approach this problem and quantitatively capture the effects of offshoring.

Offshoring The measure of offshoring in this study is constructed using the value of firm-level imported intermediate and final goods from abroad that are utilized in the production process and potentially substitute in-house workers. Conceptually, offshoring is the formation of international teams in production: firms' choice to match with foreign workers instead of home workers. In operationalizing this notion of offshoring to data, we give the following interpretation of the worker-firm international matches: firms, through their purchases of intermediate or final goods, are essentially matching with foreign workers whose value-added is encapsulated in the form of intermediate or final goods. For example, if Danish firms purchase industrial robots from South Korea, this can be interpreted as Danish firms matching with South Korean workers whose value-added is captured in the form of robots.

Identification Strategy with Offshoring As previously discussed, firms that face workers with the exact same skill qualities at home and abroad are indifferent between domestic matching and offshoring. Thus, the model implies that the per worker value-added for each firm,[53] which captures the average task output of a domestic worker through a successful match, should be equal to the per worker value-added of an offshored match: $q(x,y) = q(x_F,y)$. To obtain a relevant measure in the data, we equate the per worker value-added to the constructed firm-level offshoring measure per worker composite overseas.

$$\frac{\text{Value-Added}}{\text{Number of Domestic Workers}} = \frac{\text{Intermediate and Final Good Purchases Abroad}}{\text{Number of Offshored Composite Workers}} \tag{19}$$

Thus, the task output of one Danish worker corresponds to the equivalent output provided by a composite of workers from the South.[54] Note that there are firms that perform offshoring, yet do not hire any workers in offshorable occupations. This potentially stems from the definition of offshorability that is used for categorizing occupations or from a situation where these firms only keep the non-offshorable jobs in-house and rely on purchasing intermediates and final goods for the rest of the production process. These firms comprise a negligible portion of the sample; however, to ensure robustness, we try several different things: dropping these firms in the estimation or performing data imputation.[55] To summarize the estimation strategy with offshoring, we add on the number of offshored matches recovered using the strategy above to the supply of offshorable occupations for each firm. Then, the data moments including the offshored matches are derived, with which we match the model moments and obtain the estimated skill complementarity for each occupation with offshoring for the years 1995 and 2004.

Estimation Results with Offshoring There are several notable features from the estimation results using the dichotomous categorization of occupations (Table 6). While workers' interpersonal skills are complements with firms' productivity in both occupations, cognitive and manual skills demonstrate opposite patterns. That is, workers in non-offshorable occupations show complementarity (substitutability) in their cognitive (manual) skills with the

[53]Here, we assume that the value-added shares produced by each occupation are equal to the firm-level occupational shares.

[54]What matters in the estimation is the final quality of skill provided through a match, whether it is a single worker or a bundle of workers. Therefore, the identification strategy is not sensitive to the ratio of workers between two different origins which potentially depends on wage differences.

[55]For example, we assume that these firms match with foreign workers that provide the quality of skill equivalent to that of the average of their in-house workers with non-offshorable jobs.

qualities of the matched firms while those in offshorable occupations exhibit substitutability (complementarity). Taking into account that the occupations categorized as offshorable are stationary plant and related operators; precision, handicraft, craft printing and related trades workers; machine operators and assemblers, etc., it makes sense that workers' manual skills are important and complementary in the worker-firm matching process. Nonetheless, it is worth mentioning that the evolution of skill complementarity with firms' productivity in both occupations demonstrates that cognitive skills are becoming more complementary or less substitutable (i.e. the value of the coefficients increases) while manual skills become less complementary or more substitutable (i.e. the value of the coefficients decreases) over time.

	Offshorable Occupations			Non-offshorable Occupations		
	Cognitive	Manual	Interpersonal	Cognitive	Manual	Interpersonal
1995	-0.270	0.231	0.380	0.048	-0.088	0.061
	(0.007)	(0.007)	(0.008)	(0.004)	(0.004)	(0.004)
2005	-0.160	0.145	0.283	0.091	-0.091	0.048
	(0.007)	(0.007)	(0.006)	(0.004)	(0.004)	(0.004)
Bootstrapped standard errors in parentheses						

Table 2: Estimated Complementarity with Offshoring

5.3 Counterfactual Exercises

Here, we use the estimated model to separately quantify the effect of offshoring on changes in the worker-firm matching and the between-firm inequality for offshorable occupations.[56] As discussed earlier, changes in the feasible worker-firm matches occur not only due to access to additional workers via offshoring (O), but also due to concurrent changes in the economy such as the structural changes ($\hat{\Gamma}$) as well as shifts in the supply of skill (S) in the economy. Therefore, we disentangle the three channels and quantify the effects of each through a decomposition exercise, in which we allow only one channel to change at a time while shutting down the rest. We employ this method to examine measures of labor market inequality such as the between-firm wage inequality as well as segregation by skill.

[56]While there exist effects of offshoring that change the nature of firms' in-house production (e.g. greater intensity in R&D activities, better management and efficient organization, etc.), this lies beyond the scope of this study.

$$
\begin{aligned}
\hat{\pi}_{04}(\hat{\Gamma}_{04}, O_{04}, S_{04}) - \hat{\pi}_{95}(\hat{\Gamma}_{95}, O_{95}, S_{95}) &= \underbrace{\{\hat{\pi}_{04}(\hat{\Gamma}_{04}, O_{04}, S_{04}) - \hat{\pi}(\hat{\Gamma}_{04}, O_{95}, S_{04})\}}_{\text{offshoring}} \\
+ \underbrace{\{\hat{\pi}(\hat{\Gamma}_{04}, O_{95}, S_{04}) - \hat{\pi}(\hat{\Gamma}_{95}, O_{95}, S_{04})\}}_{\text{structural change}} &+ \underbrace{\{\hat{\pi}(\hat{\Gamma}_{95}, O_{95}, S_{04}) - \hat{\pi}_{95}(\hat{\Gamma}_{95}, O_{95}, S_{95})\}}_{\text{skill distribution}}
\end{aligned} \tag{20}
$$

Worker-Firm Matching Looking into changes in matching by each skill dimension within offshorable jobs over time (Table 7), we find that the degree of assortative matching of workers with firms has increased in terms of workers' cognitive and interpersonal skills while it has decreased in their manual skills. Comparing the magnitudes across different channels, structural change plays a major role in affecting changes in worker-firm matching among other channels. While offshoring affects matching in a qualitatively similar way, the magnitude is quite small. Note that the skill supply of workers in the manufacturing sector for offshorable jobs decreases the degree of assortative matching on workers' cognitive and interpersonal skills.

	Initial	ΔSkill Supply	ΔStructural	ΔOffshoring	**Final**
Cognitive	-0.135	-0.009	0.080	0.002	-0.064
	(0.004)	(0.002)	(0.006)	(0.000)	(0.005)
Manual	0.141	0.005	-0.074	-0.002	0.072
	(0.004)	(0.002)	(0.006)	(0.000)	(0.005)
Interpersonal	0.101	-0.007	0.010	0.000	0.113
	(0.004)	(0.002)	(0.006)	(0.000)	(0.004)

Bootstrapped standard errors in parentheses

Table 3: Decomposition in Changes in Worker-Firm Matching

Between-Firm Wage Inequality and Segregation by Skill How do changes in worker-firm matching due to globalization affect between-firm inequality in wages? In the graphs below, we show changes in log wages by decile of firms' productivity where a positive slope indicates an increase in between-firm wage inequality as high-productivity firms increase wages for their workers more than low-productivity firms do. Results from the baseline model demonstrate that the change in the average wage for each decile of firms by their productivity increases over time, which indicates an increase in between-firm wage inequality. However, in a counterfactual economy where changes in offshoring do not take place, the slope is even greater. That is, without the channel of globalization supplying additional workers for firms to match with, firms demonstrate greater differences in terms of the average wage they pay.[57]

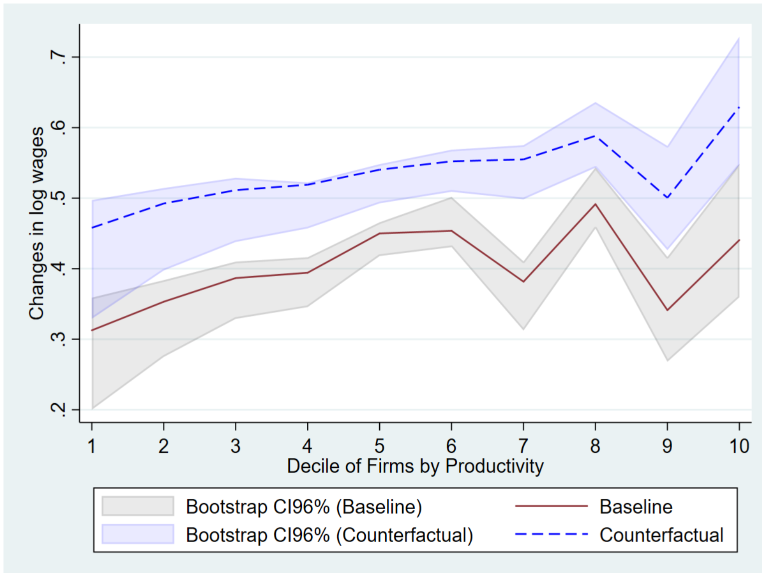

Figure 8: Changes in log(wage) by decile of firms (productivity)

As shown in Figure, examining each channel provides sharp comparisons in the effect on between-firm inequality. That is, the structural change channel mainly drives changes in the wage across firms to become more different whereas offshoring functions in a way that reduces the wage gap between firms. In terms of wage levels, formations of international teams by high-productivity firms impose direct competition in the high-skilled workers they hire, which generates an overall wage loss that is greater in magnitude for these workers with direct exposure to foreign worker competition. In support of the analysis by the decile of firms, we also compute changes in the average and variance of wages together with changes in the segregation index (Kremer and Maskin, 1996),[58] which captures how sorted the economy is in terms of the distribution of average wage payment of each firm (i.e. between-firm wage inequality). Consistent with the theoretical predictions, the offshoring channel lowers the average wage of workers in offshorable occupations; however, it brings about a decrease in wage dispersion across firms. Also, the segregation index indicates

[57] See Appendix A for the decomposition analysis using both offshorable and non-offshorable occupations.

