Offshoring, Matching, and Income Inequality: Theory and Empirics

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Abstract

This paper develops a matching framework of offshoring in which offshoring is defined as a cross-country many-to-one matching between workers and managers with complementary production technology. We embed the matching framework into two countries and two tasks with a continuum of skills to study the distributional effects of offshoring. Offshoring affects the matching mechanism, thereby it changes inequality through differential distributional impacts between-task and within-task in each country. Combining data from the U.S. Bureau of Economic Analysis, the U.S. Bureau of Labor Statistics, and the U.S. American Community Survey from 2002 to 2011, we provide empirical evidence that validates key predictions in the model. Offshoring explains about 12 to 21 percent of the widening income inequality in the U.S.

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1 Introduction

With the reduction in transportation cost and communication cost, a production process has become closely intertwined across countries. In the U.S., the number of foreign manufacturing workers working abroad for U.S. multinationals (using the BEA data) grew from 4.3 million in 2002 to 4.9 million in 2013 (a 13.8% increase) while the total number of U.S. manufacturing workers (using the BLS data) fell from 15.0 to 12.0 million during the same period (a 19.8% decrease). This trend implies that many manufacturing tasks in the U.S. have been sent to developing countries such as Brazil, China, Mexico, and India, which has led to increasing public concern in the media about offshoring U.S. jobs.

Economists also have been studying the distributional impacts of offshoring, and they have mainly focused on the *substitution effect* from offshoring, which they have approached from both theoretical and empirical perspectives (see Feenstra and Hanson, 1996; Grossman and Rossi-Hansberg, 2008, 2012; Ottaviano, Peri and Wright, 2013; Hummels, Jørgensen, Munch and Xiang, 2014; Ebenstein, Harrison, McMillan and Phillips, 2014). The *substitution effect* from offshoring is fairly straightforward. Tasks that were previously performed by domestic factors are sent abroad, and many of the studies have analyzed how the substitution of domestic factors for foreign factors has affected wages and the employment of domestic factors. However, economists have overlooked the *complementary effect* that might originate from offshoring. When the technology requires that certain groups of tasks must be performed together and there is some degree of complementary between tasks, then the distributional impacts of offshoring might be different from what economists have previously studied.

In this paper, we fill this gap in the literature by developing a matching framework of offshoring in order to analyze the distributional impact of offshoring. Our approach, which is based on complementary production technology, extends Grossman, Helpman and Kircher (2017)'s theoretical framework to two countries. The model features two countries and two tasks

that have a continuum of skills. One manager of a certain skill level hires some (endogenous) number of workers of a certain skill level (many-to-one matching) to produce a good, and we assume a log-supermodular production function between workers' skills and managers' skills. In a closed economy, an equilibrium matching pattern between workers and managers shows positive assortative matching, and log earnings schedules are strictly increasing and convex in skill levels.

Following Kremer and Maskin (1996, 2006) and Antràs, Garicano and Rossi-Hansberg (2006), offshoring is defined as a cross-country matching between workers and managers. To analyze the distributional impacts of offshoring, we first study two closed economies with no cross-country matching between workers and managers. Next, we study an integrated world economy in which frictionless cross-country matching is allowed between workers and managers. Then we compare two equilibria with that of an integrated world economy. Offshoring affects the matching mechanism between workers and managers. Because production technology is characterized by complementarity between tasks, the new matching pattern generates differential distributional impacts across heterogeneous workers and heterogeneous managers.

Applying the monotone comparative statics technique, as in Costinot and Vogel (2010), to the equilibrium condition, we derive several analytical results that shed some light on the consequences of offshoring. If two countries are identical in all aspects, moving from (complete) autarky to (complete) globalization has no implications for either matching patterns or earnings distributions in both countries. Thus, we consider a case where two countries are different in some aspects. Three main ingredients of cross-country differences provide us with meaningful insights: a) *factor endowments*, b) *factor distributions*, and c) *technology levels*.

First, we examine the impact of offshoring under cross-country differences in *factor endowments*, all other things being equal between two countries. The relative factor endowment, defined as the number of workers per manager, yields cross-country differences. We prove that offshoring

strictly increases total production in the World economy; i.e., there are gains from offshoring. On top of that, we demonstrate that the total earnings in each country, defined as the sum of total wages and total salaries in each country, strictly increases from offshoring. This result is quite surprising given that Pareto improvement can be made even without global coordination between two countries. If a lumpsum transfer within each country is feasible, everyone can be better off from offshoring. This result also revives the idea of *gains from trade* in both countries, as in David Ricardo and Heckscher-Ohlin, because, unlike the representative agent model, our model obtains the result of *gains from offshoring* in both countries even under the two-sided heterogeneous agent model. Moreover, the prices of identical factors of production are equalized. However, offshoring is not a panacea. A certain group of people is marginalized from globalization. Offshoring could generate within-country inequality, and the distributional impact of offshoring is the same as the Stolper and Samuelson (1941) theorem, in which abundant factors gain while scarcer factors lose. Furthermore, the workers' share and the managers' share in each country change in response to offshoring, even though we assume a Cobb-Douglas type parameter in production technology. This mechanism can also provide a novel explanation relevant to the current debate about the globally declining labor share (see Karabarbounis and Neiman, 2013; Elsby, Hobijn and Şahin, 2013; Autor, Dorn, Katz, Patterson and Van Reenen, 2017).

Second, we investigate the impact of offshoring under cross-country differences in *factor distributions*, all other things being equal between two countries. We conceptualize cross-country differences in *factor distributions* in two perspectives: 1) Centrality - "There are relatively more high-skilled workers/managers in the North than in the South" and 2) Dispersion - "Worker/Manager skill distribution is more diverse in the North than in the South." The underlying mechanism, which pieces together all possible cases, is that cross-country differences in *factor distributions* generate cross-country differences in matching function (a function that maps from a worker skill to a manager skill) between two countries. Suppose that

there are two managers with the same skill level, one in the North and the other in the South, and assume that the Northern manager is paired up with lower-skilled workers than the Southern manager in Autarky. If frictionless cross-country matching is allowed, then the Northern manager will desire to match with Southern workers, which will entail a change in the matching function. Due to the complementary effect, salaries of Northern managers bid up while wages of Northern workers decrease, which generates inequality between managers and workers in the North (between-task inequality). Moreover, because earnings schedules are increasing and convex in skills, more skilled managers benefit more from the re-matching, which generates a skill premium within managers in the North (within-task inequality).

Third, we study the distributional impact of cross-country differences in *technology levels*, all other things being equal between two countries. We assume that the North is relatively advanced than the South with regard to *technology levels*, and we analyze matching patterns and distributional consequences in the South if the South can adopt the advanced Northern technology. Three parameters characterize *technology levels* in both countries: a) Hicks-neutral technology; b) span of control; and c) sensitivity to manager skill level. We show that each case has a distinct distributional consequence in response to technology transfers from North to South. One interesting mechanism in case b) and case c) is that the optimal firm size changes from the technology transfer; in other words, the size of the larger firm increases whereas the size of the smaller firm decreases (the rise of superstar firms), which generates an inequality implication.

Next, we bring our theoretical model to data and test the model's key predictions. We start by testing the distributional impacts of offshoring on U.S. individuals. We use the U.S. Bureau of Economic Analysis (BEA) data on multinationals and the U.S. BLS Occupation Employment Statistics (OES) Survey data on employment to measure cross-country matchings at the industry-year level from 2002 to 2011, and we link it to the U.S. American Community Survey (ACS) data on individual-level information, such as wage, gender, age, race, occupation, and industry. Then we build on

Ebenstein, Harrison, McMillan and Phillips (2014)'s empirical framework and add to it a novel feature of our model's prediction such that offshoring has two countervailing effects: a *complementary effect* and a *substitution effect*. To capture these two distinct effects, we use broad occupation categories in the American Community Survey (ACS) to divide individuals into two groups, managers and workers, as in our theoretical specification. Furthermore, unlike previous studies on offshoring and labor markets that address only one-way impacts (e.g., offshore from the U.S. to the rest of the world) on earnings, we incorporate two-way impacts of offshoring (e.g., both offshore from the U.S. to the rest of the world and offshore from the rest of the world to the U.S.) on earnings into our main empirical specification.

Our regression analysis confirms that the earnings impacts of exposure to offshoring are statistically insignificant when we do not separate individuals into workers and managers, which is consistent with the prediction of the theory. However, we then uncover that the earnings impacts of exposure to offshoring generally are statistically significant and show expected signs when we separate individuals into workers and managers: a) When offshoring between U.S. multinationals and foreign individuals increases by 10 percent points, then the wages of U.S. workers reduce by 0.7 percent, and b) when offshoring between foreign multinationals and U.S. individuals increases by 10 percent points, then the wages of U.S. workers rise by 0.9 percent and the salaries of U.S. managers decline by 1.7 percent. The only result not consistent with our expectations is that offshoring between U.S. multinationals and foreign individuals has no impacts on U.S. managers. To reconcile this finding with the prediction of our theory, we further decompose U.S. managers into college graduates or more (high-skilled) and less than college graduates (low-skilled). In this specification, we find that the earnings impacts from offshoring are heterogeneous across high-skilled U.S. managers and low-skilled U.S. managers such that c) when offshoring between U.S. multinationals and foreign individuals increases by 10 percent points, then the salaries of high-skilled U.S. managers increase by 1.4 percent and the salaries of low-skilled U.S. managers decrease by 1.1 per-

cent. This finding suggests that only high-skilled U.S. managers benefit from the *complementary effect* when U.S. multinationals send their tasks offshore. Moreover, our core findings are robust in other specifications, such as without the financial crisis of 2008-2011 and using alternative definitions of workers and managers. Furthermore, the findings are robust even when we use alternative lag lengths. Moreover, the results are robust when we include the rising Chinese import competition shock, as in Autor, Dorn and Hanson (2013).

Based on our empirical finding that offshoring generates inequality, we further ask how much of the widening income inequality in the U.S. during the period of 2002 to 2011 can be explained by offshoring. We first note that income inequality, which is based on the variance of log earnings, rose during this period. Using the variance decomposition technique, we find that offshoring explains about 12 percent to 21 percent of the widening income inequality in the U.S. With regard to the contribution of offshoring to the change in income inequality, *Inshoring* plays a negligible role, suggesting that *Offshoring* plays a major role in the rising income inequality in the U.S.

2 Related Literature

This paper contributes to the theory of offshoring. Feenstra and Hanson (1996) develop an offshoring model in which a single manufactured good is produced from a continuum of intermediate inputs using skilled workers, unskilled workers, and capital. Grossman and Rossi-Hansberg (2008) propose a task-based offshoring model in which a continuum of tasks is performed by skilled workers and a continuum of tasks is performed by unskilled workers. They explicitly distinguish "goods" and "tasks." Both frameworks analyze the distributional impacts of offshoring when activities/tasks are transferred from North to South. Grossman and Rossi-Hansberg (2012) further explore the task-based offshoring model by extending it to a context of North-North offshoring in which two countries have identical relative factor endowments and technology levels but can differ in size. Yet

none of these models allow for the complementary effects between tasks that can arise from the offshoring process (i.e., log-supermodular production technology), and our model explicitly allows for such complementarity. Furthermore, because our model is tractable enough to study both cases, we analyze both North-South offshoring and North-North offshoring.

A few notable exceptions incorporate the complementary effect into the offshoring model. Kremer and Maskin (1996, 2006), who conceptualize globalization as workers from different countries who work together in the same firm, analyze the wage impacts of globalization. Globalization enables high-skilled workers in the developing country to match with more skilled workers in the developed country, while low-skilled workers in the developing country are marginalized because their skill levels are too low to match with workers in the developed country - which generates inequality in the developing country. However, this primary result is derived from a specific case in which the skill level of low-skilled workers in the developing country is too low from the model's strong assumption. Antràs, Garicano and Rossi-Hansberg (2006) propose a knowledge-based hierarchy model to study the effect of cross-country team formation on the structure of wages. Our model is closely related to this study but ours differs in several dimensions. First, in our model the team production function between workers and managers is general while in theirs it is derived from agent's specializations in production and knowledge (Garicano, 2000). Second, to simplify the analysis and thus obtain more tractable analytical solutions, we assume away the endogenous occupational choice problem. Third, we do not impose any particular functional forms for the distributions of skills, which enables us to analyze more general cases such as two normal distributions with different variances - for example, the North-North offshoring case.

Concerning the modeling framework, we build upon Grossman, Helpman and Kircher (2017)'s theoretical model that examines the distributional impacts of international trade in a world that has two industries and two factors of production with heterogeneous skill levels. They capture trade shocks as changes in the relative price of two industries and analyze how

these shocks affect matching, sorting, and the distributions of wages and salaries. We extend their modeling framework to allow for two countries, one sector, and two tasks with a continuum of skills to study how the matching and sorting mechanism is affected when a cross-country matching, defined as offshoring, is allowed between two countries. In an innovation distinct from Grossman, Helpman and Kircher (2017)'s model we use the concept of likelihood ratio property, as in Milgrom (1981) and Costinot and Vogel (2010), to derive analytical results on the distributional impacts of offshoring. We borrow tools and techniques developed in Costinot and Vogel (2010), whose analysis is restricted to a particular case in which workers are perfect substitutes. But going beyond the work of Costinot and Vogel (2010) we apply their techniques to the complementary production function.

Our model also is closely related to the standard two-sided one-to-one matching model originally developed by Becker (1973). More recently, Tervio (2008) has presented a one-to-one matching model between individual managers who have different abilities and firms that have different sizes. However, our paper is distinct from the one-to-one matching model in that we allow for many-to-one matching, and this enables us to speak about the size of the firm that is determined endogenously in the model. In this sense, the model is close to the span-of-control model proposed by Lucas (1978) wherein one manager manages a homogeneous workforce with diminishing returns to scale. Quite recently, Eeckhout and Kircher (2017) have proposed a unifying theoretical model of the many-to-one matching model that studies sorting and firm size simultaneously. Our conceptual framework is most closely related to this structure, and we incorporate the cross-country matching idea into the standard matching theory.

This paper contributes to empirical studies of offshoring. Feenstra and Hanson (1997, 1999) empirically find that, consistent with their theoretical model, offshoring contributes to the increase in the relative wage for skilled workers (a skill premium) both in Mexico during the period 1975-1988 and in the U.S. during the period 1979-1990. Ebenstein, Harrison, McMillan and Phillips (2014) link individual-level data from the U.S. Current Population

Survey (CPS) data to industry-level data on offshoring in order to estimate the impact of offshoring on American workers during the period 1984-2002. More recently, Hummels, Jørgensen, Munch and Xiang (2014) use Danish matched employee-employer data to evaluate the wage effects of offshoring during the period 1995-2006. They find that offshoring lowers the wages of low-skilled workers and raises the wages of skilled workers within a job spell. Our empirical study is the first attempt to distinguish between individual managers and workers, and it is first to simultaneously incorporate both offshoring from the rest of the world to the U.S and offshoring from the U.S. to the rest of the world.

This paper also is related to the literature on within-group inequality (or residual wage inequality). Juhn, Murphy and Pierce (1993) note that in the U.S., inequality within education and experience categories increased steadily throughout the 1970s and 1980s. Although they conjecture that the rapid growth in demand for skilled workers could account for this trend, they acknowledge that the exact source of the demand increase is unknown. Lemieux (2006a) argues that composition effects linked to the aging and increasing educational attainment of workforces explain a significant fraction of the within-group inequality during the period 1973-2003 in the U.S. Contrary to this finding, Autor, Katz and Kearney (2008) find that the composition effects play a minor role in explaining residual wage inequality during the period 1963-2005 in the U.S. Helpman, Itskhoki, Muendler and Redding (2017) develop a heterogeneous-firm model of trade that describes how the trade channel affects the between-firm inequality that ultimately feeds through within-sector-occupation inequality. Estimating the model using Brazilian data, they find sizable effects of trade on wage inequality. Grossman, Helpman and Kircher (2017) also develop a model to study the impact of international trade on within-occupation-industry earnings inequality. Our paper also provides a theoretical framework that allows offshoring to generate within-task inequality. Also, using U.S. data from the period 2002-2011, this paper presents empirical evidence of within-task inequality due to offshoring.

3 The Matching Model of Offshoring

The model builds upon Grossman, Helpman and Kircher (2017)'s model of the distributional effects of *international trade* in one country, two industries, and two heterogeneous factors of the production framework. We extend their modeling framework to allow for two countries to study the distributional effects of *offshoring*, which we define as a cross-country matching between workers and managers.

3.1 Environment

There are two countries, North (N) and South (S), in the world.[1] In each country, there are $\bar{M}$ units of inelastic "managers" and $\bar{L}$ units of inelastic "workers".[2] Managers are indexed by their skill level $z_M \in \mathcal{M} \subset \mathbb{R}_{++}$, and workers are indexed by their skill level $z_L \in \mathcal{L} \subset \mathbb{R}_{++}$. $\phi_M(z_M)$ is a probability density function over manager skill z_M and $\phi_L(z_L)$ is a probability density function over worker skill z_L. The probability density functions, $\phi_M(z_M)$ and $\phi_L(z_L)$, are both continuous and strictly positive over their bounded supports, $\mathcal{M} = [z_{M,min}, z_{M,max}]$ and $\mathcal{L} = [z_{L,min}, z_{L,max}]$, where $z_{M,min}, z_{M,max}, z_{L,min}$, and $z_{L,max}$ denote the lowest skill level of managers, the highest skill level of managers, the lowest skill level of workers, and the highest skill level of workers, respectively. Similarly, $\Phi_M(z_M)$ is a cumulative distribution function for manager skill z_M with continuous support $\mathcal{M} = [z_{M,min}, z_{M,max}]$ and $\Phi_L(z_L)$ is a cumulative distribution function for worker skill z_L with continuous support $\mathcal{L} = [z_{L,min}, z_{L,max}]$.

Market structure is perfect competition in which goods are produced by a large number of identical price-taking firms that can freely enter the market. There is only one final good Y in the market whose price P_Y is

[1] Section 3 characterizes the closed economy in the North. The South is defined analogously.

[2] More precisely, there are $\bar{M}^N$ units of inelastic "managers" and $\bar{L}^N$ units of inelastic "workers" in the North. In the South, there are $\bar{M}^S$ units of inelastic "managers" and $\bar{L}^S$ units of inelastic "workers." We use superscript N and S to denote countries in an open economy analysis.

normalized to one. Each firm hires a "manager" of skill $z_M \in \mathcal{M}$ and some endogenous number of "workers" of skill $z_L \in \mathcal{L}$ to produce final good Y (many-to-one matching). Specifically, we use $m(z_L)$, a matching function, to denote a worker of skill level z_L's counterpart manager skill level. Also, $m^{-1}(z_M)$ is an inverse matching function to denote a manager of skill level z_M's counterpart worker skill level.

3.2 Technology

The production function, $F : \mathbb{R}^3_+ \to \mathbb{R}_+$, describes the technology in the economy such that a firm combines manager and workers to produce output Y. A firm hiring one manager of skill level z_M paired up with some endogenous number of workers N of the same skill level z_L can produce a final good Y. The production function in the economy is defined as follows:

$$Y = F(z_M, z_L, N) = \alpha\psi(z_M, z_L)N^\gamma = \alpha e^{z_M^\beta z_L} N^\gamma, \quad 0 \leq \alpha \leq 1, \quad \beta > 1, \quad 0 < \gamma < 1$$

where α is the matching technology parameter and N is the number of workers.