[58]
$$\rho_t = \frac{\text{Between-firm variance}}{\text{Total variance}} = \frac{\sum_{i,j}(\overline{x}_{jt} - \overline{x}_t)^2}{\sum_{i,j}(x_{ijt} - \overline{x}_t)^2} \tag{21}$$

how the introduction of international teams brings about a decrease in between-firm wage inequality.

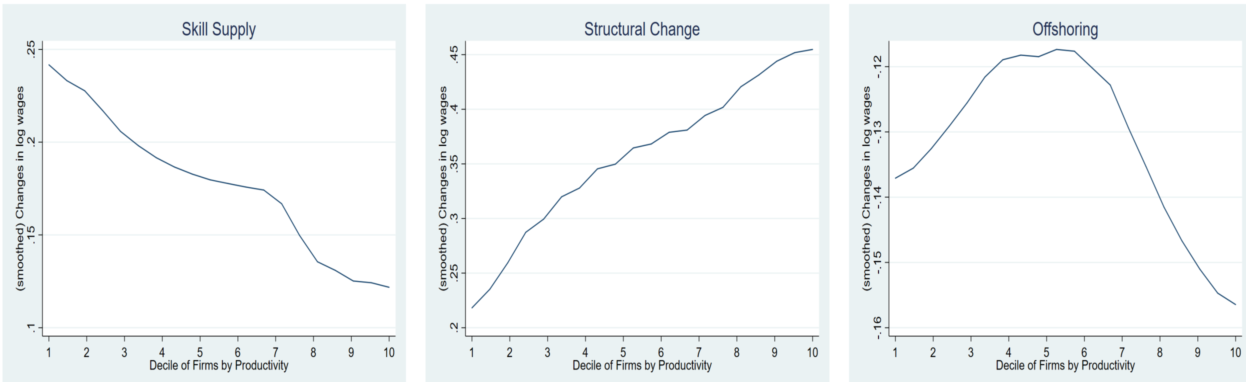

Figure 9: Changes in log(wage) by decile of firms (productivity) in each channel

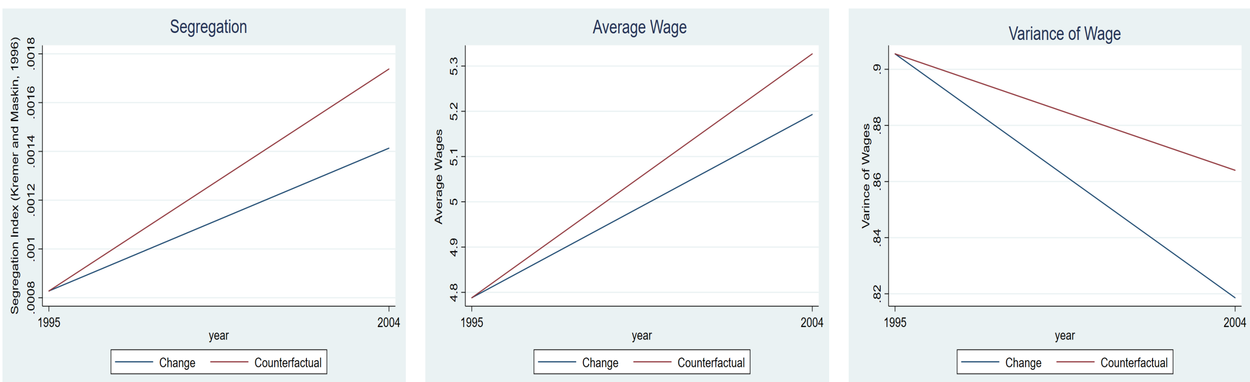

Figure 10: Changes in Segregation, Average and Dispersion in Wages

6 Conclusion

In this paper, we examine the mechanisms of how offering affects labor market inequality by altering the reallocation of workers across firms. We use the Danish employer-employee matched data together with the newly constructed skill measures to evaluate the effect of offshoring on workers across the skill distribution within offshorable occupations. Using both the model and data, we find that offshoring reduces domestic worker wages; and increases the probability of reallocation away from the high-productivity firms to the low-productivity ones. The least skilled workers further face a greater risk of switching out to a less competitive sector. On the firm-side, offshoring improves the average skill of in-house workers at a lower cost. Analyzing through the lens of a structural model, we examine the mechanisms of how offshoring affects labor market inequality and further assess the quantitative importance of various competing hypotheses such as technological change and the expansion of higher education, in addition to offshoring. We actually find substantially different effects: technology mainly increases the inequality between firms in terms of worker skill quality and average wages, while offshoring mitigates this rising trend.

The novelty in the analysis lies in examining the effects of offshoring at the within-occupation-worker level using the newly constructed skill measure. Together with the matched Danish data, we further examine changes in the skill mix of workers observed at the firm-level. This potentially provides significant implications for setting objectives and designing specific curriculums of job training or trade adjustment assistance promgrams. It may also serve as useful guidelines for individuals on making human capital investment decisions and help designing effective education policies that prepare individuals to demonstrate competitiveness as workers in a global economy setting. The structural framework, which extend the Becker-type matching model, demonstrates how offshoring contributes to recent trends in labor market inequality where we see a significant portion being explained by between-firm inequality. The significance of the model lies in not only disentangling the effects of concurrent and paramount forces affecting labor market inequality but also evaluating the quantitative importance of each channel.

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Appendices

Appendix A Tables and Graphs

A1.1. Data Description

	Variables	Mean	Standard Deviation
Worker	log(wage)	5.187	0.352
	Education (years)	16.249	4.548
	Experience (years)	13.047	6.158
Firm	Size	30.363	179.359
	Average wage	5.100	0.281
	Share of high-skilled	0.337	0.296
	Share of female	0.276	0.309
	log(value of imports)	14.062	2.829
	log(value of exports)	14.066	2.819
Aggregate	Share of exporters	0.346	0.0405
	Share of importers	0.350	0.052

Table 4: Summary Statistics for the Baseline Sample

A1.2. Empirical Evidence

A1.2.1. Industry-level

Table 5: Offshoring and Occupational Segregation

	FE				FE-IV			
	(1)[b]	(2)[c]	(3)	(4)	(1)	(2)	(3)	(4)
Offshoring[d]	0.0934***	0.0320*	0.0251	0.0228*	0.864***	0.0885	0.00716	0.120**
	(0.0246)	(0.0174)	(0.0188)	(0.0123)	(0.175)	(0.0644)	(0.0716)	(0.0532)
Observations[a]	2,097	2,097	2,097	2,097	2,097	2,097	2,097	2,097
R^2	0.757	0.790	0.850	0.833	0.399	0.785	0.850	0.819
Industry FE & Year FE	yes	yes	yes	yes	yes	yes	yes	yes
Industry Controls	yes	yes	yes	yes	yes	yes	yes	yes

Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

[a] The unit of observation is an industry (4-digit) in a given year (1995-2004).
[b] Segregation index computed for each industry where $x_{ijt} = 1$ is assigned if a worker has an offshorable occupation.
[c] Segregation index computed for each industry where x_{ijt} is cognitive (column (2)), manual (column (3)), and interpersonal (column (4)) skills of a worker, respectively.
[d] Offshoring is the share of relevant intermediate and final good purchases (narrow offshoring) from low wage countries Bernard et al. (2006) and eastern European countries (Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovakia, Slovenia, Malta, and Cyprus) to aggregate offshoring constructed at the industry level (4-digit).

A1.2.2. Firm-level

Table 6: Offshoring and Average Quality of Skill

South	FE			FE-IV		
	(1)[c]	(2)	(3)	(1)	(2)	(3)
Offshoring[b]	0.025**	0.0139	0.0202*	0.179***	-0.0533	0.0691
	(0.009)	(0.013)	(0.011)	(0.037)	(0.049)	(0.043)
Offshoring × TFP	-0.006	-0.003	-0.002	-0.0001	0.00429	0.00598
	(0.0081)	(0.002)	(0.002)	(0.005)	(0.007)	(0.005)
Observations[a]	13,614	13,614	13,614	13,614	13,614	13,614
R^2	0.115	0.415	0.164	0.069	0.448	0.159
Firm & Industry Controls	yes	yes	yes	yes	yes	yes
Industry × Year FE	yes	yes	yes	yes	yes	yes
Low Wage Countries	**FE**			**FE-IV**		
	(1)	(2)	(3)	(1)	(2)	(3)
Offshoring[c]	0.123***	-0.0659	0.130***	0.656***	-0.200	0.246
	(0.061)	(0.083)	(0.074)	(0.140)	(0.187)	(0.162)
Offshoring × TFP	-0.0207***	0.0098	-0.0155**	-0.0131	0.0179	0.0148
	(0.006)	(0.007)	(0.006)	(0.018)	(0.025)	(0.021)
Observations[a]	13,614	13,614	13,614	13,614	13,614	13,614
R^2	0.115	0.415	0.164	0.079	0.448	0.164
Firm & Industry Controls	yes	yes	yes	yes	yes	yes
Industry × Year FE	yes	yes	yes	yes	yes	yes

Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

[a] The unit of observation is a firm in a given year (1995-2004).
[b] Offshoring is the share of relevant intermediate and final good purchases (narrow offshoring) from low wage and eastern European countries constructed at the industry-level (4-digit).
[c] Columns (1) in each panel correspond to results based on the average of workers' cognitive skills as the dependent variable; columns (2), their manual skills; columns (3), their interpersonal skills.