Because the cross-country monitoring cost and the coordinating cost are higher than the within-country ones, international matching is less efficient than domestic matching. The technology parameter α captures the international matching friction such that moving from (complete) autarky to (complete) globalization can be modeled as an increase from $\alpha = 0$ to $\alpha = 1$. The falling costs of offshoring can be represented by the rise in the technology parameter α. Alternatively, an increase in the technology parameter α can be interpreted as a Hicks-neutral technology change in which the marginal productivity of the worker and the marginal productivity of the manager increase by the same proportion as the technology changes.

$\psi(z_M, z_L)$ denotes the productivity of a production team with one manager of skill z_M and some workers of skill z_L. We specify the following functional form for the productivity of a production team, $e^{z_M^\beta z_L}$, which satisfies following five properties:

1) Log-supermodular between the manager's skill and the worker's skill[3],

2) Managers of different skills are imperfect substitutes,

3) Workers of different skills are imperfect substitutes,

4) Different tasks within a firm are complementary,

5) Different tasks within a firm are differentially sensitive to skill.

With regard to 1) log-supermodularity, Teulings (1995) specifies a productivity of a worker with skill level s in job type c, $\Pi(s, c)$, as e^{sc}. This specification, which is log-supermodular between worker skill s and job complexity c, satisfies both *(a) absolute advantage* and *(b) comparative advantage*. (a) High-skilled workers are more productive regardless of the job in which they are employed. (b) High-skilled workers have a comparative advantage in complex jobs. The productivity of a production team in our specification, $e^{z_M^{\beta} z_L}$, also satisfies both *(a) absolute advantage* and *(b) comparative advantage*. With respect to 2), 3), 4) and 5), Kremer and Maskin (1996) propose a production function, H^2L, to account for segregation and inequality in a closed economy. The productivity of a production team in our model's specification, $e^{z_M^{\beta} z_L}$, captures four main ingredients, 2), 3), 4) and 5), as in Kremer and Maskin (1996). Moreover, the square term in the original production function in Kremer and Maskin (1996) is switched to β to more fully capture the flexibility of differential sensitivity to skill across tasks. A departure from Kremer and Maskin (1996)'s asymmetric and supermodular production function has some advantages and disadvantages. As is well known in the assignment literature, log-supermodularity guarantees positive assortative matching between workers and managers (Costinot and Vogel, 2010; Sampson, 2014), which simplifies a complex assignment problem. However, the disadvantage is that "cross-matching" is not allowed in our production function framework.[4] Lastly, the parameter γ captures the

[3] $e^{z_M^{\beta} z_L}$ is log-supermodular in z_M and z_L, i.e., $\dfrac{\partial^2 \ln \psi(z_M, z_L)}{\partial z_M \partial z_L} = \dfrac{\partial^2 z_M^{\beta} z_L}{\partial z_M \partial z_L} > 0$.

[4] Kremer (1993) and Grossman and Maggi (2000) show that the symmetric and supermodular production function exhibits positive assortative matching. Kremer and Maskin (1996)'s production framework is asymmetric and supermodular so that both "cross-matching" and "self-matching" are both allowed in their model.

diminishing returns to worker size from the manager's increasing span of control, as in Lucas (1978).

3.3 Profit Maximization

Consider a firm hires a manager of skill z_M. Given the output price $P_Y = 1$ and the wage schedule $w(z_L)$, the firm chooses the skill level of its workers z_L and the number of workers N to maximize profits, including salary payment to the manager:

$$\pi(N, z_L; z_M) = \alpha e^{z_M^\beta z_L} N^\gamma - w(z_L)N \tag{1}$$

where $w(z_L)$ is the wage paid to workers of skill z_L. Differentiating with respect to N yields the conditional worker demand:

$$N(z_L; z_M) = \left[\frac{\gamma \alpha e^{z_M^\beta z_L}}{w(z_L)}\right]^{1/1-\gamma} \tag{2}$$

which represents the optimal number of workers the firm would hire given that the firm hires a manager of skill level z_M, chooses workers of skill level z_L, and faces the wage schedule $w(z_L)$. Then plugging the conditional worker demand $N(z_L; z_M)$ into the profit function in (1) and calculating the first order condition with respect to z_L yields,

$$\frac{z_M^\beta}{\gamma} = \frac{w'(z_L)}{w(z_L)} \tag{3}$$

which shows the firm's optimal choice of worker skill z_L given the manager skill level z_M and the optimal number of workers N. The left-hand side represents the elasticity of productivity with respect to worker skill $\frac{\partial \psi(z_M, z_L)}{\partial z_L} \frac{z_L}{\psi(z_M, z_L)}$ divided by the parameter γ. The right-hand side denotes the elasticity of wage with respect to worker skill $\frac{\partial w(z_L)}{\partial z_L} \frac{z_L}{w(z_L)}$. The first order condition shows the trade-off relationship between productivity

and wage: hiring more high-skilled workers bids up productivity, although firms should pay more wages to the more high-skilled workers.[5]

A matching function in this economy is defined as $z_M = m(z_L)$ where $z_M \in \mathcal{M}$ and $z_L \in \mathcal{L}$. In equilibrium, there exists a unique value z_M that solves (3) for every z_L. Furthermore, the equilibrium exhibits positive assortative matching (PAM) for the economy as a whole.

Proposition 1. (Positive assortative matching) *In equilibrium, the matching function $m(z_L)$ is strictly increasing for all $z_L \in \mathcal{L}$.*

Proof. See Appendix 8.1.1. □

Using the equilibrium matching function $m(z_L)$, the first order condition in (3) can be expressed as:

$$\frac{m(z_L)^\beta}{\gamma} = \frac{w'(z_L)}{w(z_L)}, \quad \text{for all } z_L \in \mathcal{L}. \tag{4}$$

Proposition 2. (Convex log wage schedule) *The log wage schedule $\ln w(z_L)$ is strictly increasing and convex in worker skills.*[6]

Proof. See Appendix 8.1.2. □

Next, let us characterize the salary schedule $r(z_M)$ for managers. If a firm hires a manager of skill z_M and pays him the salary $r(z_M)$, its net profit $\Pi(z_M)$ would be:

$$\Pi(z_M) = \tilde{\pi}(z_M) - r(z_M), \quad \text{for all } z_M \in \mathcal{M} \tag{5}$$

[5]The same condition can be found in Costinot and Vogel (2010), Sampson (2014), and Grossman, Helpman and Kircher (2017).

[6]Mincer (1958, 1974) first modeled the log wage schedule as the sum of a linear function of years of education and a quadratic function of years of experience, known as "The Mincer earnings function." Some empirical studies note that log wages are an increasingly convex function of years of education (Lemieux, 2006b, 2008). If the skill level is captured well by years of education, the equilibrium convex log wage schedule matches well with the empirical findings. Also note that because the logarithmically convex function implies convex function, the wage schedule $w(z_L)$ also is strictly increasing and convex in worker skills.

where $\tilde{\pi}(z_M) \equiv \max_{N,z_L} \pi(N, z_L; z_M)$ is the optimal profit including salary payment which is achieved by the choice of the number of workers N and their skill level z_L from (2) and (3). Since the market is perfectly competitive and firms can freely enter the market (free entry condition), all firms in the market earn zero profits $\Pi(z_M) = 0$. Using the zero-profit condition, the following expression can be found:

$$r(z_M) = \gamma^{\gamma/1-\gamma}[1-\gamma]\alpha^{1/1-\gamma}\left[e^{z_M^{\beta} m^{-1}(z_M)}\right]^{1/1-\gamma} w(m^{-1}(z_M))^{-\gamma/1-\gamma}, \quad \text{for all } z_M \in \mathcal{M}. \tag{6}$$

Differentiating the above expression (6) with respect to z_M yields,

$$\frac{\beta z_M^{\beta-1} m^{-1}(z_M)}{1-\gamma} = \frac{r'(z_M)}{r(z_M)}, \quad \text{for all } z_M \in \mathcal{M} \tag{7}$$

where $m^{-1}(z_M)$ is the inverse matching function.[7] Similar to the first order condition in equation (3), the left-hand side of equation (4) represents the elasticity of productivity with respect to manager skill $\frac{\partial \psi(z_M, z_L)}{\partial z_M} \frac{z_M}{\psi(z_M, z_L)}$ divided by the parameter $1-\gamma$. The right-hand side denotes the elasticity of salary with respect to manager skill $\frac{\partial r(z_M)}{\partial z_M} \frac{z_M}{r(z_M)}$.

Proposition 3. (Convex log salary schedule) *The log salary schedule* $\ln r(z_M)$ *is strictly increasing and convex in manager skills.*[8]

Proof. See Appendix 8.1.3. □

3.4 Factor Market Clearing

Consider any connected set of workers $[z_{La}, z_L]$ and the set of managers $[m(z_{La}), m(z_L)]$ that match with these workers in equilibrium. A manager

[7] Because the equilibrium matching function $m(\cdot)$ shows positive assortative matching, the matching function $m(\cdot)$ is invertible.

[8] Like the wage schedule $w(z_L)$, the salary schedule $r(z_M)$ also is strictly increasing and convex in manager skills. Note also that convexities of the log wage function and the log salary function are guaranteed by the assumption of $\beta > 1$. More generally, if the production function is $\alpha e^{z_M^{\beta} z_L^{\delta}} N^{\gamma}$, then the parameter restriction, "$\beta \geq 1$ and $\delta \geq 1$," is sufficient to yield the convex log wage schedule and the convex log salary schedule.

of skill z_M is matched with $\left[\frac{\gamma\alpha e^{z_M^\beta z_L}}{w(z_L)}\right]^{1/1-\gamma}$ workers of skill z_L.[9] Since the matching function is increasing, factor market clearing condition can be expressed as:

$$\bar{M}\int_{m(z_{La})}^{m(z_L)}\left[\frac{\gamma\alpha e^{z^\beta m^{-1}(z)}}{w(m^{-1}(z))}\right]^{1/1-\gamma}\phi_M(z)dz = \bar{L}\int_{z_{La}}^{z_L}\phi_L(z)dz$$

where the left-hand side is the demand for workers by managers with a skill level between $m(z_{La})$ and $m(z_L)$ and the right-hand side is the supply of workers matched with those managers. After differentiating the factor market clearing condition with respect to z_L, we can derive a differential equation for the matching function as follows:

$$\bar{M}m'(z_L)\left[\frac{\gamma\alpha e^{m(z_L)^\beta z_L}}{w(z_L)}\right]^{1/1-\gamma}\phi_M(m(z_L)) = \bar{L}\phi_L(z_L), \quad \text{for all } z_L \in \mathcal{L}. \tag{8}$$

3.5 Equilibrium

Definition 1. (Competitive equilibrium) *A competitive equilibrium is characterized by a set of functions $m : \mathcal{L} \to \mathcal{M}$, $w : \mathcal{L} \to \mathbb{R}_{++}$, and $r : \mathcal{M} \to \mathbb{R}_{++}$ such that*

i) Optimality : Firms maximize profits that satisfy equations (4) and (7),

ii) Market Clearing : Factor market clears as in (8).

Note that either the wage schedule $w(z_L)$ or the salary schedule $r(z_M)$ can be recovered from each other due to the zero-profit condition in equation (6). This implies that there are two non-linear ordinary differential equations, (4) and (8). In addition to two equations, we have two boundary conditions from the positive assortive matching property: $z_{M,min} = m(z_{L,min})$ and $z_{M,max} = m(z_{L,max})$. If $\phi_M(z_M)$ and $\phi_L(z_L)$ are continuously differentiable, then the set of functions $m(\cdot)$, $w(\cdot)$, and $r(\cdot)$ are uniquely

[9] The conditional worker demand is derived from the profit-maximizing firm's optimal choice. See equation (2).

determined. Furthermore, as the market is complete and competitive, the equilibrium allocation is Pareto optimal.

3.6 Properties of an Equilibrium

3.6.1 Wage Schedule in Equilibrium

In equilibrium, the wage of a worker with skill level z_L is determined by several factors. First, the parameter γ governs the share of total output that goes to workers. Differentiating the profit in equation (1) with respect to N, we can derive the following result:

$$\underbrace{Nw(z_L)}_{\text{Workers' Share}} = \gamma \underbrace{\alpha e^{m(z_L)^\beta z_L} N^\gamma}_{\text{Total Output}}.$$

Next, rearranging the factor market clearing condition in (8), the equilibrium log wage schedule $\ln w(z_L)$ can be expressed as follows:

$$\ln w(z_L) = \ln \gamma + \ln \alpha + \underbrace{m(z_L)^\beta z_L}_{\text{Matching Effect}} + \underbrace{(1-\gamma) \ln \left[\frac{m'(z_L)\bar{M}\phi_M(m(z_L))}{\bar{L}\phi_L(z_L)} \right]}_{\text{Factor Intensity Effect}}. \quad (9)$$

The above log wage equation (9) indicates that there is a one-to-one relationship between the wage $w(z_L)$ and the matching technology parameter α. A one percent increase in matching technology is associated with a one percent increase in wage. An increase in the parameter β is positively associated with the wage level. The increase in the parameter β is equivalent to manager skill upgrading, and this will, in turn, increase the productivity of the production team. The increased productivity then feeds through the wage level positively. The higher skill level of a matching counterpart, $m(z_L)$, yields a higher wage level. As the productivity of a team $\psi(z_M, z_L)$ is complementary between manager skill and worker skill, a higher level of manager skill will increase the wage of a worker with skill level z_L. Hereafter we denote this effect as a "matching effect." Note that the term in

brackets represents the measure of managers to the measure of workers given one unit of skill level z_L. $\dfrac{d\Phi_M(m(z_L))}{d\Phi_L(z_L)} := \dfrac{m'(z_L)\phi_M(m(z_L))}{\phi_L(z_L)}$ is called the Radon-Nikodym derivative and it measures the rate of the change of density of the measure of managers with respect to the measure of workers. Thus, we can interpret the term in the bracket as relative factor intensity at worker skill level z_L. The relative factor intensity is positively related to wage level, which reflects the fact that more workers per production team will reduce the wage level from the competition effect. We will call it the "factor intensity effect" hereafter.

Next, let us examine the within-worker wage inequality in equilibrium. To this end, consider a connected set of workers $[z_{La}, z_{Lb}]$ and a set of managers $[m(z_{La}), m(z_{Lb})]$ that match with these workers. Then, the equilibrium condition can be expressed as follows:

$$\ln w(z_{Lb'}) - \ln w(z_{La'}) = \int_{z_{La'}}^{z_{Lb'}} \frac{m(z)^\beta}{\gamma} dz, \quad \text{for all } z_{Lb'} > z_{La'} \text{ and } z_{La'}, z_{Lb'} \in [z_{La}, z_{Lb}] \tag{10}$$

where the left-hand side expression represents the measure of the wage inequality, which is the log difference between the wage of a high-skilled worker and the wage of a low skilled worker. First, the wage inequality is positively associated with the matching function $m(\cdot)$. If the matching function shifts upward for all workers with skill level $z_L \in [z_{La}, z_{Lb}]$, then wage inequality widens. This reflects the fact that the upgrading of the managers skill is beneficial to both low-skilled and high-skilled workers, but the high-skilled workers benefit more because of the complementary effect between manager skill and worker skill. Second, the parameter β also is positively associated with the wage inequality. Since the increase in the parameter β is equivalent to the managers' skill upgrading, the effect is the same as an upward shift of the matching function. Lastly, the parameter γ is negatively associated with the wage inequality. The increase in the parameter γ induces managers to control more workers. This leads workers to match with more able managers. Thus, high-skilled workers are negatively affected by

the factor intensity effect while low-skilled workers are made better off by the factor intensity effect.

3.6.2 Salary Schedule in Equilibrium

From the zero profit condition, a manager's share of total output is as follows:

$$\underbrace{r(z_M)}_{\text{Manager's Share}} = (1-\gamma)\underbrace{\alpha e^{m(z_L)^{\beta} z_L} N^{\gamma}}_{\text{Total Output}}.$$

Plugging the equilibrium wage schedule in (9) into the zero-profit condition in (6), we can derive the equilibrium salary schedule as follows:

$$\ln r(z_M) = \ln(1-\gamma) + \ln\alpha + \underbrace{z_M^{\beta} m^{-1}(z_M)}_{\text{Matching Effect}} - \underbrace{\gamma \ln\left[\frac{m'(m^{-1}(z_M))\bar{M}\phi_M(z_M)}{\bar{L}\phi_L(m^{-1}(z_M))}\right]}_{\text{Factor Intensity Effect}}. \tag{11}$$

The matching technology parameter α and the parameter β have the same effects on salary as they did on wage. Like the equilibrium wage schedule, the salary of a manager with skill level z_M is determined by the following forces: 1) the matching effect and 2) the factor intensity effect. A Higher skill level of a matching counterpart, $m^{-1}(z_M)$, generates a higher salary level. However, unlike the wage schedule, relative factor intensity is negatively associated with salary level.

Next, let us investigate the within-manager salary inequality in equilibrium. Consider a connected set of managers $[z_{Ma}, z_{Mb}]$ and a set of workers $[m^{-1}(z_{Ma}), m^{-1}(z_{Mb})]$ that match with these managers. The equilibrium condition can be expressed as:

$$\ln r(z_{Mb'}) - \ln r(z_{Ma'}) = \int_{z_{Ma'}}^{z_{Mb'}} \frac{\beta z^{\beta-1} m^{-1}(z)}{1-\gamma} dz, \quad \text{for all } z_{Mb'} > z_{Ma'} \text{ and } z_{Ma'}, z_{Mb'} \in [z_{Ma}, z_{Mb}] \tag{12}$$

where the left-hand side expression represents the measure of the salary inequality: the log difference between the salary of a high-skilled manager and the salary of a low-skilled manager. Salary inequality is positively as-

sociated with the inverse matching function $m^{-1}(\cdot)$. Like the case of the worker's wage, skill upgrading of workers for all managers with skill level $z_M \in [z_{Ma}, z_{Mb}]$ has disproportionate effects on the managers' salary. Similar to the wage inequality, the parameter β is positively associated with the salary inequality. However, unlike the case of the wage inequality, the parameter γ is positively associated with the salary inequality.

3.6.3 Matching Function in Equilibrium

By differentiating the equation (9) with respect to z_L and substituting (4) into the result, we obtain the following second-order differential equation for the matching function:

$$\frac{m''(z_L)}{m'(z_L)} = \frac{m(z_L)^{\beta}}{\gamma} - \frac{\beta m(z_L)^{\beta-1} m'(z_L) z_L}{1-\gamma} + \frac{\phi_L'(z_L)}{\phi_L(z_L)} - \frac{\phi_M'(m(z_L))m'(z_L)}{\phi_M(m(z_L))}. \tag{13}$$

The solution to the above second-order differential equation does not depend on the parameter α and factor endowments $\bar{M}$ and $\bar{L}$. This implies that the matching function $m(z_L)$ does not depend on the parameter α and factor endowments $\bar{M}$ and $\bar{L}$; rather, it depends on the parameter β, the parameter γ, and factor distributions $\phi_M(z_M)$ and $\phi_L(z_L)$.