A1.2.3. Worker-level

Table 7: Offshoring and Worker Reallocations across Sectors

Firms		FE			FE-IV	
	(1)[c]	(2)	(3)	(1)	(2)	(3)
Offshoring[b]	0.0827***	0.0417***	0.0596***	0.0666**	-0.0403	0.0416
	(0.011)	(0.009)	(0.009)	(0.029)	(0.025)	(0.030)
Offshoring × Skill	-0.0469**	0.0437***	0.00896	-0.149***	0.0991***	-0.0770**
	(0.023)	(0.016)	(0.017)	(0.046)	(0.033)	(0.039)
Observations[a]	312,353	312,353	312,353	312,353	312,353	312,353
R^2	0.072	0.072	0.072	0.072	0.072	0.072
Controls	yes	yes	yes	yes	yes	yes
Industry × Year FE	yes	yes	yes	yes	yes	yes
Sector		**FE**			**FE-IV**	
	(1)	(2)	(3)	(1)	(2)	(3)
Offshoring	0.0085**	-0.0024	0.0043	0.0850***	0.0452***	0.0823***
	(0.004)	(0.003)	(0.003)	(0.012)	(0.011)	(0.013)
Offshoring × Skill	-0.0124**	0.0117***	-0.0018	-0.0621***	0.0031**	-0.0482***
	(0.008)	(0.005)	(0.006)	(0.017)	(0.013)	(0.014)
Observations	312,353	312,353	312,353	312,353	312,353	312,353
R^2	0.055	0.055	0.055	0.052	0.052	0.052
Controls	yes	yes	yes	yes	yes	yes
Industry × Year FE	yes	yes	yes	yes	yes	yes

Standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

[a] The unit of observation is a worker in a given year (1995-2004).

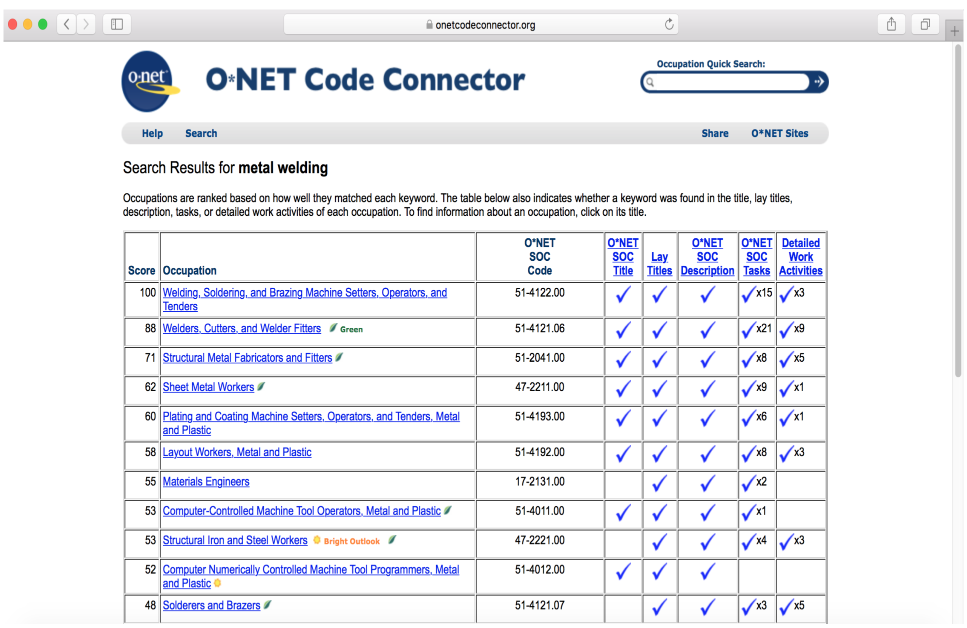
[b] Offshoring is the share of relevant intermediate and final good purchases (narrow offshoring) from low wage and eastern European countries constructed at the industry-level (4-digit).

[c] Columns (1) in each panel correspond to results based on workers' cognitive skills which are interacted with the share of offshoring; columns (2), their manual skills; columns (3), their interpersonal skills.

Appendix B Data

B1. Skill Construction

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


onetcodeconnector.org

O*NET Code Connector

Occupation Quick Search:

Help Search Share O*NET Sites

Search Results for **metal welding**

Occupations are ranked based on how well they matched each keyword. The table below also indicates whether a keyword was found in the title, lay titles, description, tasks, or detailed work activities of each occupation. To find information about an occupation, click on its title.

Score	Occupation	O*NET SOC Code	O*NET SOC Title	Lay Titles	O*NET SOC Description	O*NET SOC Tasks	Detailed Work Activities
100	Welding, Soldering, and Brazing Machine Setters, Operators, and Tenders	51-4122.00	✓	✓	✓	✓x15	✓x3
88	Welders, Cutters, and Welder Fitters Green	51-4121.06	✓	✓	✓	✓x21	✓x9
71	Structural Metal Fabricators and Fitters	51-2041.00	✓	✓	✓	✓x8	✓x5
62	Sheet Metal Workers	47-2211.00	✓	✓	✓	✓x9	✓x1
60	Plating and Coating Machine Setters, Operators, and Tenders, Metal and Plastic	51-4193.00	✓	✓	✓	✓x6	✓x1
58	Layout Workers, Metal and Plastic	51-4192.00	✓	✓	✓	✓x8	✓x3
55	Materials Engineers	17-2131.00		✓	✓	✓x2	
53	Computer-Controlled Machine Tool Operators, Metal and Plastic	51-4011.00	✓	✓	✓	✓x1	
53	Structural Iron and Steel Workers Bright Outlook	47-2221.00		✓	✓	✓x4	✓x3
52	Computer Numerically Controlled Machine Tool Programmers, Metal and Plastic	51-4012.00	✓	✓	✓		
48	Solderers and Brazers	51-4121.07		✓	✓	✓x3	✓x5

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 is that, (i) relevance scores are higher than 90; (ii) the education key words checks off with the occupation title, the lay title, the job description, the task content and work activities. For education entries that fail these criteria go through a second set of algorithm, which requires (i) relevance scores are higher than 90; (ii) the education key words checks off with the occupation title or the task content or work activities. Python codes and files are available upon request. For educational records that are too general and abstract are not included in the algorithm.

B2. Construction of Other Measures

Value Added We exactly follow Bagger et al. (2014) to construct the value added Y:

1. 1995-1998
   Y = (OMS+AUER+ADR+DLG)-(KRH+KENE+KLEO+UDHL+UASI+OEEU+SEUD)

2. 1999-2001
   Y = (OMS+AUER+ADR+DLG+TGT×0.0079)-
   (KRH+KENE+KLEO+UDHL+UASI+UDVB+ULOL+ ANEU+SEUD)

3. 2002-2003
   Y = (OMS+AUER+ADR+DLG)-
   (KRH+KENE+KLEO+UDHL+UASI+UDVB+ULOL+ANEU+SEUD)

4. 2004-2013
   Y = (OMS+AUER+ADR+DLG)-
   (KVV+KRHE+KENE+KLEO+UDHL+UASI+UDVB+ULOL+ANEU+SEUD)

OMS is revenue, AUER is work conducted at own expense, ADR is other operating revenue, DLG is ultimo inventory minus primo inventory; KRH is cost of intermediates, KENE is cost of energy, KLEO is costs of subcontractors, UDHL is housing rents, UASI is purchases of minor equipment, OEEU is other external costs, SEUD is secondary costs, TGT is total credits, UDVB is purchases of temporary employment agency, ULOL is costs of long-term leasing, ANEU is other external costs, KVV is purchases of goods for resale, and KRHE is costs of intermediates.

Occupational Offshorability There are several different methods the literature has established ways of capturing the degrees of offshorability at the occupation-level. Autor et al. (2003) and Acemoglu and Autor (2011) rely on occupation characteristics provided in O*NET to capture occupational offshorability while Blinder (2009) adds his subjective judgement to further categorize offshorable occupations. Blinder and Krueger (2013) utilizes household survey measurements of the "offshorability" of jobs while Goos et al. (2014) uses all of the pre-existing measures of offshorability listed above and also compare their own construction, which is based on the European Restructuring Monitor (ERM) contains summaries of news reports about cases of offshoring by companies located in Europe.

	Blinder and Krueger (2013)	Autor, Levy, Murnane (2003)
Offshorable	Machine operators and assemblers	Office clerks
	Precision, handicraft, craft printing and related trade workers	Precision, handicraft, craft printing and related trade workers
	Stationary plant and related operators	Customer service clerks
	Other craft and related trade workers	Other craft and related trade workers
	Physical, mathematical and engineering professionals	Machine operators and assemblers
Non-Offshorable	Drivers and mobile plant operators	Managers of small enterprises
	Personal and protective service workers	Drivers and mobile plant operators
	Extraction and building trades workers	Life science and health professionals
	Models, salespersons and demonstrators	Physical, mathematical and engineering professionals
	Sales and service elementary occupations	Corporate managers

	Blinder (2009)	Goos, Manning, Salomons (2014)
Offshorable	Physical, mathematical and engineering professionals	Machine operators and assemblers
	Precision, handicraft, craft printing and related trade workers	Stationary plant and related operators
	Machine operators and assemblers	Office clerks
	Other craft and related trade workers	Laborers in mining, construction, manufacturing and transport
	Stationary plant and related operators	Metal, machinery and related trade work
Non-Offshorable	Models, salespersons and demonstrators	Life science and health associate professionals
	Teaching associate professionals	Models, salespersons and demonstrators
	Teaching professionals	Life science and health professionals
	Drivers and mobile plant operators	Personal and protective service workers
	Personal and protective service workers	Drivers and mobile plant operators

B3. Industry and Occupation Classifications

Industry Classification We employ variables *gf_branche_93*, *gf_branche_03*, and *gf_branche_07* in MEE, which provide the Danish Industrial Classification (Dansk Branchekode; abbreviated DB) at the six-digit level to identify firms' industry categories. This classification follows the NACE system where DB93, DB03, DB07 demonstrate correspondence with the NACE Rev. 1, the NACE Rev. 1.1, and the NACE Rev. 2, respectively.