4 The Distributional Effects of Offshoring

Let us analyze how offshoring, a cross-country matching between a manager and workers, changes the matching mechanism and thereby affects the distribution of earnings (salary and wage) within and between groups (managers and workers) in the world economy composed of two countries, North and South. In the world economy, managers can match with workers in their own country or with workers in the other country. In within-country matching, we normalize $\alpha = 1$. In cross-country matching, this matching technology parameter α can take any values in $[0, 1]$. In this sec-

tion, we focus on the case of offshoring in which the cross-country matching technology parameter α changes from 0 to 1, or a move from (complete) autarky to (complete) globalization.

The equilibrium in the world economy is analogous to the equilibrium in the closed economy. The difference between the two equilibria lies in the supplies of the managers and workers. The supply of the heterogeneous managers and the supply of heterogeneous workers in the world economy, respectively, are defined by:

$$\bar{M}^W \phi_M^W(z_M) \equiv \bar{M}^N \phi_M^N(z_M) + \bar{M}^S \phi_M^S(z_M), \quad \text{for all } z_M \in \mathcal{M}^W$$

$$\bar{L}^W \phi_L^W(z_L) \equiv \bar{L}^N \phi_L^N(z_L) + \bar{L}^S \phi_L^S(z_L), \quad \text{for all } z_L \in \mathcal{L}^W$$

where $\bar{M}^W \equiv \bar{M}^N + \bar{M}^S$, $\phi_M^W(z_M) \equiv \dfrac{\bar{M}^N}{\bar{M}^N + \bar{M}^S}\phi_M^N(z_M) + \dfrac{\bar{M}^S}{\bar{M}^N + \bar{M}^S}\phi_M^S(z_M)$, $\mathcal{M}^W \equiv \mathcal{M}^N \cup \mathcal{M}^S$, $\bar{L}^W \equiv \bar{L}^N + \bar{L}^S$, $\phi_L^W(z_L) \equiv \dfrac{\bar{L}^N}{\bar{L}^N + \bar{L}^S}\phi_L^N(z_L) + \dfrac{\bar{L}^S}{\bar{L}^N + \bar{L}^S}\phi_L^S(z_L)$, and $\mathcal{L}^W \equiv \mathcal{L}^N \cup \mathcal{L}^S$.[10]

It is instructive to investigate the effects of offshoring under cross-country differences in factor endowments and factor distributions in isolation. In the following subsections, we begin by examining the impact of offshoring under cross-country differences in *factor endowments* given same factor distributions across countries. Next, we consider the effect of offshoring under cross-country differences in *factor distributions* while holding identical factor endowments across countries. Factor distributions differ across countries in terms of centrality and dispersion. For centrality, we use a concept of monotone likelihood ratio property, as in Milgrom (1981) and Costinot and Vogel (2010). For dispersion, we use a concept of diversity of skill, as in Grossman and Maggi (2000) and Costinot and Vogel (2010). In each case, we investigate how the falling costs of offshoring affect the matching function $m(\cdot)$ in each country and conclude its implications for the wage function $w(\cdot)$ and

[10]The superscripts W, N, and S denote World, North and South, respectively. The world distribution is a *mixture distribution* of the distribution in the North and the distribution in the South.

the salary function $r(\cdot)$. Along with the analytical solutions, we provide numerical simulation results in each case.

4.1 Cross-Country Differences in Factor Endowments

Proposition 4. (Gains from offshoring, global inequality, and within-country inequality) *Suppose that the North and the South are identical, except that there are relatively more managers in the North than in the South,* $\frac{\bar{M}^N}{\bar{L}^N} > \frac{\bar{M}^S}{\bar{L}^S}$. *If the economy moves from (complete) autarky to (complete) globalization, then*

(i) Total production in the World strictly increases;

(ii) Total earnings in each country strictly increases;

(iii) There exists a pattern of lump sum transfers within each country such that all agents can gain from offshoring, even without transfers between countries;

(iv) Global inequality is reduced because the prices of identical factors of production are equalized;

(v) In the North, the wage schedule shifts downward while the salary schedule shifts upward. In the South, the wage schedule shifts upward while the salary schedule shifts downward;

(vi) In the North, the workers' share reduces while the managers' share increases. In the South, the workers' share increases and the managers' share reduces.[11]

Proof. See Appendix 8.1.4. □

[11] To derive numerical simulation results, we use a bounded Pareto distribution with shape parameter $k_M > 0$ and location parameters $z_{M,min} > 0$ and $z_{M,max} > 0$ for manager skill distribution $\phi_M(z_M)$. Likewise, worker skill distribution $\phi_L(z_L)$ follows a bounded Pareto distribution with shape parameter $k_L > 0$ and location parameters $z_{L,min} > 0$ and $z_{L,max} > 0$. Next, the sensitivity to manager skill parameter β is based on Kremer and Maskin (1996, 2006)'s production function $\psi(z_M, z_L) = z_M^2 z_L$. In our specification, team productivity is $\psi(z_M, z_L) = e^{z_M^\beta z_L}$ and we set $\beta = 1.2$, implying that team productivity ranges from 2.7 (the lowest) to 99.0 (the highest). The span of control parameter γ is taken directly from the model of Atkeson and Kehoe (2005), in which the share of total output paid to the worker is 65.1 percent. In Table 1, we present sets of parameter values that characterize the move from autarky to globalization in Proposition 4. Figure 1 shows the autarky and open economy matching functions, log wage functions, and log salary functions given in Proposition 4.

The first result illustrates efficiency gains from offshoring caused by the change in matching mecha- nism between workers and managers that leads to the expansion of total production. Because the within-country matching is always possible in the integrated World economy, we can always replicate the closed economies of North and South in globalization, and competitive market forces (i.e., profit-maximizing firms) re-organize production units efficiently, which results in a higher production. A social planner who wishes to maximize total production in the World would prefer the equilibrium in globalization to those in the closed economy. The second result shows that both countries are better off from offshoring given that a social planner in each country wants to maximize total earnings in each country. The result rules out the possibilities that a) total earnings in the North increase while total earnings in the South decrease or b) total earnings in the South increase while total earnings in the North decrease. The fourth result shows that after globalization, workers of the same skill level receive the same wages and managers of the same skill level earn the same salaries. Because workers of the same skill level are perfectly substitutable, frictionless matching in the world economy will equalize wages between Northern workers and Southern workers of the same skill level. This result is consistent with Samuelson (1948)'s "Factor price equalization," which indicates that international trade equalizes the prices of identical factors of production.

The fifth result reveals that the abundant factor gains while the scarcer factor loses from offshoring, which is similar to the Stolper and Samuelson (1941) theorem (the homogenous workers and homogeneous managers case). Quantitatively, a one percent increase in factor endowment $\frac{\bar{M}}{\bar{L}}$ raises the wage schedule $w(z_L)$ by $1-\gamma$ percent for all $z_L \in \mathcal{L}^W$ and reduces the salary schedule $r(z_M)$ by γ percent for all $z_M \in \mathcal{M}^W$. When the span of control parameter γ is low, the marginal return of team production from increasing more units of workers diminishes at a higher rate. Thus, workers are more sensitive to the change in relative factor endowment $\frac{\bar{M}}{\bar{L}}$ and this

feeds through into the higher response of the wage schedule than that of the salary schedule. What are the within-country inequality implications from offshoring in this case? If the average salary of managers is higher than the average wage of workers, between-group inequality widens in the North while it narrows in the South. Note, however, that differences in factor endowments do not generate within-group inequality because the matching function does not change.

The last result demonstrates that even though the worker share of total output and the manager share of total output are pinned down by the Cobb-Douglas type parameter γ in a closed economy, offshoring can alter the workers' share and the managers' share. Because Northern managers can supervise more workers, including Southern workers, from offshoring, the managers' share rises and the workers' share shrinks in the North. If we consider managers as capital owners, then this finding has clear implications for current debates about the decline of the labor share (Karabarbounis and Neiman (2013); Elsby, Hobijn and Şahin (2013); Autor, Dorn, Katz, Patterson and Van Reenen (2017)). Our model predicts that if U.S. capital owners are more likely to match with foreign workers because of a drop in offshoring cost, then labor share in the U.S. will decline.

4.2 Cross-Country Differences in Factor Distributions (Centrality)

Definition 2. (Monotone likelihood ratio property - centrality)

(i) There are relatively more high-skilled managers in the North than in the South if $\frac{\phi_M^N(z'_M)}{\phi_M^N(z_M)} \geq \frac{\phi_M^S(z'_M)}{\phi_M^S(z_M)} \quad \forall z'_M \geq z_M$ *holds.*

(ii) There are relatively more high-skilled workers in the North than in the South if $\frac{\phi_L^N(z'_L)}{\phi_L^N(z_L)} \geq \frac{\phi_L^S(z'_L)}{\phi_L^S(z_L)} \quad \forall z'_L \geq z_L$ *holds.*[12]

[12]Examples of families of distributions with this property are the Normal (with mean θ), the Exponential (with mean θ), the Poisson (with mean θ), the Uniform (on $[0, \theta]$), and many others. The monotone likelihood ratio property extends the idea of skill abundance in a two-factor model into a continuum of skill framework. If $z_L, z'_L \in \mathcal{L}^N \cap \mathcal{L}^S$, then

4.2.1 Cross-Country Differences in Worker Distributions (Centrality)

Lemma 1. *Suppose* $\frac{\phi_L^N(z_L')}{\phi_L^N(z_L)} \geq \frac{\phi_L^S(z_L')}{\phi_L^S(z_L)} \quad \forall z_L' \geq z_L$. *Then,*

(i) $m^N(z_L) \leq m^S(z_L)$ *for all* $\mathcal{L}^N \cap \mathcal{L}^S$*;*

(ii) $\phi_L^W(z_L)$ *satisfies* $\frac{\phi_L^N(z_L')}{\phi_L^N(z_L)} \geq \frac{\phi_L^W(z_L')}{\phi_L^W(z_L)} \geq \frac{\phi_L^S(z_L')}{\phi_L^S(z_L)}$.

Proof. See Appendix 8.1.5. □

Because the relative supply of high skilled workers is more abundant in the North than in the South, Northern workers match with the less skilled manager than Southern workers although the two workers have the same skill level. From a manager's standpoint, the Northern manager can match with higher skilled workers than the Southern manager although the two managers have the same skill level. The second result shows that if the North has more high skilled workers relative to the South, then the North has more high skilled workers relative to the World and the World has more high skilled workers relative to the South.

Proposition 5. *Suppose that the North and the South are identical, except that there are relatively more high skilled workers in the North than in the South,* $\frac{\phi_L^N(z_L')}{\phi_L^N(z_L)} \geq \frac{\phi_L^S(z_L')}{\phi_L^S(z_L)} \quad \forall z_L' \geq z_L$. *If the economy moves from (complete) autarky to (complete) globalization, then*

(i) $m^W(z_L) \geq m^N(z_L) \quad \forall z_L \in \mathcal{L}^N$*;*

(ii) $m^S(z_L) \geq m^W(z_L) \quad \forall z_L \in \mathcal{L}^S$*;*

(iii) In the North, wage inequality widens and salary inequality narrows;

(iv) In the South, wage inequality narrows and salary inequality widens.[13]

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the monotone likelihood ratio property implies that $\frac{\phi_L^N(z_L')}{\phi_L^N(z_L)} \geq \frac{\phi_L^S(z_L')}{\phi_L^S(z_L)}$. The property also encompasses a case where different sets of skills are available under $\mathcal{L}^N$ and $\mathcal{L}^S$. If $z_L, z_L' \notin \mathcal{L}^N \cap \mathcal{L}^S$, then $z_L \in \mathcal{L}^S$ and $z_L' \in \mathcal{L}^N$. In other words, $\mathcal{L}^N$ is greater than $\mathcal{L}^S$ in the stronger set order: $z_{L,min}^N \geq z_{L,min}^S$ and $z_{L,max}^N \geq z_{L,max}^S$. The highest skilled worker is in $\mathcal{L}^N$ and the lowest skilled worker is in $\mathcal{L}^S$.

[13] In order to model monotone likelihood ratio property in the numerical exercise, $\frac{\phi_L^N(z_L')}{\phi_L^N(z_L)} \geq \frac{\phi_L^S(z_L')}{\phi_L^S(z_L)} \quad \forall z_L' \geq z_L$, we set the Pareto shape parameter values as follows: $k_W^N = 2$

Proof. See Appendix 8.1.6. □

From a Northern worker's standpoint, offshoring implies the upgrading of the matching partner's skill. From a Northern manager's perspective, offshoring means the downgrading of matching partner's skill. Intuitively, as the relative supply of low-skilled workers increases in the North, the positive assortative matching (PAM) condition requires that low-skilled managers match with more low-skilled workers in the North.[14]

In the North, an increase in the relative supply of the low-skilled workers triggers a matching of all workers toward high-skilled managers. Given that the production function is log-supermodular between the manager's skill and the worker's skill, high-skilled workers in the North benefit more from this re-matching process than low-skilled workers in the North, and this leads to wage inequality among Northern workers. Analogously, all Northern managers now match with lower-skilled workers. Due to the log-supermodularity, high-skilled managers lose more from this re-matching process than low-skilled managers in the North, and this narrows inequality within managers.

Equations (10) and (12) indicate that the parameter γ is associated with the sensitivity of wage inequality and salary inequality. When the parameter γ is low, wage inequality reacts sharply while salary inequality responds slowly in response to a change in the matching function. The logic is such that the marginal return of team production from increasing more units of workers diminishes at a higher rate. Unlike the parameter γ, the sensitivity of the manager's skill β is positively associated with both wage inequality and salary inequality.

and $k_W^S = 10$. In Table 2, we present sets of parameter values that characterize the move from autarky to globalization in Propostion 5. Figure 2 shows the autarky and open economy matching functions, log wage functions, and log salary functions given in Proposition 5.

[14] In the South, the results are the opposite.

4.2.2 Cross-Country Differences in Manager Distributions (Centrality)

Lemma 2. *Suppose* $\frac{\phi_M^N(z'_M)}{\phi_M^N(z_M)} \geq \frac{\phi_M^S(z'_M)}{\phi_M^S(z_M)} \quad \forall z'_M \geq z_M$. *Then,*

(i) $m^{N^{-1}}(z_M) \leq m^{S^{-1}}(z_M)$ *for all* $\mathcal{M}^N \cap \mathcal{M}^S$*;*

(ii) $\phi_M^W(z_M)$ *satisfies* $\frac{\phi_M^N(z'_M)}{\phi_M^N(z_M)} \geq \frac{\phi_M^W(z'_M)}{\phi_M^W(z_M)} \geq \frac{\phi_M^S(z'_M)}{\phi_M^S(z_M)}$.

Proof. See Proof of Lemma 1. □

Proposition 6. *Suppose that the North and the South are identical, except that there are relatively more high skilled managers in the North than in the South,* $\frac{\phi_M^N(z'_M)}{\phi_M^N(z_M)} \geq \frac{\phi_M^S(z'_M)}{\phi_M^S(z_M)} \quad \forall z'_M \geq z_M$. *If the economy moves from (complete) autarky to (complete) globalization. Then,*

(i) $m^{W^{-1}}(z_M) \geq m^{N^{-1}}(z_M) \quad \forall z_M \in \mathcal{M}^N$*;*

(ii) $m^{S^{-1}}(z_M) \geq m^{W^{-1}}(z_M) \quad \forall z_M \in \mathcal{M}^S$*;*

(iii) In the North, wage inequality narrows and salary inequality widens;

(iv) In the South, wage inequality widens and salary inequality narrows.[15]

Proof. See Proof of Proposition 5. □

This exercise describes factor distributions between the U.S. and the rest of the world. Using a management field experiment on large Indian textile firms, Bloom, Eifert, Mahajan, McKenzie and Roberts (2013) find that the management practices raised the productivity of firms. This result suggests that large productivity differences across countries have their origins in variations in management practices. Since the U.S. has higher productivity than the rest of the world, we can regard North as the U.S. and South as the rest of the world. The distributional consequences of offshoring generates some salient features of income inequality in the U.S. since the 1960s: 1) Earnings polarization, 2) Rising top one percent income, and 3) Task premium between workers and managers.

[15] In Table 3, we present sets of parameter values that characterize the move from autarky to globalization in Propostion 6. Figure 3 shows the autarky and open economy matching functions, log wage functions, and log salary functions given in Proposition 6.

First, Autor, Katz and Kearney (2008) observe that according to the U.S. CPS data, a 90/50 (upper-tail) residual wage inequality rose while a 50/10 (lower-tail) residual wage inequality fell during the period 1989 to 2005. Similarly, Kopczuk, Saez and Song (2010) show that a 80/50 (upper-tail) earnings ratio among men rose while a 50/20 (lower-tail) earnings ratio among men fell during the 1990s (data from the U.S. Social Security Administration). As managers, on average, are better paid than workers, the upper-tail inequality can be considered as within-manager inequality and the lower-tail inequality can be regarded as within-worker inequality. In the North, within-manager inequality widens and within-worker inequality narrows, which is consistent with the observations of Autor, Katz and Kearney (2008) and Kopczuk, Saez and Song (2010). Second, Piketty and Saez (2003) note that top one percent income shares have humongously risen since the 1970s using the U.S. individual tax returns data. Since top income earners are managers and within-manager inequality widens in the North, the top one percent income rises from globalization. Lastly, Acemoglu and Autor (2011) point out that individuals' tasks have become an important determinant of earnings. The earnings gap between managerial task and subordinate task widened during the period 1973 to 2009 using Census and American Community Survey data. As the matching function shifts downward in the North, Northern managers are matched with higher skilled workers while Northern workers are paired up with lesser skilled managers from globalization. Thus, task premium between managers and workers widens in the North.

4.3 Cross-Country Differences in Factor Distributions (Dispersion)

Definition 3. (Monotone likelihood ratio property - dispersion)

(i) Manager skill distribution is more diverse in the North than in the South if $\frac{\phi_M^N(z'_M)}{\phi_M^N(z_M)} \geq \frac{\phi_M^S(z'_M)}{\phi_M^S(z_M)}$ for all $z'_M \geq z_M \geq \hat{z}_M$, *and* $\frac{\phi_M^N(z'_M)}{\phi_M^N(z_M)} \leq \frac{\phi_M^S(z'_M)}{\phi_M^S(z_M)}$ for all $z_M \leq z'_M < \hat{z}_M$.

(ii) Worker skill distribution is more diverse in the North than in the South if $\frac{\phi_L^N(z_L')}{\phi_L^N(z_L)} \geq \frac{\phi_L^S(z_L')}{\phi_L^S(z_L)}$ for all $z_L' \geq z_L \geq \hat{z}_L$, *and* $\frac{\phi_L^N(z_L')}{\phi_L^N(z_L)} \leq \frac{\phi_L^S(z_L')}{\phi_L^S(z_L)}$ for all $z_L \leq z_L' < \hat{z}_L$.[16]

4.3.1 Cross-Country Differences in Worker Distributions (Dispersion)

Lemma 3. *Suppose* $\frac{\phi_L^N(z_L')}{\phi_L^N(z_L)} \geq \frac{\phi_L^S(z_L')}{\phi_L^S(z_L)}$ for all $z_L' \geq z_L \geq \hat{z}_L$, *and* $\frac{\phi_L^N(z_L')}{\phi_L^N(z_L)} \leq \frac{\phi_L^S(z_L')}{\phi_L^S(z_L)}$ for all $z_L \leq z_L' < \hat{z}_L$. *Then,*

(i) There exists $z_L^* \in \mathcal{L}^W$ *such that* $m^N(z_L) \geq m^S(z_L)$ *for all* $z_L \in [z_{L,min}^S, z_L^*]$ *and* $m^N(z_L) \leq m^S(z_L)$ *for all* $z_L \in [z_L^*, z_{L,max}^S]$*;*

(ii) $\phi_L^W(z_L)$ *satisfies* $\frac{\phi_L^N(z_L')}{\phi_L^N(z_L)} \geq \frac{\phi_L^W(z_L')}{\phi_L^W(z_L)}$ for all $z_L' \geq z_L \geq \hat{z}_L$, *and* $\frac{\phi_L^N(z_L')}{\phi_L^N(z_L)} \leq \frac{\phi_L^W(z_L')}{\phi_L^W(z_L)}$ for all $z_L \leq z_L' < \hat{z}_L$. *Also,* $\phi_L^W(z_L)$ *satisfies* $\frac{\phi_L^W(z_L')}{\phi_L^W(z_L)} \geq \frac{\phi_L^S(z_L')}{\phi_L^S(z_L)}$ for all $z_L' \geq z_L \geq \hat{z}_L$, *and* $\frac{\phi_L^W(z_L')}{\phi_L^W(z_L)} \leq \frac{\phi_L^S(z_L')}{\phi_L^S(z_L)}$ for all $z_L \leq z_L' < \hat{z}_L$.

Proof. See Appendix 8.1.7. □

Because the relative supply of higher skilled workers is larger among the high-skill worker group in the North than in the South, Northern workers in the high-skill worker group match with the less skilled manager than Southern workers in the high-skill worker group. A Northern manager in the high-skill manager group can better match with higher skilled workers than a Southern manager in the high-skill manager group.[17]

Definition 4. (Convergence and polarization of the earnings schedule)

(i) The salary schedule, $r(z_M)$*, converges if there is an increase in inequality*

[16] These properties capture the idea that there are relatively more managers with extreme skill levels in the North than in the South. The examples of distribution with this property are the Normal (with same mean θ and different variance σ), the Uniform (on $[\theta_1, \theta_2]$ vs. $[\theta_3, \theta_4]$ with $\theta_1 > \theta_3$ and $\theta_2 < \theta_4$), and many others.

[17] For the low-skill worker group and the low-skill manager group, the result is precisely the opposite.

among low-skilled managers, $z_M < z_M^*$, and a decrease in inequality among high-skilled managers, $z_M > z_M^*$. The salary schedule, $r(z_M)$, polarizes if there is a decrease in inequality among low-skilled managers, $z_M < z_M^*$, and an increase in inequality among high-skilled managers, $z_M > z_M^*$.

(ii) The wage schedule, $w(z_L)$, converges if there is an increase in inequality among low-skilled workers, $z_L < z_L^*$, and a decrease in inequality among high-skilled workers, $z_L > z_L^*$. The wage schedule, $w(z_L)$, polarizes if there is a decrease in inequality among low-skilled workers, $z_L < z_L^*$, and an increase in inequality among high-skilled workers, $z_L > z_L^*$.

Proposition 7. *Suppose that the North and the South are identical, except that worker skill distribution is more diverse in the North than in the South, $\frac{\phi_L^N(z_L')}{\phi_L^N(z_L)} \geq \frac{\phi_L^S(z_L')}{\phi_L^S(z_L)}$ for all $z_L' \geq z_L \geq \hat{z}_L$, and $\frac{\phi_L^N(z_L')}{\phi_L^N(z_L)} \leq \frac{\phi_L^S(z_L')}{\phi_L^S(z_L)}$ for all $z_L \leq z_L' < \hat{z}_L$. If the economy moves from (complete) autarky to (complete) globalization, then*

(i) $m^N(z_L) \geq m^W(z_L) \quad \forall z_L \in [z_{L,min}^N, z_L^{N*}]$ and $m^N(z_L) \leq m^W(z_L) \quad \forall z_L \in [z_L^{N*}, z_{L,max}^N]$;

(ii) $m^W(z_L) \geq m^S(z_L) \quad \forall z_L \in [z_{L,min}^S, z_L^{S*}]$ and $m^W(z_L) \leq m^S(z_L) \quad \forall z_L \in [z_L^{S*}, z_{L,max}^S]$;

(iii) In the North, the wage schedule polarizes and the salary schedule converges;

(iv) In the South, the wage schedule converges and the salary schedule polarizes.[18]

Proof. See Proof of Proposition 5. □

Offshoring implies an upgrading of the matching partner's skill for a high-skilled group of Northern workers while it means a downgrading of the matching partner's skill for a low-skilled group of Northern workers.

[18] To capture skill dispersion, we use a bounded Normal distribution with mean $\mu_M > 0$, variance $\sigma_M > 0$, and location parameters $z_{M,min} > 0$ and $z_{M,max} > 0$ for manager skill distribution $\phi_M(z_M)$. Likewise, worker skill distribution $\phi_L(z_L)$ follows a bounded Normal distribution with mean $\mu_L > 0$, variance $\sigma_L > 0$, and location parameters $z_{L,min} > 0$ and $z_{L,max} > 0$. In Table 4, we present sets of parameter values that characterize the move from autarky to globalization that Proposition 7 describes. Figure 4 shows the autarky and open economy matching functions, log wage functions, and log salary functions given in Proposition 7.

From a Northern manager's standpoint, offshoring induces the high-skilled manager group to match with lower skill workers while it leads to an upgrading of the matching partner's skill for the low-skilled manager group.[19]

In the North, the least-skilled worker benefits most from the low-skilled worker group, and the most-skilled worker benefits most from the high-skilled worker group. This leads to *polarization* of wage schedule in the North. The mid-skilled manager group, compared to the high-skilled manager group and the low-skilled manager group, benefits relatively more from globalization, which leads to *convergence* of the salary schedule in the North. Kremer and Maskin (1996) argue that a rise in skill dispersion plus an increase in mean skill level raises the wages of the high-skilled but reduces the wages of the low-skilled, thereby increasing inequality. Our result shows that when worker skill distribution is more diverse in the North than in the South wages in the lower and the upper tails of the worker distribution fall in comparison to the median of the worker distribution because there are relatively more workers in the lower and the upper tails of the worker distribution in the North.

4.3.2 Cross-Country Differences in Manager Distributions (Dispersion)

Lemma 4. *Suppose* $\frac{\phi_M^N(z'_M)}{\phi_M^N(z_M)} \geq \frac{\phi_M^S(z'_M)}{\phi_M^S(z_M)}$ for all $z'_M \geq z_M \geq \hat{z}_M$, *and* $\frac{\phi_M^N(z'_M)}{\phi_M^N(z_M)} \leq \frac{\phi_M^S(z'_M)}{\phi_M^S(z_M)}$ for all $z_M \leq z'_M < \hat{z}_M$. *Then,*

(i) There exists $z_M^* \in \mathcal{M}^W$ *such that* $m^{N^{-1}}(z_M) \geq m^{S^{-1}}(z_M)$ *for all* $z_M \in [z_{M,min}^S, z_M^*]$ *and* $m^{N^{-1}}(z_M) \leq m^{S^{-1}}(z_M)$ *for all* $z_M \in [z_M^*, z_{M,max}^S]$*;*

(ii) $\phi_M^W(z_M)$ *satisfies* $\frac{\phi_M^N(z'_M)}{\phi_M^N(z_M)} \geq \frac{\phi_M^W(z'_M)}{\phi_M^W(z_M)}$ for all $z'_M \geq z_M \geq \hat{z}_M$, *and* $\frac{\phi_M^N(z'_M)}{\phi_M^N(z_M)} \leq \frac{\phi_M^W(z'_M)}{\phi_M^W(z_M)}$ for all $z_M \leq z'_M < \hat{z}_M$. *Also,* $\phi_M^W(z_M)$ *satisfies* $\frac{\phi_M^W(z'_M)}{\phi_M^W(z_M)} \geq \frac{\phi_M^S(z'_M)}{\phi_M^S(z_M)}$ for all $z'_M \geq z_M \geq \hat{z}_M$, *and* $\frac{\phi_M^W(z'_M)}{\phi_M^W(z_M)} \leq \frac{\phi_M^S(z'_M)}{\phi_M^S(z_M)}$ for all $z_M \leq z'_M < \hat{z}_M$.

[19] In the South, results are the opposite.

Proof. See Proof of Lemma 3. □

Proposition 8. *Suppose that the North and the South are identical, except that manager skill distribution is more diverse in the North than in the South,* $\frac{\phi_M^N(z'_M)}{\phi_M^N(z_M)} \geq \frac{\phi_M^S(z'_M)}{\phi_M^S(z_M)}$ for all $z'_M \geq z_M \geq \hat{z}_M$, *and* $\frac{\phi_M^N(z'_M)}{\phi_M^N(z_M)} \leq \frac{\phi_M^S(z'_M)}{\phi_M^S(z_M)}$ for all $z_M \leq z'_M < \hat{z}_M$. *If the economy moves from (complete) autarky to (complete) globalization, then*

(i) $m^{N^{-1}}(z_M) \geq m^{W^{-1}}(z_M)$ $\forall z_M \in [z_{M,min}^N, z_M^{N*}]$ *and* $m^{N^{-1}}(z_M) \leq m^{W^{-1}}(z_M)$ $\forall z_M \in [z_M^{N*}, z_{M,max}^N]$*;*

(ii) $m^{W^{-1}}(z_M) \geq m^{S^{-1}}(z_M)$ $\forall z_M \in [z_{M,min}^S, z_M^{S*}]$ *and* $m^{W^{-1}}(z_M) \leq m^{S^{-1}}(z_M)$ $\forall z_M \in [z_M^{S*}, z_{M,max}^S]$*;*

(iii) In the North, the wage schedule converges and the salary schedule polarizes;

(iv) In the South, the wage schedule polarizes and the salary schedule converges.[20]

Proof. See Proof of Proposition 5. □

5 The Distributional Effects of Technology Transfer

Let us investigate how changes in technology parameters α, β, and γ affect the matching function $m(\cdot)$, the wage function $w(\cdot)$, and the salary function $r(\cdot)$. Suppose there are two countries in the world and the North is technologically advanced than the South in terms of different parameter values of α, β, and γ. We assume that only within-country matching is allowed and compare two economies that have different parameter values. Throughout the analysis, we assume that factor endowments and factor distributions are identical between North and South.

[20] In Table 5, we present sets of parameter values that characterize the move from autarky to globalization as described in Proposition 8. Figure 5 shows the autarky and open economy matching functions, log wage functions, and log salary functions given in Proposition 8.

5.1 Hicks-Neutral Technology Transfer

Proposition 9. *Suppose that the South can adopt a Northern technology - i.e., from* $\alpha^S \psi(z_M, z_L) N^\gamma$ *to* $\alpha^{S'} \psi(z_M, z_L) N^\gamma$ *where* $\alpha^{S'} = \alpha^N > \alpha^S$*. Then, in the South,*

(i) The matching function does not change;

(ii) The wage schedule shifts upward and the salary schedule shifts upward.[21]

Proof. See Appendix 8.1.8. □

This exercise illustrates that Southern firms can use superior Northern technology through technology transfer. The technology transfer is modeled as a Hicks-neutral technical progress such that the marginal product of the manager and the marginal product of the worker increase in the same proportion. In addition, the technology transfer does not affect the trade-off relation between the productivity and wage/salary in equations (4) and (7). The Hicks-neutral technology progress does not affect the matching function; thus, the ratio of managers and workers stays the same for all production units. Quantitatively, a one percent increase in technology level α raises $w(z_L)$ and $r(z_M)$ by one percent.

5.2 Improvement in Management Technology

Proposition 10. *Suppose that the South can adopt a Northern management technology - i.e., from* $\alpha^S \psi(z_M, z_L) N^{\gamma^S}$ *to* $\alpha^S \psi(z_M, z_L) N^{\gamma^{S'}}$ *such that* $\gamma^{S'} = \gamma^N > \gamma^S$*. Then, in the South,*

(i) The matching function shifts upward;

(ii) The workers' share increases and the managers' share reduces;

(iii) The size of the most skilled firms (weakly) increases, whereas the size of the least skilled firms (weakly) decreases.[22]

[21] In Table 6, we present sets of parameter values that characterize Propostion 9. Figure 6 shows North and South matching functions, log wage functions, and log salary functions given in Proposition 9.

[22] In Table 7, we present sets of parameter values that characterize Propostion 10. Figure 7 shows North and South matching functions, log wage functions, and log salary functions given in Proposition 10.

Proof. See Appendix 8.1.9. □

Contrary to the Hicks-neutral technology transfer case, the ratio of the marginal product of the manager to the marginal product of the worker changes due to the adoption of management technology. This implies that the optimal number of workers given a production unit could be affected, which results in the change of the matching function. Because each manager can accommodate the larger number of workers, workers now match higher skilled managers. The size of the production unit per manager increases in the high-skilled manager group while the size decreases in the low-skilled manager group. The change in the relative factor endowment will feed through into higher salaries (lower wages) for the high-skilled manager group (the high-skilled worker group) and lower salaries (higher wages) for the low- skilled manager group (the low-skilled worker group). The increase in management technology also can be interpreted as an increase in the marginal product of the worker. In each production unit, the workers share increases and the managers share decreases. As the matching function shifts upward, workers gain while managers lose from the matching effect.

5.3 Manager-Biased Technical Change

Proposition 11. *Suppose that the South can adopt a manager-biased Northern technology - i.e., from* $\alpha e^{z_M^{\beta^S} z_L} N^\gamma$ *to* $\alpha e^{z_M^{\beta^{S'}} z_L} N^\gamma$ *such that* $\beta^{S'} = \beta^N > \beta^S$*. Also, assume that* $z^N_{L,min} = z^S_{L,min} \geq 1$ *and* $z^N_{M,min} = z^S_{M,min} \geq 1$*. Then, in the South,*

(i) The matching function shifts upward;

(ii) The wage schedule shifts upward and wage inequality rises;

(iii) The highest skilled manager's salary rises;

(iv) The size of the most skilled firms (weakly) increases, whereas the size of the least skilled firms (weakly) decreases.[23]

[23] In Table 8, we present sets of parameter values that characterize Propostion 11. Figure 8 shows North and South matching functions, log wage functions, and log salary functions given in Proposition 11.

Proof. See Appendix 8.1.10. □

As in the Hicks-neutral technology transfer case, the ratio of the marginal product of the manager to the marginal product of the worker does not change. However, the elasticity of productivity with respect to worker skill and the elasticity of productivity with respect to manager skill are affected by the manager-biased technical change. This, in turn, affects the trade-off relation between productivity and wage (salary), which changes the matching function. The increase in the parameter β is equivalent to a skill upgrading for managers. This leads to an upward shift in the matching function. The highest-skilled manager can manage more workers, which bids up the salary of the manager through the factor intensity effect. Also, the skill upgrading effect feeds through the salary positively. When these two effects are combined the highest-skilled manager's salary rises. As the matching function and the parameter β increase, wage inequality widens among workers. The minimum wage rises because the size of production units diminishes among low-skilled worker groups, and an increase in the parameter β is equivalent to a partner's skill upgrading.

6 Empirical Analysis

In this section, we subject our model's predictions to empirical tests. We test the prediction of Proposition 4: if Northern firms (U.S. multinationals) send their tasks abroad, they can hire more workers per manager and this leads to a decrease in wages for workers and an increase in salaries for managers, which generates between-task inequality in the U.S. We exploit industry-year variations in the number of foreign employees who work abroad for U.S. multinationals per total U.S. employees as a proxy to capture cross-country matching between Northern managers and Southern workers. Conversely, Southern firms lose workers per manager, and the distributional impacts on Southern agents are exactly the opposite. We exploit industry-year variations in the number of U.S. employees who work for

foreign multinationals per total U.S. employees as a proxy to capture cross-country matching between Northern workers and Southern managers. To explore the differential impacts of offshoring across tasks, we divide individuals into two groups: managers and workers.[24] The notable feature of the empirical analysis is that, unlike previous works on offshoring and labor markets that address only a one-way impact (e.g., offshoring from the U.S. to the rest of the world) on earnings, we simultaneously incorporate into the main empirical specification the two-way impacts of offshoring on earnings (e.g., both offshoring from the U.S. to the rest of the world and offshoring from the rest of the world to the U.S.). We also quantify the contribution of offshoring to rising income inequality in the U.S.

6.1 Data Description

We exploit industry-year variation of cross-country matches in the U.S. and link this to individual-level earnings data. We use U.S. individual-level data from the American Community Survey (ACS) from 2002 to 2011, which provides consistent information for each worker, such as wage, gender, age, race, occupation, and industry during this period. To measure cross-country matches at the industry-year level, we draw data from the Bureau of Economic Analysis (BEA) U.S. Direct Investment Abroad dataset, the Bureau of Economic Analysis (BEA) Foreign Direct Investment in the U.S. dataset, and total employment data from the BLS Occupation Employment Statistics (OES) Survey. Finally, we draw industry-year level data on total factor productivity and the capital-value added ratio from the NBER-CES Manufacturing Industry Database. The industry classification in the ACS data is the 1997 North American Industry Classification System (NAICS). Since other industry-level data also are based on NAICS, we can easily link the industry-level dataset with the ACS dataset. In Table 9, we construct

[24] Ebenstein, Harrison, McMillan and Phillips (2014) also study the differential impacts of offshoring across occupation groups. However, their main focus is the substitution effect from foreign competition, and consequently they classify individuals by occupational exposure to offshoring activities - that is, routine versus non-routine tasks.

a concordance table between the industry code from the American Community Survey (ACS) and the industry code from the Bureau of Economic Analysis (BEA). There are 76 industries in the American Community Survey (ACS) that we can consistently link between the two datasets.[25]

6.1.1 Measure of Offshoring and Inshoring

For our primary explanatory variable, we follow Ottaviano, Peri and Wright (2013) and Ebenstein, Harrison, McMillan and Phillips (2014), who use information on the industry-year level total number of foreign employees who work abroad for U.S. multinationals. More importantly, we also use the industry-year level total number of U.S. employees who work for foreign multinational enterprises. For each industry-year, we define $\mathit{Offshoring}_{jt}$ and $\mathit{Inshoring}_{jt}$ as follows:

$$\mathit{Offshoring}_{jt} \equiv \frac{\text{The number of foreign employees who work abroad for U.S. multinationals}_{jt}}{\text{The total number of U.S. employees}_{jt}},$$

$$\mathit{Inshoring}_{jt} \equiv \frac{\text{The number of U.S. employees who work for foreign multinationals}_{jt}}{\text{The total number of U.S. employees}_{jt}}$$

where j indexes industry and t indexes year.