Occupation Classification We use variables *discoalle_indk* (1991-2009) and *disco08alle_indk* (2010-) in MEE to obtain information regarding individuals' occupations. Denmark assigns the Danish version of ISCO (International Standard Classification of Occupations), DISCO, to these variables, which at the first two-digit level demonstrates high correspondence with the ISCO.[59] While *discoalle_indk* provides six-digit level occupational categories, we use this variable at the two-digit level, as there have changes over time in the way the codes are formulated in the higher digits.[60]

[59] http://www.ilo.org/public/english/bureau/stat/isco/isco88/publ3.htm
https://www.dst.dk/en/Statistik/dokumentation/nomenklaturer/disco-88

[60] https://www.dst.dk/da/Statistik/dokumentation/Times/personindkomst/discoalle-indk

Appendix C Tables and Graphs

C1. Global Economy Equilibrium

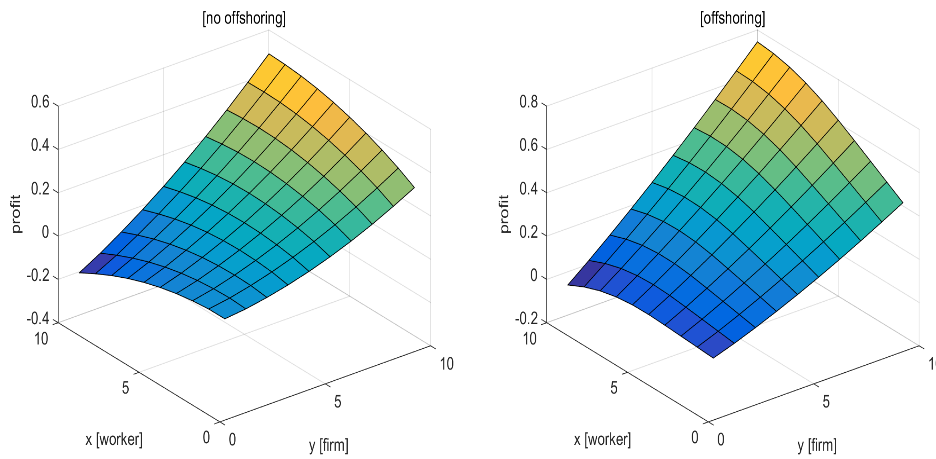


Figure 11: Equilibrium Wages and Profits under Closed Economy (top), Global Economy (bottom)

C2. Structural Estimation

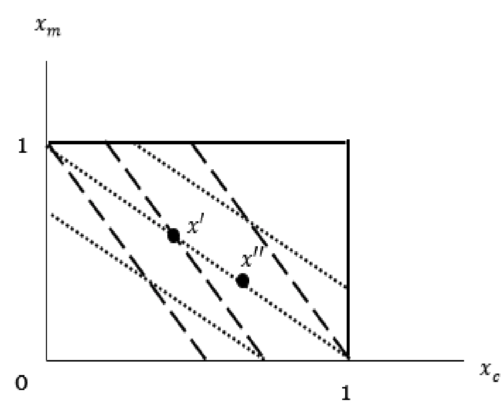


Figure 12: Multidimensional Skill and Technological Change

Suppose there exist workers $x' = x'' \equiv \hat{x}$ with skill bundles $x' = [x'_c, x'_m]$ and $x'' = [x''_c, x''_m]$ where $x'_c < x''_c$, $x'_m > x''_m$ with γ_c, γ_m. If there is an increase in cognitive skill complementarity γ'_c (dashed line) compared to the previous one $> \gamma_c$ (dotted line), then the following holds: $\hat{x}' = \hat{x} + x'_c(\gamma'_c - \gamma_c) < \hat{x} + x''_c(\gamma'_c - \gamma_c) = \hat{x}''$. Thus, workers x' and x'' that were previously matched with the same firm-type $\hat{y}$, are now separated into different firms $\hat{y}'$ and $\hat{y}''$, respectively, where $\hat{y}' < \hat{y}''$.

C3. Counterfactuals

Between and Within Occupation Channel What happens if we consider average wages combined across offshorable and non-offshorable jobs? As discussed earlier, the overall between-firm wage inequality combining across occupations depends on the relative magnitudes of the within-occupation versus between-occupation channels. As high-productivity firms trim down their offshorable occupations in-house, the average wage for their domestic workers largely accounts for those in non-offshorable jobs. Low-productivity firms, on the other hand, keep both the non-offshorable jobs and offshorable jobs in-house so that the average wage they pay reflects the overall wage loss workers with offshorable occupations have undergone due to globalization taking place. Thus, in the following we show changes in average wages weighted by occupation shares of offshorable and non-offshorable occupations by decile of firms' productivity, which we compare with the counterfactual economy where changes in occupations shares are not reflected.

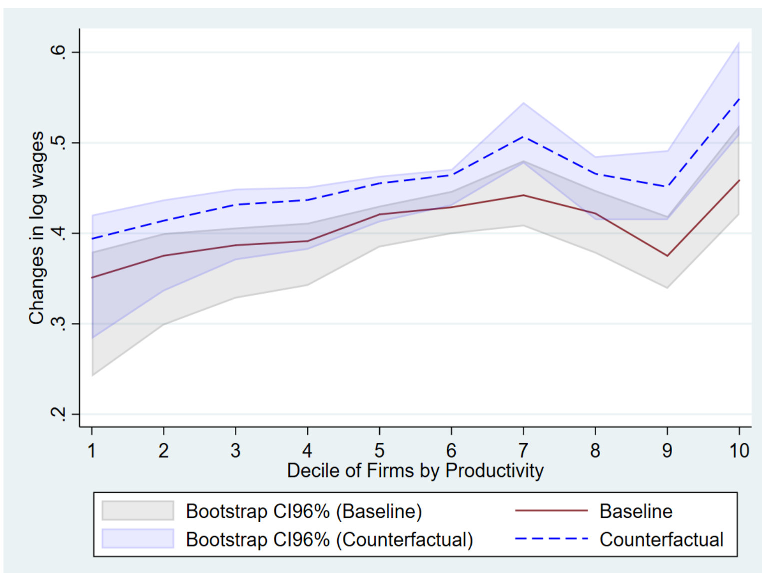


Figure 13: Changes in log(wage) by decile of firms (productivity)

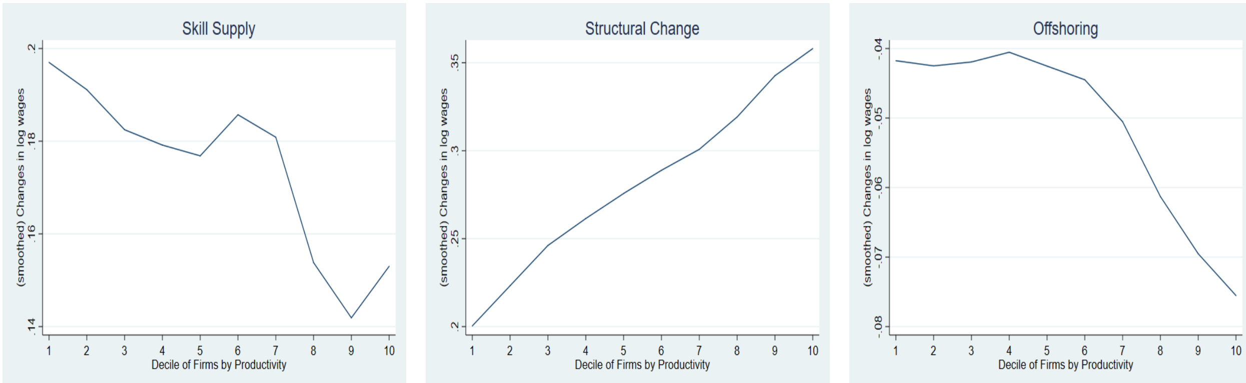


Figure 14: Changes in log(wage) by decile of firms (productivity) in each Channel

Appendix D Theory and Proofs

D1. Unobserved Preferences

We closely follow Dupuy and Galichon (2014) in the assumptions for unobserved heterogeneities. Each worker with observable skill x has a set composed of random realization of "acquaintances," which follows a Poisson point process on $Y \times R$ of intensity $\exp(-e)dedy$. If a point (y,e) is in the acquaintance set, this implies that the individual's unobserved preference for firm with productivity y is equal to e.[61] 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,

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

In addition, each individual has a random preference on the choice of outside option of being unmatched, also given by an analogous Poisson point process $\exp(-e)de$. Taking maximum of the given points, this assumption is exactly the same as assuming a Gumbel distribution for this preference shock.[62] Note that in order to maintain the analytical tractability of standard logit problem with discrete choice, the same scale parameter λ_x is used for both

[61] 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.

[62] Dupuy and Galichon (2014) also consider this case with outside option in their appendix D, and show that there is no meaningful changes in their results.

outside option and each of the matching option y. All of the above description of preference shocks apply equally to both Home and Foreign workers.

Firms also face exactly the same preference shocks, defined by the same Poisson point process if matched and a Gumbel distribution if unmatched, as described above. The only potential difference is that the degree of unobserved heterogeneity may be different: $\lambda_x \neq \lambda_y$ in general. It turns out that only $\lambda = \lambda_x + \lambda_y$ matters for the matching function $\pi(x, y)$, but each λ_x, λ_y does matter for determining how the output is shared between workers and firms.[63]

D2. Derivation of Closed Economy Equilibrium

Each worker makes an idiosyncratic decision, but because of the convenient assumptions of Poisson point process (which leads to an continuous analog of the standard logit models), the distributions of these choices conditional on observable type x can be characterized as follows. Recall that the skill distribution of workers that choose to be unmatched is $f_0(x)$, and the distribution of matched workers is $f(x)$. Then

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

holds in equilibrium, which is directly comparable to the conditional choice probabilities in standard logit case. Similarly, the distribution of unmatched and matched firms $g_0(y)$ and $g(y)$ satisfy

$$\frac{g_0(y)}{\overline{g}(y)} = \frac{1}{1 + \int \exp(\frac{r(x,y)}{\lambda_y})dx}, \quad \frac{g(y)}{\overline{g}(y)} = \frac{\int \exp(\frac{r(x,y)}{\lambda_y})dx}{1 + \int \exp(\frac{r(x,y)}{\lambda_y})dx}$$

where 1's correspond to the firm's outside option of zero. The conditional probability of a worker with observable type x choosing firm y satisfies:

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

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

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

[63] When $\lambda \to 0$, the equilibrium converges to a perfect sorting or pure matching. When $\lambda \to \infty$, the equilibrium converges to a purely random matching, i.e., $\pi(x,y) = f(x)g(y)$. Any finite, positive value of λ describes an environment in between these extreme cases: a smaller value of λ indicates more sorted economy, and vice versa.

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,

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

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

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

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

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

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

$$\exp(-\frac{b(y)}{\lambda_y}) = \frac{g(y)}{\int \exp(\frac{r(x,y)}{\lambda_y})dx} = \frac{\overline{g}(y)}{1 + \int \exp(\frac{r(x,y)}{\lambda_y})dx} = \hat{b}(y)^{\frac{\lambda}{\lambda_y}}$$

From these equations, it immediately follows that

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

$$g_0(y) = \frac{\overline{g}(y)}{1 + \int \exp(\frac{r(x,y)}{\lambda_y})dx} = \hat{b}(y)^{\frac{\lambda}{\lambda_y}}$$

Now the exogenously given marginal distributions can be expressed as

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

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

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.[64] 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 $w(x,y), r(x,y)$.

D3. Derivation of 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: $max(w_F + \lambda_{x_F} e, max_y\{w_F(x_F,y) + \lambda_{x_F} e(y)\})$. The utility shocks are defined in the same way as before. Foreign workers may have different outside wage option of w_F, different wage $w_F(x_F,y)$, and different degree of heterogeneity λ_{x_F}.

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: $max(\lambda_y e, max_x\{r(x,y) + \lambda_y e(x)\}, max_z\{V_F(x_F,y) + \lambda_y e(x_F)\})$. As before, competitive equilibrium implies $w_F(x_F,y) + V_F(x_F,y) = q_F(x_F,y)$.

The conditional distributions of choices for Home and Foreign workers are the same as before:

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

$$\frac{h_0(x_F)}{\overline{h}(x_F)} = \frac{\exp(\frac{w_F}{\lambda_{x_F}})}{\exp(\frac{w_F}{\lambda_{x_F}}) + \int \exp(\frac{w_F(x_F,y)}{\lambda_{x_F}})dy}, \quad \frac{h(x_F)}{\overline{h}(x_F)} = \frac{\int \exp(\frac{w_F(x_F,y)}{\lambda_{x_F}})dy}{\exp(\frac{w_F}{\lambda_{x_F}}) + \int \exp(\frac{w_F(x_F,y)}{\lambda_{x_F}})dy}$$

Distributions for firms need to be modified to incorporate the newly available choice of offshoring:

$$\frac{g_0(y)}{\overline{g}(y)} = \frac{1}{D}, \quad \frac{g(y)}{\overline{g}(y)} = \frac{\int \exp(\frac{r(x,y)}{\lambda_y})dx}{D}, \quad \frac{g_F(y)}{\overline{g}(y)} = \frac{\int \exp(\frac{V_F(x_F,y)}{\lambda_y})dz}{D}$$

where $D \equiv 1 + \int \exp(\frac{r(x,y)}{\lambda_y})dx + \int \exp(\frac{V_F(x_F,y)}{\lambda_y})dz$.

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

The conditional probabilities for those who form matches are:

$$\pi(y|x) = \frac{\pi(x,y)}{f(x)} = \frac{\exp(\frac{w(x,y)}{\lambda_x})}{\int \exp(\frac{w(x,y)}{\lambda_x})dy}, \quad \pi(x|y) = \frac{\pi(x,y)}{g(y)} = \frac{\exp(\frac{r(x,y)}{\lambda_y})}{\int \exp(\frac{r(x,y)}{\lambda_y})dx}$$

$$\pi_F(y|z) = \frac{\pi_F(x_F,y)}{h(x_F)} = \frac{\exp(\frac{w_F(x_F,y)}{\lambda_{x_F}})}{\int \exp(\frac{w_F(x_F,y)}{\lambda_{x_F}})dy}, \quad \pi_F(z|y) = \frac{\pi_F(x_F,y)}{g(y)} = \frac{\exp(\frac{V_F(x_F,y)}{\lambda_y})}{\int \exp(\frac{V_F(x_F,y)}{\lambda_y})dz}$$

Taking logs on both sides and rearranging,

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

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

$\log \pi_F(x_F,y) = \frac{w_F(x_F,y)}{\lambda_{x_F}} - \log \frac{\int \exp(\frac{w_F(x_F,y)}{\lambda_{x_F}})dy}{h(x_F)} = \frac{w_F(x_F,y)-c(x_F)}{\lambda_{x_F}}$, where $c(x_F) \equiv \lambda_{x_F} \log \frac{\int \exp(\frac{w_F(x_F,y)}{\lambda_{x_F}})dy}{h(x_F)}$

$\log \pi_F(x_F,y) = \frac{V_F(x_F,y)}{\lambda_y} - \log \frac{\int \exp(\frac{V_F(x_F,y)}{\lambda_y})dz}{g(y)} = \frac{V_F(x_F,y)-b_F(y)}{\lambda_y}$, where $b_F(y) \equiv \lambda_y \log \frac{\int \exp(\frac{V_F(x,y)}{\lambda_y})dz}{g(y)}$

Again, it is straightforward to obtain $\lambda \log \pi(x,y) = q(x,y) - a(x) - b(y)$ and $\lambda_F \log \pi_F(x_F,y) = q_F(x_F,y) - c(x_F) - b_F(y)$, and thus

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

$$\pi_F(x_F,y) = \exp(-\frac{c(x_F)}{\lambda_F})\exp(-\frac{b_F(y)}{\lambda_F})\exp(\frac{q_F(x_F,y)}{\lambda_F}) = \hat{c}(x_F)\hat{b}_F(y)\exp(\frac{q_F(x_F,y)}{\lambda_F})$$

where $\lambda \equiv \lambda_x + \lambda_y$, $\lambda_F \equiv \lambda_{x_F} + \lambda_y$, $\hat{a}(x) \equiv \exp(-\frac{a(x)}{\lambda})$, $\hat{b}(y) \equiv \exp(-\frac{b(y)}{\lambda})$, $\hat{c}(x_F) \equiv \exp(-\frac{c(x_F)}{\lambda_F})$, $\hat{b}_F(y) \equiv \exp(-\frac{b_F(y)}{\lambda_F})$.

Note that following equations hold, as before:

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

$$\exp(-\frac{c(x_F)}{\lambda_{x_F}}) = \frac{h(x_F)}{\int \exp(\frac{w_F(x_F,y)}{\lambda_{x_F}})dy} = \frac{\overline{h}(x_F)}{\exp(\frac{w_F}{\lambda_{x_F}}) + \int \exp(\frac{w_F(x_F,y)}{\lambda_{x_F}})dy} = \hat{c}(x_F)^{\frac{\lambda_F}{\lambda_{x_F}}}$$

$$\exp(-\frac{b(y)}{\lambda_y}) = \frac{g(y)}{\int \exp(\frac{r(x,y)}{\lambda_y})dx} = \frac{\overline{g}(y)}{1 + \int \exp(\frac{r(x,y)}{\lambda_y})dx + \int \exp(\frac{V_F(x_F,y)}{\lambda_y})dz} = \hat{b}(y)^{\frac{\lambda}{\lambda_y}}$$

$$\exp(-\frac{b_F(y)}{\lambda_y}) = \frac{g_F(y)}{\int \exp(\frac{V_F(x_F,y)}{\lambda_y})dz} = \frac{\overline{g}(y)}{1 + \int \exp(\frac{r(x,y)}{\lambda_y})dx + \int \exp(\frac{V_F(x_F,y)}{\lambda_y})dz} = \hat{b}_F(y)^{\frac{\lambda_F}{\lambda_y}}$$

As is evident from above, it turns out that $\hat{b}_F(y) = \hat{b}(y)^{\frac{\lambda}{\lambda_F}} = \hat{b}(y)^{\lambda_R}$ must hold, which allows for a simple characterization of the equilibrium under offshoring.

Combining these results, the exogenously given marginal distributions can be expressed as

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

$$\overline{h}(x_F) = \hat{c}(x_F)^{\frac{\lambda_F}{\lambda_{x_F}}} \exp(\frac{w_F}{\lambda_{x_F}}) + \hat{c}(x_F) \int \hat{b}(y)^{\lambda_R} \exp(\frac{q_F(x_F,y)}{\lambda_F}) dy$$

$$\overline{g}(y) = \hat{b}(y)^{\frac{\lambda}{\lambda_y}} + \hat{b}(y) \int \hat{a}(x) \exp(\frac{q(x,y)}{\lambda}) dx + \hat{b}(y)^{\lambda_R} \int \hat{c}(x_F) \exp(\frac{q_F(x_F,y)}{\lambda_F}) dz$$

Similar to the previous section, the equilibrium boils down to solving for the endogenous objects $\hat{a}(x), \hat{b}(y), \hat{c}(x_F)$, taking as given: marginal distributions $\overline{f}(x), \overline{g}(y), \overline{h}(x_F)$, production functions $q(x,y), q_F(x_F,y)$, and the degree of unobserved heterogeneity $\lambda_x, \lambda_y, \lambda_{x_F}$. 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 $\hat{a}(x), \hat{c}(x_F)$, then plug in to (3) to obtain $\hat{b}(y)$, and repeat until convergence. Again, once $\hat{a}(x), \hat{b}(y), \hat{c}(x_F)$ are found, it is straightforward to recover all other endogenous objects, including the matching function $\pi(x,y), \pi_F(x_F,y)$ as well as wages and profits $w(x,y), r(x,y), w_F(x_F,y), V_F(x_F,y)$.

D4. Global Economy Equilibrium with $\lambda = 0$

Here, we demonstrate the model with $\lambda = 0$ where worker-firm matching is realized on the observable characteristics of workers and firms and draw clear predictions of the model mechanisms. In order to characterize the equilibrium with no unobserved heterogeneities, we begin by showing the following: for any firm that obtains the same profits through offshoring and domestic hires, the best possible domestic or foreign worker match in equilibrium must have exactly the same skill.

Lemma 1 *Let* $b^* = \inf\{y \mid r(y) = r_F(y)\}$ *and* $b^{**} = \sup\{y \mid r(y) = r_F(y)\}$. *Then,* $x(y) = x_F(y)$, $\forall\ y \in (b^*, b^{**})$.