6.1.2 Wages and Salaries

Data on wages and salaries are obtained from ACS variable *incwage*, which reports each respondent's yearly total pre-tax wage and salary income. Amounts are expressed in contemporary dollars, and we adjust for inflation to construct real yearly wages and salaries. We use the logarithm of real yearly wages and logarithm of real yearly salaries for our dependent variable.

[25] The BLS OES survey data set and the NBER-CES Manufacturing Industry dataset also are based on the 4-digit NAICS system as in Bureau of Economic Analysis (BEA) industry classification.

6.1.3 Workers and Managers

Our theoretical model emphasizes that offshoring affects workers and managers differentially. To implement such a test, we need appropriate measures to distinguish between workers and managers. We use the ACS variable to classify *occ1990* into six broad occupation categories in Table 11. Then, we propose two alternative measures to capture "managers" in the model: i) A broad definition of managers, $ManagerB$ ($000 \leq occ1990 \leq 200$) and ii) A narrow definition of managers, $ManagerN$ ($000 \leq occ1990 \leq 37$). Similarly, we define "workers" as follows: iii) A broad definition of workers, $WorkerB$ ($501 \leq occ1990 \leq 900$) and iv) A narrow definition of workers, $WorkerN$ ($701 \leq occ1990 \leq 900$).[26]

6.1.4 Other Control Variables

The American Community Survey (ACS) provides each individual's socioeconomic characteristics, such as age, sex, race, and education. We use these variables as control variables. Lastly, we include total factor productivity and the capital-value added ratio, which are taken from the NBER-CES Manufacturing Industry Database, to capture industry-year level productivity changes that may affect wages and salaries for each individual.

6.2 Empirical Context

We outline historical trends in $Offshoring_{jt}$ and $Inshoring_{jt}$ during the period 2002 to 2013 that enable us to identify the earnings impacts of offshoring. In Table 12, which is based on the BLS employment data, total manufacturing employment fell from 15.0 in 2002 to 12.0 million in 2013 (U.S. manufacturing employment declined by 19.8%). Approximately 3 million manufacturing jobs in the U.S. were lost during this period, and some economists

[26] In the empirical analysis, we drop the following occupations: Technical, Sales, and Administrative ($201 \leq occ1990 \leq 400$), Service ($401 \leq occ1990 \leq 470$), and Farming, Forestry, and Fishing ($471 \leq occ1990 \leq 500$).

coined the phrase "US employment 'sag' of the 2000s" to describe the period (see Acemoglu, Autor, Dorn, Hanson and Price, 2016; Pierce and Schott, 2016). In contrast, the number of foreign employees working abroad for U.S. multinationals (using the BEA data) continued to grow from 4.3 million in 2002 to 4.9 million in 2013 (an increase of 13.8%). Approximately 0.6 million manufacturing jobs were newly created abroad by US multinationals. If the lost jobs in the U.S. during the period had been ascribed to the newly created jobs abroad, then about a 20% job loss would have been the result of offshoring. The total number of foreign employees working abroad for U.S. multinationals per total number of U.S. employees (our measure of offshoring abroad) rose from 28.7% in 2002 to 40.8% in 2013 (an increase of 12.1% points). We now turn to a trend in the number of U.S. workers employed by foreign multinationals in the U.S., which has been overlooked by the offshoring literature. The number of U.S. employees who work for foreign multinationals in the U.S. (using the BEA data) remained roughly constant: 2.2 million in 2002 and 2.3 million in 2013 (an increase of 3.5%). It is worth mentioning that there is a sizable amount of employment by foreign multinationals in the U.S., albeit not as much as offshoring abroad. Also during the period from 2002 and 2013, the number of U.S. workers employed by foreign multinationals in the U.S. rose while total employment declined. Hence, our measure of offshoring in the U.S. (the share of the number of U.S. employees by foreign multinationals in total employment) rose from 15.0% in 2002 to 19.3% in 2013 (an increase of 4.4% points).

Let us investigate in more detail (i.e., at the industry-year level) our two sources of variation, $Offshoring_{jt}$ and $Inshoring_{jt}$. In Table 13, we present industries with the highest 10 and the lowest 10 offshoring as measured by changes in $Offshoring_{jt}$ during the period 2002 to 2013. While the average change in $Offshoring_{jt}$ is 12.1%p (see Table 12), there is large variation in changes in $Offshoring_{jt}$: between 523.3%p (Tobacco: 3122) and -19.6%p (Electric lighting: 3351). In Table 14, we provide industries with the highest 10 and the lowest 10 inshoring as measured by changes in $Inshoring_{jt}$ during the period 2002 to 2013. Again, across industries we find large variation in

changes in $\textit{Inshoring}_{jt}$: between 50.5%p (Iron and steel: 3311) and -22.8%p (Medical: 3391), even though there is a small variation of average changes in $\textit{Inshoring}_{jt}$ (4.4%p).

6.3 Main Empirical Specification

Motivated by the theoretical relationship in equations (9) and (11), we are interested in estimating the following modified Mincer-type earnings regression:

$$\begin{aligned}\ln w_{ijt} &= \alpha + \mathbf{x'_{ijt}}\beta + \mathbf{g'_{jt-1}}\theta + \gamma_1 Worker_{ijt} \times \textit{Offshoring}_{jt-1} + \gamma_2 Manager_{ijt} \times \textit{Offshoring}_{jt-1} \\ &+ \gamma_3 Worker_{ijt} \times \textit{Inshoring}_{jt-1} + \gamma_4 Manager_{ijt} \times \textit{Inshoring}_{jt-1} \\ &+ \upsilon \times Manager_{ijt} + \delta_j + \xi_t + \psi_r + \epsilon_{ijt} \qquad (14)\end{aligned}$$

where i indexes the individual, j denotes the industry, and t represents the year. The dependent variable, $\ln w_{ijt}$, is the logarithm of the real yearly wage/salary. $\mathbf{x_{ijt}}$ is a vector of individual characteristics, such as age, age squared, sex, race, and education. $\mathbf{g_{jt}}$ is a vector of time-varying industry characteristics, such as total factor productivity and capital intensity. δ_j is the industry fixed effect, ξ_t is the year fixed effect and ψ_r is the regional fixed effect. $\textit{Offshoring}_{jt}$ is a proxy variable for cross-country matching between U.S. firms and foreign workers. $\textit{Inshoring}_{jt}$ is a proxy variable for cross-country matching between foreign firms and U.S. workers. $Worker_{ijt}$ is a dummy variable for worker and $Manager_{ijt}$ is a dummy variable for manager.

6.3.1 Identification Strategy

The above baseline empirical specification seeks to identify the causal impacts of offshoring on earnings. We rely on several strategies that deal with an endogeneity problem. First, we construct our main explanatory variables, $\textit{Offshoring}_{jt}$ and $\textit{Inshoring}_{jt}$, based on the share of total employees instead of the absolute number of employees. This alleviates the concern

that changes in technology or other factors within the industry could lead to changes in the cross-country matchings that are not driven by the offshoring factor. Second, instead of using the current measure of offshoring, we use lagged measures of cross-country matchings to capture wage/salary adjustment in response to offshoring because the adjustment is not instantaneous. This also alleviates a concern about reverse causality between earnings and offshoring. Third, we link individual-level data from ACS and industry-level offshoring data from BEA and BLS. This strategy alleviates the issue of reverse causality because it is difficult for individuals to affect the industry-level offshoring measure. Fourth, offshoring to foreign countries and offshoring to the U.S. might simultaneously affect wages/salaries in industry j. We include both regressors in the baseline specification to account for differential impacts of both measures on earnings. Fifth, one might be concerned that offshoring and wages/salaries are jointly affected by unobserved industry-specific, region-specific, and common time-varying shocks. We address this concern by including industry fixed effects (δ_j), region fixed effects (ψ_r) and year fixed effects (ξ_t). We also attempt to add region-year fixed effects (ζ_{rt}) and industry-region fixed effects (ω_{jr}) in order to control for missing unobserved factors. Sixth, we include a industry-year varying confounding variable - total factor productivity - because it can affect the demand for labor. We also include a industry-year varying capital-value added ratio.

6.3.2 Testable Hypothesis

The theory predicts that the effects of offshoring are different between outward (from the U.S. to the rest of the world) and inward (from the rest of the world to the U.S.) and also between workers and managers. We use industry-year variation in $\textit{Offshoring}_{jt-1}$ and $\textit{Inshoring}_{jt-1}$ to account for offshoring and inshoring. We also include the interaction terms $Worker_{ijt} \times \textit{Offshoring}_{jt-1}$ and $Manager_{ijt} \times \textit{Offshoring}_{jt-1}$ to capture U.S. multinational's differential offshoring impacts on U.S. individuals. Also, we include interaction terms $Worker_{ijt} \times \textit{Inshoring}_{jt-1}$ and $Manager_{ijt} \times \textit{Inshoring}_{jt-1}$ to

capture foreign multinational's differential offshoring impacts on U.S. individuals. The basic intuition behind this prediction is that offshoring has two sides impacts on U.S. individuals: the complementary effect and the substitution effect. To sum up, we expect that $\gamma_1 < 0$, $\gamma_2 > 0$, $\gamma_3 > 0$, and $\gamma_4 < 0$.

6.4 Empirical Results

6.4.1 Main Findings

In Table 15, we present adjusted individual-level Mincer regressions to replicate some prior studies on the determinants of the logarithm of real wages/salaries. We verify that individual characteristics such as, gender, age, and race, all are expected signs and are statistically significant. The college earnings premium, or the earnings gap between college degree holders and individuals without a degree, is estimated to be around 34%. Managerial task premium, the earnings gap between managers and workers, is estimated to be about 63%. When it is compared to the narrow definition of workers, the managerial task premium is estimated to be around 72%. We also find that capital intensity displays a negative and statistically significant association with real income, which suggests that an increase in capital intensity has substituted for labor, and this, in turn, puts downward pressure on labor wages/salaries. Total factor productivity, which could affect the demand for labor, does not associate with real income. Given that productivity changes can be labor-saving or labor-complementary, the insignificant result is not surprising.

The coefficients of *Offshoring*, γ_A, and *Inshoring*, γ_B, capture the impact on earnings of individuals who were most exposed to offshoring. In columns (1) through (4) in Table 15, a broad measure of the worker ($WorkerB$) is included in the estimation. In columns (5) through (8) in Table 15, we redo the analysis using the narrow measure of workers ($WorkerN$). For *Offshoring*, we find small negative wage effects in Baseline specifications and insignificant earnings effects in the Narrow Workers specification. This result is

similar to that of Ebenstein, Harrison, McMillan and Phillips (2014), who found no substantial negative impacts of offshoring on log wages when offshoring is defined (as is ours) at the industry level. Turning to the *Inshoring* measure, we also find no statistically significant results. The F-tests for joint significance, $\gamma_A = \gamma_B = 0$, yields high p-values that range from 0.160 to 0.255. The tests of $\gamma_A = \gamma_B$ also are insignificant at the 5% significance level in Baseline specifications and yield high p-values in the Narrow Workers specifications. In the theory section, we noted that the distributional impacts of cross-country matching are heterogeneous and, thus, average impacts of cross-country matching are ambiguous. The empirical results are consistent with the predictions of the theory.

To capture the heterogeneous effects of cross-country matching on U.S. individuals, we run a benchmark regression from equation (14), which includes the interactions of $\textit{Offshoring}_{jt-1}$ with $Worker$ and $ManagerN$ cases and the interactions of $\textit{Inshoring}_{jt-1}$ with $Worker$ and $ManagerN$ cases, as well as a dummy variable for the manager. In Table 16, the empirical results are broadly supportive of the model's key predictions. In the Baseline specification, the effect of exposure to offshoring between U.S. multinationals and foreign workers on U.S. workers is negative and statistically significant at the 5% level ($\gamma_1 < 0$). In the first row of column (4), the coefficient on Lagged *Offshoring* $\times$ $Worker$ suggests that a 10% point increase in the employment share of offshored employment within an industry is associated with 0.7% wage reduction for U.S. workers. In the case of U.S. managers, we do not find strong evidence of the salary impacts of offshoring between U.S. multinationals and foreign workers. Perhaps this is because only the high-skilled manager group can benefit from offshoring - a point that we explore in the next empirical analysis. However, the test of $\gamma_1 = \gamma_2$ is statistically significant at the 5% significance level, which supports the model's prediction that the exposure to offshoring between U.S. multinationals and foreign workers has heterogeneous impacts across workers and managers.

Conversely, the effect of exposure to cross-country matching between foreign multinationals and U.S. workers on U.S. workers is positive and

statistically significant at the 5% level ($\gamma_3 > 0$). In the third row of column (4), the coefficient on Lagged *Inshoring* $\times$ $Worker$ suggests that a 10% point increase in the employment share of offshored employment within an industry is associated with a 0.9% wage increase for U.S. workers. The effect of exposure to cross-country matching between foreign multinationals and U.S. workers on U.S. managers is negative and statistically significant at the 5% level ($\gamma_4 < 0$). In the fourth row of column (4), the coefficient on Lagged *Inshoring* $\times$ $ManagerN$ suggests that a 10% point increase in the employment share of offshored employment within an industry is associated with 1.7% salary reduction for U.S. managers. Reassuringly, the test of $\gamma_3 = \gamma_4$ is statistically significant at the 5% significance level. Lastly, we can also confirm that offshoring inward and outward have different impacts on U.S. workers and U.S. mangers because the tests of $\gamma_1 = \gamma_3$ and $\gamma_2 = \gamma_4$ are statistically significant at the 5% significance levels in column (4).

Even though the impact of cross-country matching between U.S. multinationals and foreign workers on the U.S. manager is statistically insignificant, all other empirical results are consistent with the model's predictions: Cross-country matching between U.S. multinationals and foreign workers substitutes for workers in the U.S., which puts downward pressure on the workers' wages. Cross-country matching between foreign multinationals and U.S. workers substitutes for managers in the U.S while it complements workers in the U.S., which puts downward pressure on the managers' salaries and upward pressure on the workers' wages.

6.4.2 Alternative Specification

We now address a potential concern regarding the null effect of cross-country matching between U.S. multinationals and foreign workers on U.S. managers ($\gamma_2 \approx 0$). Given that not all firms in each industry can send their tasks abroad, the complementary effects from offshoring might vary across U.S. managers. Thus, it would be reasonable to conjecture that the complementary effects of cross-country matching would be heterogeneous across manager groups, and the positive complementary impacts would be con-

centrated in high-skilled manager groups that can take advantage of offshoring. This leads us to modify equation (14) that splits the interaction term $Manager_{ijt} \times \textit{Offshoring}_{jt-1}$ into two parts: i) $Manager_{ijt} \times \textit{Offshoring}_{jt-1} \times Noncol_{ijt}$ and ii) $Manager_{ijt} \times \textit{Offshoring}_{jt-1} \times College_{ijt}$ as follows:

$$\begin{aligned}
&\ln w_{ijt} = \alpha + \mathbf{x'_{ijt}}\beta + \mathbf{g'_{jt-1}}\theta + \gamma_1 Worker_{ijt} \times \textit{Offshoring}_{jt-1} \\
&+ \gamma_2 Manager_{ijt} \times \textit{Offshoring}_{jt-1} \times Noncol_{ijt} + \gamma_3 Manager_{ijt} \times \textit{Offshoring}_{jt-1} \times College_{ijt} \\
&+ \gamma_4 Worker_{ijt} \times \textit{Inshoring}_{jt-1} + \gamma_5 Manager_{ijt} \times \textit{Inshoring}_{jt-1} \\
&+ \upsilon \times Manager_{ijt} + \delta_j + \xi_t + \psi_r + \epsilon_{ijt}
\end{aligned}$$

where $College_{ijt}$ is a dummy variable equal to 1 if individual i has college or an additional degree and $Noncol_{ijt}$ is a dummy variable equal to 1 if individual i does not have college degree. We use $College$ and $Noncol$ dummies to proxy for high-skilled and low-skilled managers because we cannot directly observe the skill levels of managers. We expect that $\gamma_1 < 0$, $\gamma_2 < 0$, $\gamma_3 > 0$, $\gamma_4 > 0$, and $\gamma_5 < 0$.

Reassuringly, in Table 17 we find that the previous results stand still ($\gamma_1 < 0$, $\gamma_4 > 0$, and $\gamma_5 < 0$) even though we split the interaction term $Manager_{ijt} \times \textit{Offshoring}_{jt-1}$. More importantly, we confirm the conjecture that only high-skilled managers can benefit from cross-country matching between U.S. multinationals and foreign workers. In the Baseline specification, the effect of exposure to cross-country matching between U.S. multinationals and foreign workers on low-skilled U.S. managers is negative and statistically significant at the 5% level ($\gamma_2 < 0$). In the second row of column (4), the coefficient of $\textit{Offshoring}_{t-1} \times ManagerN \times Noncol$ suggests that a 10% point increase in the employment share of offshored employment within an industry is associated with 1.1% salary reduction for low-skilled U.S. managers. Conversely, the effect of exposure to cross-country matching between U.S. multinationals and foreign workers on high-skilled U.S. managers is positive and statistically significant at the 5% level ($\gamma_3 > 0$). In the third row of column (4), the coefficient of $\textit{Offshoring}_{t-1} \times ManagerN \times College$ suggests that a 10% point increase in the employment share of offshored

employment within an industry is associated with 1.4% salary increase for high-skilled U.S. managers. The test of $\gamma_2 = \gamma_3$ is statistically significant at the 1% significance level, which substantiates the view that only high-skilled U.S. managers benefit from cross-country matching between U.S. multinationals and foreign workers.

6.4.3 Robustness Checks

We check the validity of the main estimation result in Table 17 by providing thorough robustness checks of the result. First, we repeat the key estimation by excluding Global Financial Crisis period 2008 - 2011 from the analysis because it might disturb the mechanism of the impact of offshoring on U.S. workers and managers. In Table 18, we report our results, which are mostly consistent. In column (4) of Table 18, we confirm that the signs of the coefficients ($\gamma_1 < 0$, $\gamma_2 < 0$, $\gamma_3 > 0$, $\gamma_4 > 0$, and $\gamma_5 < 0$) show exactly the same pattern with statistical significance. However, the significance of the coefficient of $\textit{Offshoring}_{t-1} \times Worker$, γ_1, becomes insignificant.

Next, we seek to allay concerns regarding definitions of workers and managers in the theoretical model that are not precisely matched to categorization in the American Community Survey (ACS). To this end, we repeat the key estimation equation by including a broad definition of managers, $ManagerB$ ($000 \leq occ1990 \leq 200$), instead of a narrow definition of managers, $ManagerN$ ($000 \leq occ1990 \leq 37$). In Table 19, we again find that our results are still robust, except in the case of the significance of the coefficient of $\textit{Offshoring}_{t-1} \times ManagerN \times College$, γ_3, although the sign is still positive. Because the Broad definition of managers includes more occupations than the Narrow definition of managers, we obtain an insignificant result. Consequently, we reasonably conjecture that the positive impact of cross-country matching between U.S. multinationals and foreign workers is limited to a group of narrow managers who have a college education or more.