Proof We begin by showing that if there exists any two distinct firms y_1 and y_2 that are indifferent between offshoring and domestic hires, then any firm y between y_1 and y_2 is also indifferent. And if so, workers that each firm optimally finds from Home and Foreign are equally talented.

Result 1 Suppose $r(y) = r_F(y)$ holds for $y \in \{y_1, y_2\}$. Then, $r(y) = r_F(y)$, $\forall y \in [y_1, y_2]$.

Suppose $\exists y \in (y_1, y_2)$ s.t. $r(y) \neq r_F(y)$. Without loss of generality, we can assume that $\forall y \in (y_1, y_2), r(y) \neq r_F(y)$ by redefining the interval $[y_1, y_2]$. Without loss of generality, assume $r(y) > r_F(y), \forall y \in (y_1, y_2)$. This implies that all firms between y_1 and y_2 matches with domestic workers only. The matching function with foreign workers $x_F(y)$ stays constant: $x'_F(y) = 0$. Since $x_F(y) = r'_F(y)$, $x'_F(y) = r''_F(y) = 0$. So $r_F(y)$ must be linear in the range of (y_1, y_2). In addition, $r(y)$ must be strictly convex in (y_1, y_2). Combining these two statements, $r(y) < r_F(y), \forall y \in (y_1, y_2)$. But this contradicts with the assumption that $r(y) > r_F(y), \forall y \in (y_1, y_2)$. Q.E.D.

Result 2 Suppose $r(y) = r_F(y)\ \forall y \in [y_1, y_2]$. Then, $x(y) = x_F(y)$, $\forall y \in [y_1, y_2]$.

Suppose that firm y is indifferent between matching with the best possible worker x from Home and x_F from Foreign given the wage schedules $w(x)$ and $w_F(x_F)$. Recall the matching function $\mu : X \to Y$ where $\mu(X) = \tilde{G}^{-1}(\tilde{F}(X))$ and $\mu^{-1}(Y) = \tilde{F}_P^{-1}(\tilde{G}(Y))$ with $\tilde{G}(y) \equiv 1 - G(y)$, $\tilde{F}(x) \equiv 1 - F(x)$. And we similarly define a matching function assigning foreign workers to doemstic firms, $\mu_F(X_F) \to Y$ where $\mu(X_F) = \tilde{G}^{-1}(\tilde{F}_R(X_F))$ and $\mu^{-1}(Y) = \tilde{F}_R^{-1}(\tilde{G}(Y))$ with $\tilde{F}_R(x_F) \equiv 1 - F_R(x_F)$. Using the properties of the wage schedule together with the market clearing conditions, the following two conditions must hold.

$$\mu(x) = w'(x) \ \text{ and } \ \mu_F(x_F) = w'_F(x_F) \tag{22}$$

$$f_Y(y)dy = f_X(x)dx + f_Z(x_F)dx_F \ \Leftrightarrow \ \tilde{F}_Y(y) = \tilde{F}_X(x) + \tilde{F}_Z(x_F) \tag{23}$$

As the matching functions can also be written as $\mu'(x) = \frac{dy}{dx}$ and $\mu'_F(x_F) = \frac{dy}{dx_F}$, the market clearing condition can be re-formulated as follows.

$$f_Y(y) = \frac{f_X(x)}{\mu'(x)} + \frac{f_Z(x_F)}{\mu'_F(x_F)} \tag{24}$$

Plugging in the assumed matching functions into the indifference condition, the following must hold at all x and x_F that are indifferent to some firm y: $x\mu(x) - w(x) = x_F\mu_F(x_F) - w_F(x_F) - C$. Taking derivatives of both sides where the following is obtained.

$$(x\mu'(X) + \mu(x) - w'(x))dx = (x_F\mu'_F(x_F) + \mu_F(x_F) - w'_F(x_F))dx_F \tag{25}$$

As $\mu(x) = w'(x)$ and $\mu_F(x_F) = w'(x_F)$, as well as $\mu'(x) = \frac{dy}{dx}$ and $\mu'_F(x_F) = \frac{dy}{dx_F}$, it follows that $x = x_F$ must hold. That is, when a firm y optimally chooses the best domestic worker x and the best foreign worker x_F, in equilibrium these workers must have exactly the same skill. Q.E.D.

Next, we show that even when $\overline{x} = \overline{x}_F = \infty$, the firm with the highest productivity that finds indifference between Home and Foreign optimally matches with the best possible workers.

Result 3 Suppose $\overline{x} = \overline{x}_F = \infty$. Then, $y(\overline{x}) = y(\overline{x}_F) = \overline{y}$.

Suppose $\overline{x} = \infty$ and $y(\overline{x}) = y^* < \overline{y}$ such that all $y \geq y^*$ is matched with x_F. Using the wage functions, $y(\overline{x}) = w'(x) = y^*$, $w(x) \approx y^* x + k$. For $\forall y > y^*$, $r(y) = \max_x xy - w(x) = \max_x (y - y^*)x + k = \infty$ holds. All $y > y^*$ chooses x_F with $r_F(y) > r(y)$. As there is positive assortative matching between $(y^*, \overline{y})$ and $(x_F^*, \overline{x}_F = \infty)$. That is, any finite y is matched with finite z. Thus, $r_F(y)$ is finite, which means $r(y) > r_F(y)$. Then, $\overline{x} = \infty$ is a better match to $y > y^*$ than some finite x_F. This is a contradiction. Therefore, $\overline{x}$ must be matche with $\overline{y}$. Q.E.D.

Use Result 3 and Result 1 to show that $r(y) = r_F(y)$, $\forall y \geq b^*$. Then, using Result 2 we can show that, $x(y) = z(y)$, $\forall y \geq b^*$. Q.E.D.

It also follows from Lemma 1 that the wage difference between the two countries should equal the fixed cost C. Thus, for each occupation, when the cost of offshoring becomes negligible ($C \to 0$), which indicates a convergence to a perfectly integrated world economy, the wage profile does not differ between workers from home and foreign within these jobs.

Corollary 1 *The wage difference between Home and Foreign is equivalent to the cost of offshoring.*

$$w(x) - w_F(x) = C \quad \textit{for} \quad a_2^* \leq x$$

Proof From Lemma 1, it follows immediately that $q(x, y) = q(x_F, y)$ holds. Using the indifference condition, it is straightforward to see that, $w(x) = w_F(x_F) + C$ holds. Thus, the two wage schedules must be parallel with each other with a constant gap equal to the fixed cost of offshoring C. Q.E.D.

Hence, the equilibrium matching functions $\mu(x)$ and $\mu_F(x_F)$ that map domestic workers and foreign workers to domestic firms, respectively, are as follows.

$$\mu(x) = \begin{cases} \tilde{G}^{-1}(\tilde{F}(x) - \tilde{F}(a_1^*) + \tilde{G}(\underline{y})) & \text{for} \quad a_1^* \leq x \leq a_2^* \\ \tilde{G}^{-1}(\tilde{H}(x)) & \text{for} \quad a_2^* \leq x \end{cases} \tag{26}$$

$$\mu_F(x_F) = \tilde{G}^{-1}(\tilde{H}(x_F)) \quad \text{for} \quad a_2^* \leq x_F \tag{27}$$

We denote the c.d.f of workers and firms from Home as $F(x)$ and $G(y)$ respectively. Also, $H(x)$ indicates the aggregate worker endowment; and $\tilde{G}(y) \equiv 1 - G(y)$, $\tilde{F}(x) \equiv 1 - F(x)$. That is, the densities in the aggregate worker endowment in the global economy $h_w(x)$ is the sum of densities from home and foreign.[65] Next, equilibrium wages in the global economy are given as follows, where $q(x, y) = w(x) + r(y)$ and $q(x_F, y) = w_F(x_F) + r(y)$ hold.

$$w(x) = \begin{cases} c_1 + \int_{a_2^*}^{x} \frac{\partial q}{\partial x}(t, \tilde{G}^{-1}(\tilde{H}(t)))dt \quad \text{when} \quad a_2^* \le x \\ c_2 + \int_{a_1^*}^{x} \frac{\partial q}{\partial x}(t, \tilde{G}^{-1}(\tilde{F}(t) - \tilde{F}(a_1^*) + \tilde{G}(\underline{y})))dt \quad \text{when} \quad a_1^* \le x \le a_2^* \end{cases} \tag{28}$$

$$w_F(x_F) = c_3 + \int_{a_2^*}^{x_F} \frac{\partial q}{\partial x}(t, \tilde{G}^{-1}(\tilde{H}(t)))dt \quad \text{when} \quad a_2^* \le x_F \tag{29}$$

$$r(y) = \begin{cases} c_4 + \int_{b^*}^{y} \frac{\partial q}{\partial y}(\tilde{H}^{-1}(\tilde{G}(s)), s)ds \quad \text{when} \quad b^* \le y \quad \text{(offshoring)} \\ c_5 + \int_{b^*}^{y} \frac{\partial q}{\partial y}(\tilde{H}^{-1}(\tilde{G}(s)), s)ds \quad \text{when} \quad b^* \le y \quad \text{(domestic hires)} \\ c_6 + \int_{\underline{y}}^{y} \frac{\partial q}{\partial y}(\tilde{F}_P^{-1}(\tilde{G}(s) - \tilde{G}(\underline{y}) + \tilde{F}(a_1^*), s)ds \quad \text{when} \quad \underline{y} \le y \le b^* \quad \text{(domestic hires)} \end{cases} \tag{30}$$

Here, $w(a_1^*) = \underline{w}$, $w_F(a_2^*) = \underline{w}_F$, $c_1 + c_5 = q(a_2^*, b^*)$, $c_3 + c_4 = q(a_2^*, b^*) - C$, and $c_2 + c_6 = q(a_1^*, \underline{y})$ hold. Since firms above b^* are indifferent between offshoring and matching with domestic workers, which imposes $c_4 = c_5$, it follows that the difference in wages between foreign and home must equal to the fixed cost of offshoring.[66]
As a result of offshoring, workers above a_2^* match with firms that are indifferent between matching with workers from home and foreign; those between a_1^* and a_2^* match with firms that do not offshore; and those below a_1^* switch out to the traditional sector.[67]

Theorem 1 *For a given offshoring cost C, there exists a unique equilibrium of the global economy: there exists a threshold $b^* = \tilde{G}^{-1}(\tilde{H}(a_2^*))$ above which firms perform offshoring and below which firms domestically hire workers. The equilibrium demonstrates positive assortative matching with strictly convex profiles of wages and profits.*

[65]Note that we do not normalize the mass of workers in the aggregate endowment to 1 since an increase in the mass of workers in the global economy is an important channel that alters worker-firm matches. As before, the following notation is used: $\tilde{H}(x) \equiv 2 - H(x)$.