We also explore as follows whether our results are robust to the inclusion

of industry-specific time trends and region-specific time trends:

$$\begin{aligned}
&\ln w_{ijt} = \alpha + \mathbf{x'_{ijt}}\beta + \mathbf{g'_{jt-1}}\theta + \gamma_1 Worker_{ijt} \times \textit{Offshoring}_{jt-1} \\
&+ \gamma_2 Manager_{ijt} \times \textit{Offshoring}_{jt-1} \times Noncol_{ijt} + \gamma_3 Manager_{ijt} \times \textit{Offshoring}_{jt-1} \times College_{ijt} \\
&+ \gamma_4 Worker_{ijt} \times \textit{Inshoring}_{jt-1} + \gamma_5 Manager_{ijt} \times \textit{Inshoring}_{jt-1} + \upsilon \times Manager_{ijt} \\
&+ \delta_j + \xi_t + \psi_r + \underbrace{\chi_j \times t}_{\text{Industry specific time trends}} + \underbrace{\kappa_r \times t}_{\text{Region specific time trends}} + \epsilon_{ijt}.
\end{aligned}$$

It could be argued that the earnings impact comes from pre-existing industry-specific time trends or region-specific time trends and not from offshoring. The above specification seeks to identify the causal effects of offshoring on earnings by separating out the effects of industry-specific time trends or region-specific time trends.[27] In Table 20, reassuringly, the signs, significance, and magnitude of the key parameters are still robust to the inclusion of industry-specific time trends and region-specific time trends.

Finally, we check the robustness of the results using alternative lag lengths as follows:

$$\begin{aligned}
&\ln w_{ijt} = \alpha + \mathbf{x'_{ijt}}\beta + \mathbf{g'_{jt-k}}\theta + \gamma_1 Worker_{ijt} \times \textit{Offshoring}_{jt-k} \\
&+ \gamma_2 Manager_{ijt} \times \textit{Offshoring}_{jt-k} \times Noncol_{ijt} + \gamma_3 Manager_{ijt} \times \textit{Offshoring}_{jt-k} \times College_{ijt} \\
&+ \gamma_4 Worker_{ijt} \times \textit{Inshoring}_{jt-k} + \gamma_5 Manager_{ijt} \times \textit{Inshoring}_{jt-k} \\
&+ \upsilon \times Manager_{ijt} + \delta_j + \xi_t + \psi_r + \epsilon_{ijt}
\end{aligned}$$

where $k = \{2, 3, 4\}$. In Table 21, we report the dynamic responses of offshoring. We find, reassuringly, that the signs and the significance are still robust even after four years. Interestingly, over time the negative impact of offshoring on workers and managers with no college degree fades away while the positive impact of offshoring on managers with college or more strengthens. In contrast, the impacts of inshoring on both workers and man-

[27] Besley and Burgess (2004), who study the impact of labor regulation on economic performance, add state-specific time trends in their robustness check analysis to separate out the effects of labor regulation from state-specific time trends.

agers diminishes over time.

6.4.4 Quantitative Assessment

We have estimated a series of regression coefficients of the impact of offshoring on U.S. individuals. Given these estimates, we further explore the magnitude of changes in earnings that originate from changes in offshoring, measured by $Offshoring_{jt}$ and $Inshoring_{jt}$, during the period 2002 - 2013 in the U.S. In Table 12, during the period 2002 - 2013, $Offshoring_{jt}$ increased by 12.1%p and $Inshoring_{jt}$ rose by 4.4%p. In column (4) of Table 17, we use the estimated coefficients, $\hat{\gamma}_1, \hat{\gamma}_2, \hat{\gamma}_3, \hat{\gamma}_4,$ and $\hat{\gamma}_5$, and multiply them by 12.1%p or by 4.4%p. From the above formula we know that a change in the employment share of offshoring abroad, $Offshoring_{jt}$, was associated with a 0.87% (=12.1%p $\times$ -0.072) wage reduction for U.S. workers, a 1.31% (=12.1%p $\times$ -0.108) salary reduction for U.S. non-college managers, and a 1.63% (=12.1%p $\times$ 0.135) salary rise for U.S. college managers during the period 2002 - 2013. A change in the employment share of offshoring by foreign multinationals, $Inshoring_{jt}$, was associated with a 0.42% (=4.4%p $\times$ 0.096) wage increase for U.S. workers 0.72% (=4.4%p $\times$ -0.164) salary reduction for U.S. managers during the period 2002 - 2013.

6.5 Rising Chinese Import Competition

Autor, Dorn and Hanson (2013) find that exposure to Chinese import competition caused higher unemployment, lower labor force participation, and reduced wages in local labor markets in the U.S. during the period between 1990 - 2007 that encompasses import-competing manufacturing industries. Using individual-level longitudinal data from U.S. Social Security Administration data during the period 1992 - 2007, Autor, Dorn, Hanson and Song (2014) find a similar pattern at the industry-level.

Based on this empirical evidence, one might argue that the distributional impacts of offshoring are confounded with the distributional impacts of rising Chinese import competition. To address this concern, we construct Chi-

nese import exposure per employee in an industry j and a year t as follows:

$$\textit{Chinese Import}_{jt} \equiv \frac{\text{The real U.S. imports from China}_{jt}}{\text{The total number of U.S. employees}_{jt}}.$$

We use data from the UN Comtrade Database on U.S. nominal imports from China at the six-digit Harmonized System (HS) product level. Using crosswalk files from David Dorn's website, we can convert imports data at the six-digit HS product level to the 1997 North American Industry Classification System (NAICS).[28] Then, we adjust for inflation to construct the real U.S. imports from China. We conjecture that the distributional effect of the rising Chinese import competition has been heterogeneous across groups, which leads us to specify following regression equation:

$$\begin{aligned}
&\ln w_{ijt} = \alpha + \mathbf{x'_{ijt}}\beta + \mathbf{g'_{jt-1}}\theta + \gamma_1 Worker_{ijt} \times \textit{Offshoring}_{jt-1} \\
&+ \gamma_2 Manager_{ijt} \times \textit{Offshoring}_{jt-1} \times Noncol_{ijt} + \gamma_3 Manager_{ijt} \times \textit{Offshoring}_{jt-1} \times College_{ijt} \\
&+ \gamma_4 Worker_{ijt} \times \textit{Inshoring}_{jt-1} + \gamma_5 Manager_{ijt} \times \textit{Inshoring}_{jt-1} \\
&+ \upsilon \times Manager_{ijt} + \delta_j + \xi_t + \psi_r + \vartheta_1 Worker_{ijt} \times \ln \textit{Chinese Import}_{jt-1} \\
&+ \vartheta_2 Manager_{ijt} \times \ln \textit{Chinese Import}_{jt-1} \times Noncol_{ijt} \\
&+ \vartheta_3 Manager_{ijt} \times \ln \textit{Chinese Import}_{jt-1} \times College_{ijt} + \epsilon_{ijt}.
\end{aligned}$$

Reassuringly, the results in Table 22 are mostly robust to the inclusion of the rising Chinese import competition shock except for the coefficient of the impact of offshoring on non-college managers. Also, the effect of offshoring on college or a higher degree is reduced quantitatively, which could originate from the confounding effect of the rising Chinese import penetration. Interestingly, the exposure to Chinese import competition has positive earnings impacts on U.S. managers and insignificant impacts on U.S. workers. Quantitatively, a 100% increase in Chinese import exposure per person within an industry is associated with a 2.2% salary rise for U.S. managers with a non-college degree and a 3.7% salary increase for U.S. managers with

[28] http://www.ddorn.net/data.htm

college or a higher degree. One possible explanation for this positive impact is that Chinese import competition accelerates technology innovation within firms and reallocates employment toward technologically advanced firms (Bloom, Draca and Van Reenen, 2016). In that case, the trade-induced technical change increases earnings of U.S. individuals, which favors managers over workers. In Table 22, the test of $\vartheta_1 = \vartheta_2$, $\vartheta_1 = \vartheta_3$, and $\vartheta_2 = \vartheta_3$ all are statistically significant at the 5% significance level, which substantiate the view of Bloom, Draca and Van Reenen (2016).[29]

6.6 The Contribution of Offshoring to Rising Income Inequality in the U.S.

We present a variance decomposition analysis that quantifies the relative contribution of offshoring to the change in income inequality during the period from 2002 to 2011 in the U.S. To this end, we decompose the total income inequality $\text{var}(\ln w_{ijt})$ into the contributions of the offshoring effect, the other control variables effect, the covariance between the offshoring effect and the other control variables effect, and the residual component as follows:

$$\text{var}(\ln w_{ijt}) = \text{var}(\mathbf{Z'_{ijt}}\hat{\mathbf{\Xi}}) + \text{var}(\mathbf{\Pi'_{ijt}}\hat{\mathbf{\Theta}}) + 2 \times \text{cov}(\mathbf{Z'_{ijt}}\hat{\mathbf{\Xi}}, \mathbf{\Pi'_{ijt}}\hat{\mathbf{\Theta}}) + \text{var}(\hat{\epsilon}_{ijt})$$

where $\mathbf{Z'_{ijt}}\hat{\mathbf{\Xi}} \equiv \hat{\gamma}_1 Worker_{ijt} \times \textit{Offshoring}_{jt-1} + \hat{\gamma}_2 Manager_{ijt} \times \textit{Offshoring}_{jt-1} \times Noncol_{ijt} + \hat{\gamma}_3 Manager_{ijt} \times \textit{Offshoring}_{jt-1} \times College_{ijt}$ and $\mathbf{\Pi'_{ijt}}\hat{\mathbf{\Theta}} \equiv \hat{\alpha} + \mathbf{x'_{ijt}}\hat{\beta} + \mathbf{g'_{jt-1}}\hat{\theta} + \hat{\gamma}_4 Worker_{ijt} \times \textit{Inshoring}_{jt-1} + \hat{\gamma}_5 Manager_{ijt} \times \textit{Inshoring}_{jt-1} + \hat{\upsilon} \times Manager_{ijt} + \hat{\delta}_j + \hat{\xi}_t + \hat{\psi}_r$. The residual term $\hat{\epsilon}_{ijt}$ is orthogonal to the other terms by construction. The contributions of the offshoring component, the other control variables component, and the residual component to

[29] In previous studies on the impact of Chinese import competition shock on earnings, Autor, Dorn and Hanson (2013) and Ebenstein, Harrison, McMillan and Phillips (2014) note that import exposure has no significant effects on wages in the manufacturing sector. Instead, Autor, Dorn, Hanson and Song (2014) find that Chinese import exposure is negatively associated with cumulative earnings at the U.S. manufacturing industry level and earnings losses are larger for individuals who are low-skilled workers.

the change in the total income inequality can be measured, respectively, as follows:

$$\frac{\Delta\left[\text{var}(\mathbf{Z}'_{\mathbf{ijt}}\hat{\mathbf{\Xi}}) + 2 \times \text{cov}(\mathbf{Z}'_{\mathbf{ijt}}\hat{\mathbf{\Xi}}, \mathbf{\Pi}'_{\mathbf{ijt}}\hat{\mathbf{\Theta}})\right]}{\Delta\text{var}(\ln w_{ijt})},$$

$$\frac{\Delta\text{var}(\mathbf{\Pi}'_{\mathbf{ijt}}\hat{\mathbf{\Theta}})}{\Delta\text{var}(\ln w_{ijt})},$$

$$1 - \frac{\Delta\text{var}(\mathbf{\Pi}'_{\mathbf{ijt}}\hat{\mathbf{\Theta}})}{\Delta\text{var}(\ln w_{ijt})} - \frac{\Delta\left[\text{var}(\mathbf{Z}'_{\mathbf{ijt}}\hat{\mathbf{\Xi}}) + 2 \times \text{cov}(\mathbf{Z}'_{\mathbf{ijt}}\hat{\mathbf{\Xi}}, \mathbf{\Pi}'_{\mathbf{ijt}}\hat{\mathbf{\Theta}})\right]}{\Delta\text{var}(\ln w_{ijt})}$$

where $\Delta X_t \equiv X_{2011} - X_{2003}$. Note that we can also decompose the total income inequality into the inshoring effect, the other control variables effect, and the residual component in an analogous way.

In Table 23, we report the contributions made by offshoring, other controls, and residual inequality to the growth of total income inequality. Each column corresponds to the specifications of each column in Table 17. We separate total offshoring into offshoring and inshoring. Panel A uses offshoring, Panel B applies inshoring, and Panel C utilizes total offshoring to measure the contribution of offshoring. During the period from 2002 to 2011, the growth rate in the variance of log income was about 6.8 percent to 7.8 percent, according to the American Community Survey data. In Panel C - column (4) of Table 23, total offshoring, other controls, and residual inequality account for 12.1 percent, 83.5 percent, and 4.4 percent, respectivley, of the widening total income inequality. In Panel A - column (4) and Panel B - column (4) of Table 23, we find that offshoring explains about 12.1 percent of the widening income inequality while the contribution of inshoring is almost negligible. We would expect that inshoring would act as an alleviating force for income inequality because inshoring bids up the wages of workers and reduces the salaries of managers. However, as indicated in Table 12, there was a less variation of inshoring, *Inshoring*, than variation of offshoring, *Offshoring*, during the period 2002 to 2011, which explains why inshoring had (almost) no impact on income inequality in the U.S.

We note that the majority (83.5 percent) of the widening inequality orig-

inates from the other controls factor. We further decompose this factor into several factors to explain the change in income inequality. Comparing Panel C - column (1) to Panel C - column (2) of Table 23, we find that the contribution of the other controls factor increases by 8.9 percent. The only difference is the inclusion of industry-year confounders, total factor productivity, and capital-value added ratio, and we reasonably conjecture that both factors account for 8.9 percent of rising inequality. Next, we find that there is a 69.2 percent increase in the contribution of other controls when we move from Panel C - column (2) to Panel C - column (3). The only difference is the components of the fixed effect; column (2) includes the region fixed effect and the year fixed effect separately while column (3) contains the region-year fixed effect. This implies that the unobserved region-year specific factor played a central role in shaping the growth of income inequality from 2002 to 2011 in the U.S.

We further examine whether the contribution of offshoring is robust to another measure of workers. In column (5) through (8) of Table 23, we repeat the variance decomposition analysis using a narrow definition of workers ($701 \leq$ occ1990 ≤ 900) instead of a broad definition of workers ($501 \leq$ occ1990 ≤ 900). In Panel C - column (8) of Table 23, offshoring accounts for 20.6 percent of the widening total income inequality, which is 8.5 percent points larger than the baseline specification. This result may originate from the fact that workers of occupations in operatives and laborers ($701 \leq$ occ1990 ≤ 900) are more concentrated in industries that are more exposed to offshoring than workers of occupations in precision production, craft, and repairing ($501 \leq$ occ1990 ≤ 700).

7 Conclusion

This paper develops a matching framework of offshoring where offshoring is defined as a cross-country matching between a manager and workers. Our model features two countries, one industry, and two factors of production with heterogeneous skills in perfect competition. Most importantly,

production technology is characterized by complementarity between workers and managers. We have analyzed the effects of offshoring on the matching patterns and the structure of earnings of heterogeneous individuals when two countries are different in aspects such as factor endowments, factor distributions, and technology levels. The model accommodates various cases of offshoring and generates rich predictions about the distributional impacts of offshoring.

We bring our theory to data to test the model's key predictions. First, our novel prediction from the model is that offshoring has two countervailing effects - a complementary effect and a substitution effect - on labor markets. We use data on U.S. BEA multinationals and U.S. BLS employment and link them to U.S. ACS individual-level information, and we distinguish individuals by occupation, workers and managers. Then, exploiting industry-year variation in the offshoring measure, we find compelling evidence that offshoring has differential impacts on workers and managers. Furthermore, we quantify the relative contribution of offshoring to the widening income inequality and find that offshoring explains about 12 to 21 percent of the rising income inequality during the period 2002 to 2011 in the U.S.

8 Appendix

8.1 Proofs

8.1.1 Proof of Proposition 1

Proof. Let $\pi(z_M, z_L)$ denote the profit of a firm hiring a manager of skill z_M and employing the optimal number of workers $L(z_L; z_M)$ of skill z_L. Plugging the conditional worker demand in equation (2) into (1) yields,

$$\begin{aligned}\pi(z_M, z_L) &= \alpha e^{z_M^\beta z_L} \left[\frac{\gamma\alpha e^{z_M^\beta z_L}}{w(z_L)}\right]^{\gamma/(1-\gamma)} - w(z_L)\left[\frac{\gamma\alpha e^{z_M^\beta z_L}}{w(z_L)}\right]^{1/(1-\gamma)} \\ &= \gamma^{\gamma/(1-\gamma)}(1-\gamma)\alpha^{1/(1-\gamma)}\left[e^{z_M^\beta z_L}\right]^{1/(1-\gamma)} w(z_L)^{-\gamma/1-\gamma}.\end{aligned}$$

In equilibrium, firms choose workers' skill level z_L to maximize profits:

$$\frac{\partial \pi(z_M, z_L)}{\partial z_L} = \gamma^{\gamma/(1-\gamma)} \alpha^{1/(1-\gamma)} \left[e^{z_M^\beta z_L} \right]^{1/(1-\gamma)} \left[z_M^\beta w(z_L)^{-\gamma/1-\gamma} - \gamma w(z_L)^{-1/1-\gamma} w'(z_L) \right] = 0. \tag{15}$$

Totally differentiating the expression yields,

$$\frac{\partial z_M}{\partial z_L} = -\frac{\partial^2 \pi(z_M, z_L)/\partial z_L^2}{\partial^2 \pi(z_M, z_L)/\partial z_L \partial z_M}.$$

Given that firms maximize profits in equilibrium, the numerator must be negative. To show that $m(z_L)$ is an increasing function for $z_L \in \mathcal{L}$, the denominator must be positive.

$$\begin{aligned}
\frac{\partial^2 \pi(z_M, z_L)}{\partial z_L \partial z_M} &= \gamma^{\gamma/(1-\gamma)} \alpha^{1/(1-\gamma)} \frac{1}{1-\gamma} \left[e^{z_M^\beta z_L} \right]^{1/1-\gamma} \beta z_M^{\beta-1} z_L \left[z_M^\beta w(z_L)^{-\gamma/1-\gamma} - \gamma w(z_L)^{-1/1-\gamma} w'(z_L) \right] \\
&+ \gamma^{\gamma/(1-\gamma)} \alpha^{1/(1-\gamma)} \left[e^{z_M^\beta z_L} \right]^{1/1-\gamma} \beta z_M^{\beta-1} w(z_L)^{-\gamma/1-\gamma} \\
&= \left[\gamma^{\gamma/1-\gamma} \alpha^{1/1-\gamma} \left[e^{z_M^\beta z_L} \right]^{1/1-\gamma} \beta z_M^{\beta-1} w(z_L)^{-\gamma/1-\gamma} \right].
\end{aligned}$$

where the last equality follows from equation (15). To show that the denominator is positive, we must show that $w(z_L)$ is strictly positive. From the profit maximization problem, we know that the (optimal) conditional worker demand $N(z_L; z_M)$ is strictly positive conditional on $\alpha > 0$. This implies that wage schedule $w(z_L)$ is positive. Therefore, in equilibrium, the matching function $m(z_L)$ is a strictly increasing function for $z_L \in \mathcal{L}$. □

8.1.2 Proof of Proposition 2

Proof. To show that the log wage schedule $\ln w(z_L)$ is strictly increasing, differentiate $\ln w(z_L)$ with respect to z_L:

$$\frac{d \ln w(z_L)}{dz_L} = \frac{m(z_L)^\beta}{\gamma} > 0.$$

Next, to prove that the log wage schedule $\ln w(z_L)$ is convex in skills, differentiate $\dfrac{d \ln w(z_L)}{dz_L}$ with respect to z_L:

$$\frac{d^2 \ln w(z_L)}{dz_L^2} = \frac{\beta m(z_L)^{\beta-1} m'(z_L)}{\gamma} > 0$$

where the last inequality follows from the positive assortative matching property of the matching function $m(z_L)$. □

8.1.3 Proof of Proposition 3

Proof. To show that the log salary schedule $\ln r(z_M)$ is strictly increasing, differentiate $\ln r(z_M)$ with respect to z_M:

$$\frac{d \ln r(z_M)}{dz_M} = \frac{\beta z_M^{\beta-1} m^{-1}(z_M)}{1-\gamma} > 0.$$

Next, to prove that the log salary schedule $\ln r(z_M)$ is convex in skills, differentiate $\dfrac{d \ln r(z_M)}{dz_M}$ with respect to z_M:

$$\frac{d^2 \ln r(z_M)}{dz_M^2} = \frac{\beta(\beta-1) z_M^{\beta-2} m^{-1}(z_M)}{1-\gamma} + \frac{\beta z_M^{\beta-1} m^{-1\prime}(z_M)}{1-\gamma} > 0$$

where the last inequality follows from the positive assortative matching property of the matching function $m(z_L)$ and $\beta > 1$. □

8.1.4 Proof of Proposition 4

Proof. (i) In Autarky, total production in the World is defined as:

$$\int_{z_{M,min}}^{z_{M,max}} e^{z_M^{\beta} m^{-1}(z_M)} (N^N)^{\gamma} \bar{M}^N \phi_M(z_M) dz_M + \int_{z_{M,min}}^{z_{M,max}} e^{z_M^{\beta} m^{-1}(z_M)} (N^S)^{\gamma} \bar{M}^S \phi_M(z_M) dz_M \tag{16}$$

where $N^N = \left[\dfrac{\gamma e^{z_M^{\beta} m^{-1}(z_M)}}{w^N(z_L)} \right]^{1/1-\gamma}$ and $N^S = \left[\dfrac{\gamma e^{z_M^{\beta} m^{-1}(z_M)}}{w^S(z_L)} \right]^{1/1-\gamma}$.