[66]This equation determines the threshold b^*, which also subsequently pins down a_1^* and a_2^*. See Appendix C for derivations.

[67]With firms offshoring, the traditional sector expands and improves in the workers' skill quality as those who become unmatched in the competitive sector and sort into the traditional sector are more skilled than those who were in the traditional sector under the closed economy assumptions.

Proof From Lemma 1, some firm y that is indifferent between offshoring and domestic hires and optimally chooses either x or x_F, finds the same quality of workers, $x = x_F$. Also, from Corollary 1, the wage difference between Homa and Foriegn is equal to the cost of offshoring C. Using the indifference condition, it immediately follows that, $\mu(x) = \mu_F(x_F)$ for these firms that are indifferent. Therefore, the market clearing condition can be re-arranged and simplified as follows:

$$g(y) = \frac{f_P(x)}{\mu'(x)} + \frac{f_R(x_F)}{\mu_F'(x_F)} = \frac{f_P(x) + f_R(x)}{\mu'(x)} \quad \Leftrightarrow \quad \mu'(x) = \frac{f_P(x) + f_R(x)}{g(y)} \tag{31}$$

Thus, for a particular offshoring cost C, there exists a threshold b^* above which firms find indifference in workers from home and foreign, $a_2^* \leq x$ and $a_2^* \leq x_F$ where $\tilde{G}(b^*) = \tilde{H}(a_2^*)$ with $\tilde{H}(x) = \tilde{F}(x) + \tilde{F}_R(x_F)$. As for firms below b^* who match with domestic workers $a_1^* \leq x \leq a_2^*$, as they cannot afford the cost of offshoring, the market clears, $\tilde{G}(b^*) - \tilde{G}(\underline{y}) = \tilde{F}(a_2^*) - \tilde{F}(a_1^*)$ and the following holds.

$$g(y) = \frac{f_P(x)}{\mu'(x)} \quad \text{and} \quad \mu(x) = w'(x) \;\text{ for }\; a_1^* \leq x \leq a_2^* \tag{32}$$

Taking anti-derivatives of $\mu'(x)$ and subsequently for $w'(x)$ provides the equilibrium matching and wage schedules for each interval of firms and the corresponding workers. Note that the profile of wages and profits are strictly convex as $w'(x)$ increases in x and $r'(y)$ inreases in y due to the nondecreasing matching function $\mu(x)$ derived from the supermodular production function $q(x,y)$. This indicates the existence of the equilibrium. Furthermore, Lemma 1 shows that $x = x_F$ is a necessary condition for an equilibrium in order to sustain the indifference condition in this range of firms. Thus, the equilibrium is unique. Q.E.D.

Derivation of Wage and Profits In matching problems, wage and profits are endogenously shared as follows:

$$w(x) = c_1 + \int_{x_0}^{x} \frac{\partial q}{\partial x}(t, \mu(t))dt \tag{33}$$

$$r(y) = c_2 + \int_{\mu(x_0)}^{y} \frac{\partial q}{\partial y}(\mu^{-1}(s), s)ds \tag{34}$$

with $c_1 + c_2 = q(x_0, \mu(x_0))$. As shown in Galichon (2016), we can use properties of *comonotonicity* of random variables to derive the wage and profit equations with different distributional assumptions for the endowment. Suppose that X has a c.d.f of $F(X)$ and Y, a c.d.f of $G(Y)$.

Definition 1 *Random variables X and Y are comonotone if there is U following uniform distribution such that $X = F_P^{-1}(U)$ and $Y = G^{-1}(U)$. Equivalently, X and Y are said to exhibit positive assortative matching.*

Thus, $X = F_P^{-1}(U)$ and $Y = G^{-1}(U)$ match in a positively assortative way with a nondecreasing assignment function $Y = G^{-1}(F(X))$: equilibrium matching between X and Y and that between $F(X)$ and $G(Y)$ are equivalent. Wages and profits can be solved numerically using c.d.f's of whichever distribution we assume to have as follows with a matching function $\mu(X) = G^{-1}(F(X))$.

D5. Global Economy Equilibrium: Uniform Distribution

Assuming uniform distributions for domestic and foreign endowments, domestic worker's skill x, firm's productivity y, and skill of foreign worker composites x_F are realizations of X, Y, and X_F, respectively where $X \sim U[0,1]$, $Y \sim U[0,1]$, and $X_F \sim U[0,\sigma]$.[68] with mass $\rho > 1$ where $\sigma > 1$. Using the same production technology as before, the optimal assignment of workers to firms in a global economy equilibrium is given as,

$$\mu(x) = \begin{cases} \frac{\rho+\sigma}{\sigma}x - \rho & \text{when} \quad a_2 \le x \le 1 \\ x - \frac{(\sigma-b_1)\rho}{\sigma+\rho} & \text{when} \quad a_1 \le x \le a_2 \end{cases}$$

$$\mu_F(x_F) = \begin{cases} \frac{\rho}{\sigma}x_F + (1-\rho) & \text{when} \quad 1 \le x_F \le \sigma \\ \frac{\rho+\sigma}{\sigma}x_F - \rho & \text{when} \quad a_2 \le x_F \le 1 \end{cases}$$

where $a_1 = \underline{y} + \frac{(\sigma-b_1)\rho}{\sigma+\rho}$; $a_2 = \frac{(\rho+b_1)\sigma}{\sigma+\rho}$ and $b_2 = \frac{\sigma-\rho\sigma+\rho}{\sigma}$. b_1 will be determined using wages and profits below. Again, equilibrium wages and profits under global economy are given as follows where $q(x,y) = w(x) + r(y)$ and $q(x_F,y) = w_F(x_F) + r(y)$ hold.

$$w(x) = \begin{cases} \frac{1}{2}(\frac{\sigma+\rho}{\sigma})x^2 - \rho x + d_1 & \text{when} \quad a_2 \le x \le 1 \\ \frac{1}{2}x^2 - \frac{(\sigma-b_1)\rho}{\sigma+\rho}x + d_2 & \text{when} \quad a_1 \le x \le a_2 \end{cases}$$

$$w_F(x_F) = \begin{cases} \frac{1}{2}\frac{\rho}{\sigma}x_F^2 + (1-\rho)x_F + d_3 & \text{when} \quad 1 \le x_F \le \sigma \\ \frac{1}{2}(\frac{\sigma+\rho}{\sigma})x_F^2 - \rho x_F + d_4 & \text{when} \quad a_2 \le x_F \le 1 \end{cases}$$

[68] The situation where $\sigma > 1$ arises when the worker composites from the foreign country delivers a higher quality of skill compared to home workers. In particular, if the wage differences between home and foreign is significantly large, allowing domestic firms to hire foreign workers in greater quantities, it is possible that the skill output of these foreign worker composites is high enough that there are no home workers to compete with the corresponding level of skill output.

$$r(y) = \begin{cases} \frac{1}{2}\frac{\sigma}{\rho}y^2 + \frac{\sigma(\rho-1)}{\rho}y + d_5 & \text{when} \quad b_2 \leq y \leq 1 \quad \text{(offshore)} \\ \frac{1}{2}(\frac{\sigma}{\sigma+\rho})y^2 + (\frac{\sigma\rho}{\sigma+\rho})y + d_6 & \text{when} \quad b_1 \leq y \leq b_2 \quad \text{(offshore)} \\ \frac{1}{2}(\frac{\sigma}{\sigma+\rho})y^2 + (\frac{\sigma\rho}{\sigma+\rho})y + d_7 & \text{when} \quad b_1 \leq y \leq b_2 \quad \text{(domestically hire)} \\ \frac{1}{2}y^2 + \frac{(\sigma-b_1)\rho}{\sigma+\rho}y + d_8 & \text{when} \quad \underline{y} \leq y \leq b_1 \quad \text{(domestically hire)} \end{cases}$$

where $d_1 = \frac{\sigma}{\sigma+\rho}\frac{\rho^2-b_1^2}{2} + \frac{b_1^2}{2} - \frac{\underline{y}^2}{2} + \underline{w}$; $d_2 = \frac{1}{2}(\frac{(\sigma-b_1)\rho}{\sigma+\rho})^2 - \frac{\underline{y}^2}{2} + \underline{w}$; $d_3 = \frac{\sigma}{\sigma+\rho}\frac{\rho^2-b_1^2}{2} + \underline{w}_F - \frac{1}{2}$; $d_4 = \frac{\sigma}{\sigma+\rho}\frac{\rho^2-b_1^2}{2} + \underline{w}_F$; $d_5 = \frac{1}{2}\frac{(\sigma+\rho-\sigma\rho)^2}{(\sigma+\rho)\rho} + \frac{b_1^2}{2}\frac{\sigma}{\sigma+\rho} - \underline{w}_F - C$; $d_6 = \frac{b_1^2}{2}\frac{\sigma}{\sigma+\rho} - \underline{w}_F - C$; $d_7 = \frac{b_1^2}{2}\frac{\sigma}{\sigma+\rho} - \frac{b_1^2}{2} + \frac{\underline{y}^2}{2} - \underline{w}$; and $d_8 = \frac{\underline{y}^2}{2} - \underline{w}$. Using the indifference condition that firms between b_1 and b_2 are indifferent between offshoring and hiring domestically (i.e. $d_6 = d_7$), b_1 is pinned down: $b_1 = \sqrt{2(C + \frac{1}{2}\underline{y}^2 + \underline{w}_F - \underline{w})}$.