In Globalization, total production in the World is defined as:

$$\int_{z_{M,min}}^{z_{M,max}} e^{z_M^{\beta} m^{-1}(z_M)} (N^W)^{\gamma} (\bar{M}^N + \bar{M}^S) \phi_M(z_M) dz_M \tag{17}$$

where $N^W = \left[\frac{\gamma e^{z_M^{\beta} m^{-1}(z_M)}}{w^W(z_L)} \right]^{1/1-\gamma}$. Using the market clearing condition in equation (8), the conditional worker demand N can be represented as:

$$N = \frac{\bar{L}}{\bar{M}} \frac{\phi_L(m^{-1}(z_M))}{\phi_M(z_M)} \frac{1}{m'(m^{-1}(z_M))}.$$

Plugging this conditional worker demand into equations (16) and (17), we can obtain total production in Autarky and in Globalization, respectively, as follows:

$$\left[(\bar{M}^N)^{1-\gamma} (\bar{L}^N)^{\gamma} + (\bar{M}^S)^{1-\gamma} (\bar{L}^S)^{\gamma} \right] \int_{z_{M,min}}^{z_{M,max}} e^{z_M^{\beta} m^{-1}(z_M)} \left(\frac{\phi_L(m^{-1}(z_M))}{\phi_M(z_M)} \frac{1}{m'(m^{-1}(z_M))} \right)^{\gamma} \phi_M(z_M) dz_M,$$

$$(\bar{M}^N + \bar{M}^S)^{1-\gamma} (\bar{L}^N + \bar{L}^S)^{\gamma} \int_{z_{M,min}}^{z_{M,max}} e^{z_M^{\beta} m^{-1}(z_M)} \left(\frac{\phi_L(m^{-1}(z_M))}{\phi_M(z_M)} \frac{1}{m'(m^{-1}(z_M))} \right)^{\gamma} \phi_M(z_M) dz_M.$$

Using Theorem 9.4 **(Generalized Hölder's inequality)** in Cvetkovski (2012), for any $\gamma \in (0, 1)$ and positive real numbers $\bar{M}^N$, $\bar{M}^S$, $\bar{L}^N$, and $\bar{L}^S$, the following inequality holds:

$$(\bar{M}^N + \bar{M}^S)^{1-\gamma} (\bar{L}^N + \bar{L}^S)^{\gamma} \geq \left[(\bar{M}^N)^{1-\gamma} (\bar{L}^N)^{\gamma} + (\bar{M}^S)^{1-\gamma} (\bar{L}^S)^{\gamma} \right].$$

Equality occurs if and only if $\frac{\bar{M}^N}{\bar{L}^N} = \frac{\bar{M}^S}{\bar{L}^S}$. Therefore, total production in the World strictly increases from globalization.

(ii) & (iii) In Autakry, total earnings in the North is defined as:

$$(\bar{M}^N)^{1-\gamma} (\bar{L}^N)^{\gamma} \int_{z_{M,min}}^{z_{M,max}} e^{z_M^{\beta} m^{-1}(z_M)} \left(\frac{\phi_L(m^{-1}(z_M))}{\phi_M(z_M)} \frac{1}{m'(m^{-1}(z_M))} \right)^{\gamma} \phi_M(z_M) dz_M.$$

In Globalization, total earnings in the North is defined as:

$$
\begin{aligned}
&\frac{\bar{M}^N}{\bar{M}^N+\bar{M}^S}(1-\gamma)(\bar{M}^N+\bar{M}^S)^{1-\gamma}(\bar{L}^N+\bar{L}^S)^{\gamma} \\
&\times \int_{z_{M,min}}^{z_{M,max}} e^{z_M^{\beta} m^{-1}(z_M)} \left(\frac{\phi_L(m^{-1}(z_M))}{\phi_M(z_M)} \frac{1}{m'(m^{-1}(z_M))}\right)^{\gamma} \phi_M(z_M) dz_M \\
&+ \frac{\bar{L}^N}{\bar{L}^N+\bar{L}^S}\gamma(\bar{M}^N+\bar{M}^S)^{1-\gamma}(\bar{L}^N+\bar{L}^S)^{\gamma} \\
&\times \int_{z_{M,min}}^{z_{M,max}} e^{z_M^{\beta} m^{-1}(z_M)} \left(\frac{\phi_L(m^{-1}(z_M))}{\phi_M(z_M)} \frac{1}{m'(m^{-1}(z_M))}\right)^{\gamma} \phi_M(z_M) dz_M \\
&= (\bar{M}^N+\bar{M}^S)^{1-\gamma}(\bar{L}^N+\bar{L}^S)^{\gamma}\left[\frac{\bar{M}^N}{\bar{M}^N+\bar{M}^S}(1-\gamma)+\frac{\bar{L}^N}{\bar{L}^N+\bar{L}^S}\gamma\right] \\
&\times \int_{z_{M,min}}^{z_{M,max}} e^{z_M^{\beta} m^{-1}(z_M)} \left(\frac{\phi_L(m^{-1}(z_M))}{\phi_M(z_M)} \frac{1}{m'(m^{-1}(z_M))}\right)^{\gamma} \phi_M(z_M) dz_M.
\end{aligned}
$$

Using Theorem 7.6 **(Weighted AM-GM inequality)** in Cvetkovski (2012), for any $\gamma \in (0,1)$ and positive real numbers $\bar{M}^N$, $\bar{M}^S$, $\bar{L}^N$, and $\bar{L}^S$, the following inequality holds:

$$
\frac{\bar{M}^N}{\bar{M}^N+\bar{M}^S}(1-\gamma)+\frac{\bar{L}^N}{\bar{L}^N+\bar{L}^S}\gamma \geq \left(\frac{\bar{M}^N}{\bar{M}^N+\bar{M}^S}\right)^{1-\gamma}\left(\frac{\bar{L}^N}{\bar{L}^N+\bar{L}^S}\right)^{\gamma}.
$$

Equality occurs if and only if $\frac{\bar{M}^N}{\bar{L}^N} = \frac{\bar{M}^S}{\bar{L}^S}$. Therefore, total earnings in the North strictly increases from globalization. In the South, the argument is identical and, hence, it is omitted.

(iv) Because agents of the same skill within task are perfectly substitutable in globalization, they receive the same earnings.

(v) The matching function $m(z_L)$ does not depend on the factor endowments $\bar{M}$ and $\bar{L}$ from equation (13). From equation (9), a one percent increase in $\frac{\bar{M}}{\bar{L}}$ raises $w(z_L)$ by $1-\gamma$ percent for all $z_L \in \mathcal{L}^W$. From equation (6), a one percent increase in $\frac{\bar{M}}{\bar{L}}$ reduces $r(z_M)$ by γ percent for all $z_M \in \mathcal{M}^W$.

(vi) The managers' share and the workers' share in the North are de-

fined, respectively, as follows:

$$\frac{\int_{z^N_{M,min}}^{z^N_{M,max}} r^N(z_M)\bar{M}^N\phi^N_M(z_M)dz_M}{\int_{z^N_{M,min}}^{z^N_{M,max}} r^N(z_M)\bar{M}^N\phi^N_M(z_M)dz_M + \int_{z^N_{L,min}}^{z^N_{L,max}} w^N(z_L)\bar{L}^N\phi^N_L(z_L)dz_L},$$

$$\frac{\int_{z^N_{L,min}}^{z^N_{L,max}} w^N(z_L)\bar{L}^N\phi^N_L(z_L)dz_L}{\int_{z^N_{M,min}}^{z^N_{M,max}} r^N(z_M)\bar{M}^N\phi^N_M(z_M)dz_M + \int_{z^N_{L,min}}^{z^N_{L,max}} w^N(z_L)\bar{L}^N\phi^N_L(z_L)dz_L}.$$

Since $r^N(z_M)$ shifts upward for all $z_M \in \mathcal{M}^N$ and $w^N(z_L)$ shifts downward for all $z_L \in \mathcal{L}^N$, the managers' share rises while the workers' share reduces in the North in the above equations. In the South, the argument is identical and, hence, it is omitted. □

8.1.5 Proof of Lemma 1

Proof. (i) Suppose that there exists $z_L \in \mathcal{L}^N \cap \mathcal{L}^S$ such that $m^N(z_L) > m^S(z_L)$. Since $\frac{\phi^N_L(z'_L)}{\phi^N_L(z_L)} \geq \frac{\phi^S_L(z'_L)}{\phi^S_L(z_L)}$, we know that $\mathcal{L}^N \cap \mathcal{L}^S = [z^N_{L,min}, z^S_{L,max}]$. The positive assortative matching property of the matching function implies that $m^N(z^N_{L,min}) = z_{M,min} \leq m^S(z^N_{L,min})$ and $m^S(z^S_{L,max}) = z_{M,max} \geq m^N(z^S_{L,max})$. So there must exist $z^N_{L,min} \leq z^1_L \leq z^2_L \leq z^S_{L,max}$ and $z_{M,min} \leq z^1_M \leq z^2_M \leq z_{M,max}$ such that

i) $m^N(z^1_L) = m^S(z^1_L) = z^1_M$ and $m^N(z^2_L) = m^S(z^2_L) = z^2_M$,

ii) $m^{N'}(z^1_L) \geq m^{S'}(z^1_L)$ and $m^{S'}(z^2_L) \geq m^{N'}(z^2_L)$,

iii) $m^N(z_L) > m^S(z_L)$ for all $z_L \in (z^1_L, z^2_L)$.

$m^{N'}(z^1_L) \geq m^{S'}(z^1_L)$ and $m^{S'}(z^2_L) \geq m^{N'}(z^2_L)$ implies that:

$$\frac{m^{S'}(z^1_L)}{m^{S'}(z^2_L)} \leq \frac{m^{N'}(z^1_L)}{m^{N'}(z^2_L)}.$$

Using equation (8), we can derive the following inequality:

$$\frac{\phi_L^N(z_L^2)}{\phi_L^N(z_L^1)}\left[\frac{w^N(z_L^2)}{w^N(z_L^1)}\right]^{1/1-\gamma} \leq \frac{\phi_L^S(z_L^2)}{\phi_L^S(z_L^1)}\left[\frac{w^S(z_L^2)}{w^S(z_L^1)}\right]^{1/1-\gamma}.$$

$\frac{\phi_L^N(z_L^2)}{\phi_L^N(z_L^1)} \geq \frac{\phi_L^S(z_L^2)}{\phi_L^S(z_L^1)}$ requires that:

$$\frac{w^N(z_L^2)}{w^N(z_L^1)} \leq \frac{w^S(z_L^2)}{w^S(z_L^1)}.$$

However, this is a contradiction. Since $m^N(z_L) > m^S(z_L)$, it must be that

$$\frac{w^N(z_L^2)}{w^N(z_L^1)} > \frac{w^S(z_L^2)}{w^S(z_L^1)}.$$

Consequently, if $\frac{\phi_L^N(z_L')}{\phi_L^N(z_L)} \geq \frac{\phi_L^S(z_L')}{\phi_L^S(z_L)}$, then $m^N(z_L) \leq m^S(z_L)$ for all $\mathcal{L}^N \cap \mathcal{L}^S$.

(ii) First, let's prove that $\frac{\phi_L^N(z_L')}{\phi_L^N(z_L)} \geq \frac{\phi_L^S(z_L')}{\phi_L^S(z_L)}$ implies $\frac{\phi_L^N(z_L')}{\phi_L^N(z_L)} \geq \frac{\phi_L^W(z_L')}{\phi_L^W(z_L)}$. For any z_L' and z_L, $\frac{\phi_L^N(z_L')}{\phi_L^N(z_L)} \geq \frac{\phi_L^S(z_L')}{\phi_L^S(z_L)}$ implies that

$$\frac{\phi_L^N(z_L')}{\phi_L^N(z_L)} \geq \frac{\omega_L^N\phi_L^N(z_L') + \omega_L^S\phi_L^S(z_L')}{\omega_L^N\phi_L^N(z_L) + \omega_L^S\phi_L^S(z_L)}.$$

where $\omega_L^N \equiv \frac{\bar{L}^N}{\bar{L}^N + \bar{L}^S}$ and $\omega_L^S \equiv \frac{\bar{L}^S}{\bar{L}^N + \bar{L}^S}$. The right-hand side is $\frac{\phi_L^W(z_L')}{\phi_L^W(z_L)}$. Thus, $\frac{\phi_L^N(z_L')}{\phi_L^N(z_L)} \geq \frac{\phi_L^W(z_L')}{\phi_L^W(z_L)}$. Next, we prove that $\frac{\phi_L^N(z_L')}{\phi_L^N(z_L)} \geq \frac{\phi_L^S(z_L')}{\phi_L^S(z_L)}$ implies $\frac{\phi_L^W(z_L')}{\phi_L^W(z_L)} \geq \frac{\phi_L^S(z_L')}{\phi_L^S(z_L)}$. For any z_L' and z_L, $\frac{\phi_L^N(z_L')}{\phi_L^N(z_L)} \geq \frac{\phi_L^S(z_L')}{\phi_L^S(z_L)}$ implies that

$$\frac{\omega_L^N\phi_L^N(z_L') + \omega_L^S\phi_L^S(z_L')}{\omega_L^N\phi_L^N(z_L) + \omega_L^S\phi_L^S(z_L)} \geq \frac{\phi_L^S(z_L')}{\phi_L^S(z_L)}.$$

The left-hand side is $\frac{\phi_L^W(z_L')}{\phi_L^W(z_L)}$. Thus, $\frac{\phi_L^W(z_L')}{\phi_L^W(z_L)} \geq \frac{\phi_L^S(z_L')}{\phi_L^S(z_L)}$. Therefore, $\frac{\phi_L^N(z_L')}{\phi_L^N(z_L)} \geq$

$\frac{\phi_L^S(z_L')}{\phi_L^S(z_L)}$ implies $\frac{\phi_L^N(z_L')}{\phi_L^N(z_L)} \geq \frac{\phi_L^W(z_L')}{\phi_L^W(z_L)} \geq \frac{\phi_L^S(z_L')}{\phi_L^S(z_L)}$. □

8.1.6 Proof of Proposition 5

Proof. (i) & (ii) Using Lemma 1, the proof is straightforward. The result also implies that $m^{N^{-1}}(z_M) \geq m^{W^{-1}}(z_M) \geq m^{S^{-1}}(z_M) \quad \forall z_M \in \mathcal{M}^W$.

(iii) & (iv) Define $\mathcal{I}_L^W = [z_{La}, z_{Lb}]$ as any connected subsets of $\mathcal{L}^W$ and $\mathcal{I}_M^W = [z_{Ma}, z_{Mb}]$ as any connected subsets of $\mathcal{M}^W$. By equations (10) and (12), the following world equilibrium conditions hold.

$$\ln w(z_{Lb'}) - \ln w(z_{La'}) = \int_{z_{La'}}^{z_{Lb'}} \frac{m(z)^\beta}{\gamma} dz, \quad \text{for all } z_{Lb'} > z_{La'} \text{ and } z_{La'}, z_{Lb'} \in \mathcal{I}_L^W,$$

$$\ln r(z_{Mb'}) - \ln r(z_{Ma'}) = \int_{z_{Ma'}}^{z_{Mb'}} \frac{\beta z^{\beta-1} m^{-1}(z)}{1-\gamma} dz, \quad \text{for all } z_{Mb'} > z_{Ma'} \text{ and } z_{Ma'}, z_{Mb'} \in \mathcal{I}_M^W.$$

Therefore, in the North, wage inequality widens as the matching function shifts upward while salary inequality narrows as the inverse matching function shifts downward. In the South, wage inequality narrows and salary inequality widens.