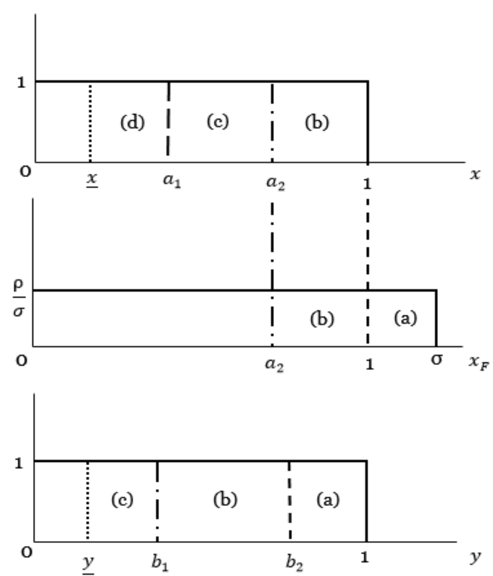


Figure 15: Equilibrium Matching with Offshoring

Each panel in the figure above illustrates endowments of domestic workers, foreign workers, and firms, respectively. In the bottom panel, area (a) corresponds to firms that only offshore; area (b), firms that are indifferent between offshoring and domestic hires; and area (c), firms that do not offshore. Firms below $\underline{y}$ exit the market. Corresponding labels in the workers' endowment indicate the respective worker matches. Area (d) indicate the mass of workers driven out to the traditional sector due to worker competition from abroad.

D6. Foreign Endowment with Lower Quality

The result of the model based on the assumed mechanism holds even when we assume an introduction of a foreign endowment that provides an inferior quality of skill output where the bottom end of the domestic distribution of workers face competition from abroad. While the high productive firms find no incentives to offshore, the low productive ones would be indifferent between offshoring and domestic matching, as they face the same quality of workers from home and foreign, assuming they can afford the cost of offshoring.[69] Suppose for a particular fixed cost of offshoring, there exists an interval of firms with relatively low productivity that choose to offshore. While those who face foreign competition in the distribution of workers have changed, the fact that the economy is provided with additional supply of workers and therefore driving out the least productive ones in the domestic labor market does not change. Again, the result of the model delivers skill-upgrading and improved homogeneity; however, the magnitude of the change from globalization would be smaller compared to a situation where the economy faces a more competitive foreign labor force, as assumed in the main part of the model.

D7. Comparison with Technological Change: Automation

Many studies that investigate the phenomena of "hollowing out" of the labor market or the disappearance of middle-skill occupations discuss such job replacements with respect to automation technology or offshoring. Although the focus of this paper mainly lies in examining the effect of offshoring on labor market outcomes, here, we briefly discuss how the model can be applied to examining a situation where occupations are replaced by machines instead of a distribution of workers.

Assuming constant productivity of machines brings about identical structure as to thinking about domestic firms facing a distribution of domestic workers and a *Dirac delta* measure of constant productivity generated by machines,

$$\delta(x_T) = \begin{cases} +\infty, & x_T = \kappa \\ 0, & x_T \neq \kappa \end{cases}$$

where $\int_{-\infty}^{+\infty} \delta(x_T) dx_T = 1$. Thus, firms can buy a machine instead of hiring a worker with occupation o, which generates a productivity of κ with cost C_T. Thus, when a firm decides

[69] When the cost of offshoring is high enough or the skill quality of foreign endowment is far too inferior that there is no overlap with the domestic workers, the result of the model is equivalent to that of a closed economy.

to employ a machine instead of a worker, the profit is $y\kappa - C_T$ where $\kappa < \overline{\kappa}$, and $C_T \geq w(\underline{x})$, and the firm's choice of technology adoption depends on the following:

$$\max\left[y\kappa - C_T, xy - w(x)\right] \quad \text{where} \quad \kappa < \overline{\kappa}, \quad C_T \geq w(\underline{x}) \tag{35}$$

Then, we solve for an equilibrium where technology adoption decision differs across the distribution of firms. Firms at the top-end who face workers with better productivity than the machine's output and the firms in the bottom-end who cannot afford the cost of adopting machines would continue to match with workers; and firms in the middle will end up adopting machines. There exist thresholds a_3, b_3 such that positive assortative matching is optimal with matching:

$$\mu(x) = \begin{cases} \tilde{G}^{-1}(\tilde{F}(x) - \tilde{F}(a_3^*)) & \text{for} \quad a_3^* \leq x \leq a_4^* \\ \tilde{G}^{-1}(\tilde{F}(x)) & \text{for} \quad x \geq a_4^* \end{cases} \tag{36}$$

where the least productive workers $x \leq a_3^*$ remains unmatched due to technology adoption by firms in the middle of the distribution. Next, we derive the profiles of wage and profit using optimal conditions above. We set the value of outside option to remain unmatched for workers to be 0. Since $h(x,y) = w(x) + r(y)$ must hold, equilibrium wages and profits are as follows:

$$w(x) = \begin{cases} c_1' + \int_{a_3^*}^{x} \frac{\partial h}{\partial x}(t, \tilde{G}^{-1}(\tilde{F}(t) - \tilde{F}(a_3^*)))dt & \text{when} \quad a_3^* \leq x \leq a_4^* \\ c_2' + \int_{b_3}^{x} \frac{\partial h}{\partial x}(t, \tilde{G}^{-1}(\tilde{F}(t)))dt & \text{when} \quad x \geq a_4^* \end{cases} \tag{37}$$

$$r(y) = \begin{cases} c_3' + \int_{\underline{y}}^{y} \frac{\partial h}{\partial y}(a_3^* + \tilde{F}^{-1}(\tilde{G}(s)), s)ds & \text{when} \quad y \leq b_1^* \\ c_4' + \int_{b_4}^{\overline{y}} \frac{\partial h}{\partial y}(\tilde{F}^{-1}(\tilde{G}(s)), s)ds & \text{when} \quad y \geq b_2^* \end{cases} \tag{38}$$

where $c_1' + c_3' = h(a_3^*, \underline{y})$ and $c_2' + c_4' = h(a_4^*, b_2^*)$. Examining how firms $y = b_1^* = \tilde{G}^{-1}(\tilde{F}(a_4^*) - \tilde{F}(a_3^*))$ and $y = b_2^* = \tilde{G}^{-1}(\tilde{F}(a_4^*))$ should be indifferent between employing a worker versus adopting technology, allows the model to determine the output and cost of the machine that defines such equilirbium:

$$\begin{aligned} \tilde{G}^{-1}(\tilde{F}(a_4^*) - \tilde{F}(a_3^*))\kappa - C_T &= a_4^*(\tilde{G}^{-1}(\tilde{F}(a_4^*) - \tilde{F}(a_3^*))) - w(a_4^*) \\ \tilde{G}^{-1}(\tilde{F}(a_4^*))\kappa - C_T &= a_4^*(\tilde{G}^{-1}(\tilde{F}(a_4^*))) - w(a_4^*) \end{aligned} \tag{39}$$

Solving this system of two equations gives the thresholds a_3, b_3 as a function of technological output κ and its cost C_T where the interval of firms that adopt technology $\tilde{G}^{-1}(\tilde{F}(a_4^*) - \tilde{F}(a_3^*)) \leq y \leq \tilde{G}^{-1}(\tilde{F}(a_4^*))$ increases with κ and decreases with C_T.

Example: Uniform Distribution Again, we assume uniform distributions for both skill endowments: $X \sim U[0,1]$, $Y \sim U[0,1]$. Analytically solving for the matching function, we obtain the following:

$$\mu(x) = \begin{cases} x \quad \text{for} \quad B \le x \le 1 \\ x - (B - A) \quad \text{for} \quad B - A \le x \le B \end{cases} \tag{40}$$

Again, when technology is costless with productivity greater than any worker in this economy, such occupation is completely substituted by automation while in the opposite case, there will be no technology adoption. Firms in the top ($B \le y \le 1$) and the bottom ($0 \le y \le A$) continue to employ occupation o while those in the middle ($A \le y \le B$) do not.

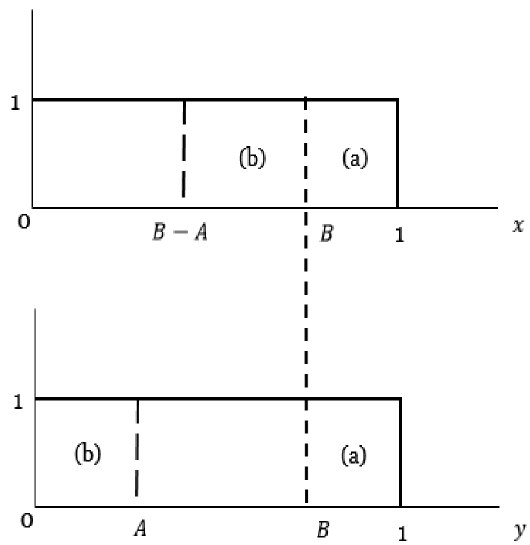


Figure 16: Equilibrium Matching with Technology Adoption

Equilibrium profiles of wages and profits are pinned down as follows:

$$w(x) = \begin{cases} \frac{1}{2}x^2 - \frac{1}{2}(B^2 - A^2) \quad \text{when} \quad B \le x \le 1 \\ \frac{1}{2}x^2 - (B - A)x + \frac{1}{2}(B - A)^2 \quad \text{when} \quad B - A \le x \le B \end{cases}$$

$$r(y) = \begin{cases} \frac{1}{2}y^2 + (B - A)B \quad \text{when} \quad B \le y \le 1 \\ y\kappa - C_T \quad \text{when} \quad A \le y \le B \\ \frac{1}{2}y^2 + (B - A)y \quad \text{when} \quad 0 \le y \le A \end{cases}$$

Furthermore, using indifferent conditions for firms between matching with workers and employing machines at thresholds A and B allows the model to analytically pin down values of A and B:

$$A = \sqrt{2C_T}, \quad B = \kappa$$

Due to changes in the demand for workers with technological change, workers $0 \le x \le A$ are unmatched, and even for those who are matched $A \le x \le 1$ undergo a wage loss. Firms in the top and bottom continue to hire workers with occupation o, and the mass of firms that decide to employ machines increases as the productivity of machine goes up ($\kappa \uparrow$) and the cost goes down ($C_T \downarrow$). Also, firms in the bottom match with better quality workers than before.