□

8.1.7 Proof of Lemma 3

Proof. (i) Suppose that there does not exist $z_L^* \in \mathcal{L}^N \cap \mathcal{L}^S$ such that $m^N(z_L) \geq m^S(z_L)$ for all $z_L \in [z_{L,min}^S, z_L^*]$ and $m^N(z_L) \leq m^S(z_L)$ for all $z_L \in [z_L^*, z_{L,max}^S]$. Since $\frac{\phi_L^N(z_L')}{\phi_L^N(z_L)} \geq \frac{\phi_L^S(z_L')}{\phi_L^S(z_L)}$ for all $z_L' \geq z_L \geq \hat{z}_L$, and $\frac{\phi_L^N(z_L')}{\phi_L^N(z_L)} \leq \frac{\phi_L^S(z_L')}{\phi_L^S(z_L)}$ for all $z_L \leq z_L' < \hat{z}_L$, we know that $\mathcal{L}^N \cap \mathcal{L}^S = [z_{L,min}^S, z_{L,max}^S]$. The positive assortative matching property of the matching function implies that $m^S(z_{L,min}^S) = z_{M,min} \leq m^N(z_{L,min}^S)$ and $m^S(z_{L,max}^S) = z_{M,max} \geq m^N(z_{L,max}^S)$. So there must exist $z_{L,min}^S \leq z_L^0 < z_L^1 < z_L^2 \leq z_{L,max}^S$ and $z_{M,min} \leq z_M^0 < z_M^1 < z_M^2 \leq z_{M,max}$

such that

i) $m^N(z_L^0) = m^S(z_L^0) = z_M^0$, $m^N(z_L^1) = m^S(z_L^1) = z_M^1$ and $m^N(z_L^2) = m^S(z_L^2) = z_M^2$,

ii) $m^{N'}(z_L^0) \leq m^{S'}(z_L^0)$, $m^{N'}(z_L^1) \geq m^{S'}(z_L^1)$ and $m^{N'}(z_L^2) \leq m^{S'}(z_L^2)$,

iii) $m^N(z_L) < m^S(z_L)$ for all $z_L \in (z_L^0, z_L^1)$ and $m^N(z_L) > m^S(z_L)$ for all $z_L \in (z_L^1, z_L^2)$.

There are two possible cases: a) $z_L^1 < \hat{z}_L$ and b) $z_L^1 \geq \hat{z}_L$. In case a), $m^{N'}(z_L^0) \leq m^{S'}(z_L^0)$ and $m^{N'}(z_L^1) \geq m^{S'}(z_L^1)$ implies that:

$$\frac{m^{N'}(z_L^1)}{m^{N'}(z_L^0)} \geq \frac{m^{S'}(z_L^1)}{m^{S'}(z_L^0)}.$$

Using equation (8), we can derive the following inequality:

$$\frac{\phi_L^N(z_L^1)}{\phi_L^N(z_L^0)} \left[\frac{w^N(z_L^1)}{w^N(z_L^0)}\right]^{1/1-\gamma} \geq \frac{\phi_L^S(z_L^1)}{\phi_L^S(z_L^0)} \left[\frac{w^S(z_L^1)}{w^S(z_L^0)}\right]^{1/1-\gamma}.$$

$\frac{\phi_L^N(z_L^1)}{\phi_L^N(z_L^0)} \leq \frac{\phi_L^S(z_L^1)}{\phi_L^S(z_L^0)}$ requires that:

$$\frac{w^N(z_L^1)}{w^N(z_L^0)} \geq \frac{w^S(z_L^1)}{w^S(z_L^0)}.$$

However, this is a contradiction. Since $m^N(z_L) < m^S(z_L)$ for all $z_L \in (z_L^0, z_L^1)$, it must be that

$$\frac{w^N(z_L^1)}{w^N(z_L^0)} \leq \frac{w^S(z_L^1)}{w^S(z_L^0)}.$$

In case b), the argument is identical and, hence, it is omitted. □

8.1.8 Proof of Proposition 9

Proof. The matching function $m(z_L)$ does not depend on technology level α from equation (13), which implies that the matching function $m(z_L)$ does not change. From equation (9) and equation (11), a one percent increase in α raises both $r(z_M)$ and $w(z_L)$ by one percent for all $z_M \in \mathcal{M}$ and $z_L \in \mathcal{L}$. □

8.1.9 Proof of Proposition 10

Proof. Since γ governs the share of output that goes to workers and managers, we can easily show that the workers' share increases and the managers' share declines due to an increase in the parameter γ.

Next, we show that if $\gamma^N > \gamma^S$, then $m^N(z_L) \geq m^S(z_L)$ for all $\mathcal{L}^N \cap \mathcal{L}^S$. Suppose that there exists $z_L \in \mathcal{L}^N \cap \mathcal{L}^S$ such that $m^N(z_L) < m^S(z_L)$. Since $\phi_L^N(z_L) = \phi_L^S(z_L)$, we know that $\mathcal{L}^N \cap \mathcal{L}^S = [z_{L,min}^N, z_{L,max}^N] = [z_{L,min}^S, z_{L,max}^S]$. There must exist $z_{L,min} \leq z_L^1 \leq z_L^2 \leq z_{L,max}$ and $z_{M,min} \leq z_M^1 \leq z_M^2 \leq z_{M,max}$ such that

$$\begin{aligned}
&\text{i)} \;\; m^N(z_L^1) = m^S(z_L^1) = z_M^1 \;\text{ and }\; m^N(z_L^2) = m^S(z_L^2) = z_M^2, \\
&\text{ii)} \;\; m^{N'}(z_L^1) \leq m^{S'}(z_L^1) \;\text{ and }\; m^{S'}(z_L^2) \leq m^{N'}(z_L^2), \\
&\text{iii)} \;\; m^N(z_L) < m^S(z_L) \;\text{ for all }\; z_L \in (z_L^1, z_L^2).
\end{aligned}$$

$m^{N'}(z_L^1) \leq m^{S'}(z_L^1)$ and $m^{S'}(z_L^2) \leq m^{N'}(z_L^2)$ implies that:

$$\frac{m^{S'}(z_L^1)}{m^{S'}(z_L^2)} \geq \frac{m^{N'}(z_L^1)}{m^{N'}(z_L^2)}.$$

Using equation (8), we can derive the following inequality:

$$\left[\frac{w^S(z_L^1)}{w^S(z_L^2)}\right]^{1/1-\gamma^S} \geq \left[\frac{w^N(z_L^1)}{w^N(z_L^2)}\right]^{1/1-\gamma^N}.$$

$\gamma^N > \gamma^S$ requires that:

$$\frac{w^N(z_L^2)}{w^N(z_L^1)} \geq \frac{w^S(z_L^2)}{w^S(z_L^1)}.$$

However, this is a contradiction. Since $\gamma^N > \gamma^S$ and $m^N(z_L) < m^S(z_L)$, it must be that

$$\frac{w^N(z_L^2)}{w^N(z_L^1)} < \frac{w^S(z_L^2)}{w^S(z_L^1)}.$$

Consequently, if $\gamma^N > \gamma^S$, then $m^N(z_L) \geq m^S(z_L)$ for all $\mathcal{L}^N \cap \mathcal{L}^S$.

Lastly, the size of the most skilled firms in the North is given by the

inverse of $\frac{m^{N'}(z_{L,max})\bar{M}^N\phi_M^N(m^N(z_{L,max}))}{\bar{L}^N\phi_L^N(z_{L,max})}$ and the size of the most skilled firms in the South is given by the inverse of $\frac{m^{S'}(z_{L,max})\bar{M}^S\phi_M^S(m^S(z_{L,max}))}{\bar{L}^S\phi_L^S(z_{L,max})}$. Since $m^N(z_L) \geq m^S(z_L)$ for all $\mathcal{L}^N \cap \mathcal{L}^S$ and $m^N(z_{L,max}) = m^S(z_{L,max})$, it must be that $m^{N'}(z_{L,max}) \leq m^{S'}(z_{L,max})$. Hence, the size of the most skilled firms (weakly) increases in the South. The proof is identical in the case of the size of the least skilled firms and, hence, it is omitted. □

8.1.10 Proof of Proposition 11

Proof. Suppose that there exists $z_L \in \mathcal{L}^N \cap \mathcal{L}^S$ such that $m^N(z_L) < m^S(z_L)$. Since $\phi_L^N(z_L) = \phi_L^S(z_L)$, we know that $\mathcal{L}^N \cap \mathcal{L}^S = [z_{L,min}^N, z_{L,max}^N] = [z_{L,min}^S, z_{L,max}^S]$. There must exist $z_{L,min} \leq z_L^1 \leq z_L^2 \leq z_{L,max}$ and $z_{M,min} \leq z_M^1 \leq z_M^2 \leq z_{M,max}$ such that

$$\begin{aligned}
&\text{i)} \;\; m^N(z_L^1) = m^S(z_L^1) = z_M^1 \;\text{ and }\; m^N(z_L^2) = m^S(z_L^2) = z_M^2, \\
&\text{ii)} \;\; m^{N'}(z_L^1) \leq m^{S'}(z_L^1) \;\text{ and }\; m^{S'}(z_L^2) \leq m^{N'}(z_L^2), \\
&\text{iii)} \;\; m^N(z_L) < m^S(z_L) \;\text{ for all }\; z_L \in (z_L^1, z_L^2).
\end{aligned}$$

$m^{N'}(z_L^1) \leq m^{S'}(z_L^1)$ and $m^{S'}(z_L^2) \leq m^{N'}(z_L^2)$ implies that:

$$\frac{m^{S'}(z_L^1)}{m^{S'}(z_L^2)} \geq \frac{m^{N'}(z_L^1)}{m^{N'}(z_L^2)}.$$

Using equation (8), we can derive the following inequality:

$$\left[\frac{e^{m(z_L^2)^{\beta^S} z_L^2}}{e^{m(z_L^1)^{\beta^S} z_L^1}}\right]\left[\frac{w^S(z_L^1)}{w^S(z_L^2)}\right] \geq \left[\frac{e^{m(z_L^2)^{\beta^N} z_L^2}}{e^{m(z_L^1)^{\beta^N} z_L^1}}\right]\left[\frac{w^N(z_L^1)}{w^N(z_L^2)}\right].$$

Given that $z^N_{L,min} = z^S_{L,min} \geq 1$ and $z^N_{M,min} = z^S_{M,min} \geq 1$, $\beta^N > \beta^S$ implies $\left[\frac{e^{m(z^2_L)^{\beta^S} z^2_L}}{e^{m(z^1_L)^{\beta^S} z^1_L}}\right] \leq \left[\frac{e^{m(z^2_L)^{\beta^N} z^2_L}}{e^{m(z^1_L)^{\beta^N} z^1_L}}\right]$. This, in turn, requires that:

$$\frac{w^N(z^2_L)}{w^N(z^1_L)} \geq \frac{w^S(z^2_L)}{w^S(z^1_L)}.$$

However, this is a contradiction. Since $\beta^N > \beta^S$ and $m^N(z_L) < m^S(z_L)$, it must be that

$$\frac{w^N(z^2_L)}{w^N(z^1_L)} < \frac{w^S(z^2_L)}{w^S(z^1_L)}.$$

Consequently, if $\beta^N > \beta^S$, then $m^N(z_L) \geq m^S(z_L)$ for all $\mathcal{L}^N \cap \mathcal{L}^S$. In equation (10), since $\beta^N > \beta^S$ and $m^N(z_L) \geq m^S(z_L)$ for all $\mathcal{L}^N \cap \mathcal{L}^S$, wage inequality rises. From equation (9), we can easily show that $w^N(z_{L,min}) > w^S(z_{L,min})$ using $\beta^N > \beta^S$ and $m^{N'}(z_{L,min}) > m^{S'}(z_{L,min})$. From equation (11), since $\beta^N > \beta^S$ and $m^{N'}(m^{-1}(z_{M,max})) < m^{S'}(m^{-1}(z_{M,max}))$, we can show that $r^N(z_{M,max}) > r^S(z_{M,max})$. Therefore, in the South, the wage schedule shifts upward, wage inequality rises, and the highest skilled manager's salary rises due to the manager-biased technical change. □

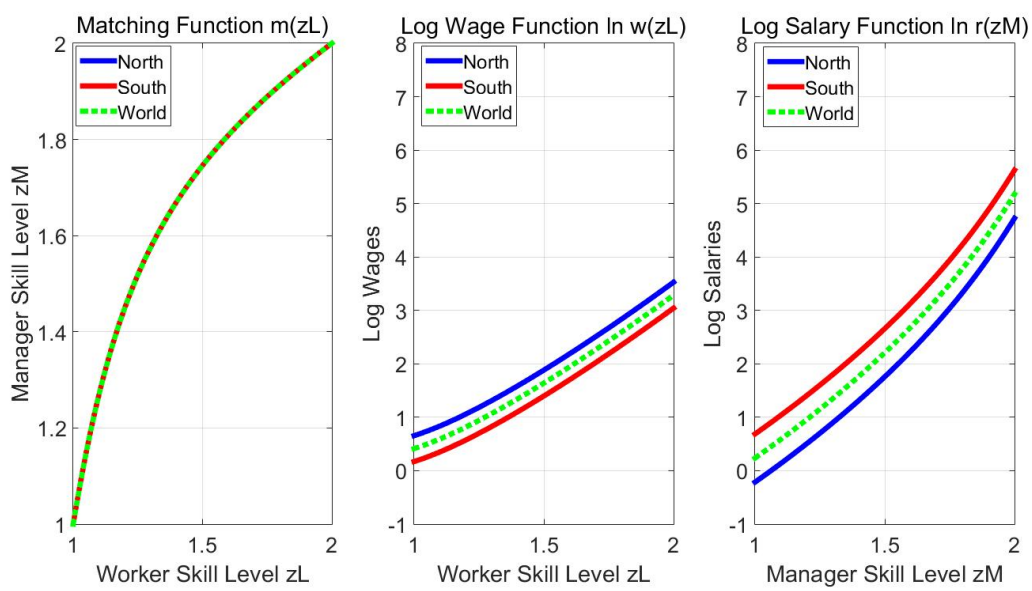
8.2 Numerical Simulations

8.2.1 Numerical Simulations for Proposition 4

Table 1: Sets of parameter values for Proposition 4

Parameter	Description	North	South	World
$\bar{M}$	Number of managers	**200**	**100**	**300**
$\bar{L}$	Number of workers	**500**	**1,000**	**1,500**
$\mathcal{M}$	Set of manager skill levels	[1,2]	[1,2]	[1,2]
$\mathcal{L}$	Set of worker skill levels	[1,2]	[1,2]	[1,2]
k_M	Shape parameter for manager skill distribution	2	2	2
k_L	Shape parameter for worker skill distribution	2	2	2
β	Sensitivity to manager skill level	1.2	1.2	1.2
γ	Span of control	0.65	0.65	0.65

Figure 1: The impact of offshoring under cross-country differences in endowments

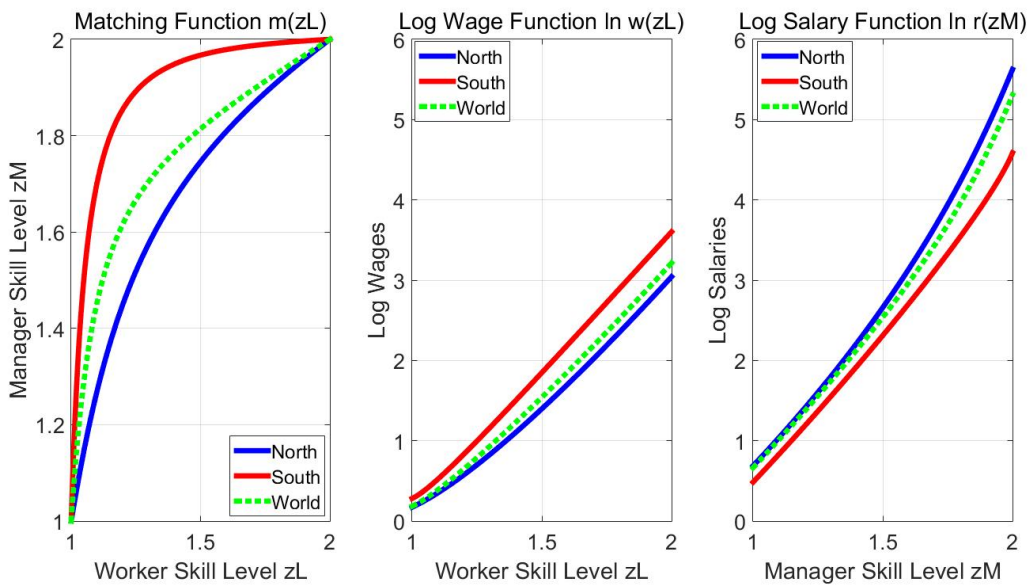


8.2.2 Numerical Simulations for Proposition 5

Table 2: Sets of parameter values for Proposition 5

Parameter	Description	North	South	World
M	Number of managers	100	100	200
$\bar{L}$	Number of workers	1,000	1,000	2,000
$\mathcal{M}$	Set of manager skill levels	[1,2]	[1,2]	[1,2]
$\mathcal{L}$	Set of worker skill levels	[1,2]	[1,2]	[1,2]
k_M	Shape parameter for manager skill distribution	2	2	2
k_L	Shape parameter for worker skill distribution	**2**	**10**	$\mathbf{k_L} \in (\mathbf{2}, \mathbf{10})$
β	Sensitivity to manager skill level	1.2	1.2	1.2
γ	Span of control	0.65	0.65	0.65

Figure 2: The impact of offshoring under cross-country differences in worker distribution

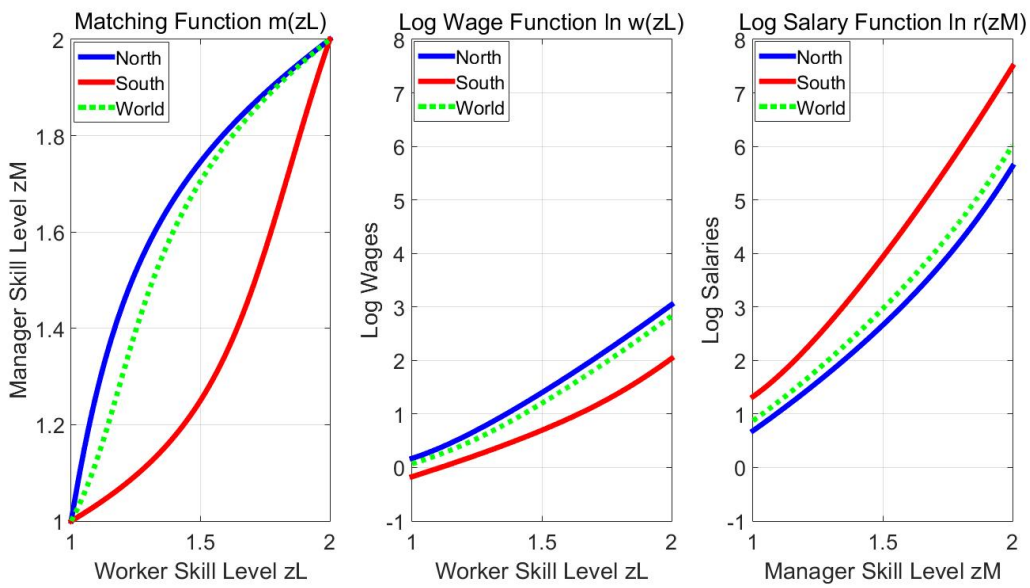


8.2.3 Numerical Simulations for Proposition 6

Table 3: Sets of parameter values for Proposition 6

Parameter	Description	North	South	World
M	Number of managers	100	100	200
$\bar{L}$	Number of workers	1,000	1,000	2,000
$\mathcal{M}$	Set of manager skill levels	[1,2]	[1,2]	[1,2]
$\mathcal{L}$	Set of worker skill levels	[1,2]	[1,2]	[1,2]
k_M	Shape parameter for manager skill distribution	**2**	**10**	$\mathbf{k_M} \in (\mathbf{2}, \mathbf{10})$
k_L	Shape parameter for worker skill distribution	2	2	2
β	Sensitivity to manager skill level	1.2	1.2	1.2
γ	Span of control	0.65	0.65	0.65

Figure 3: The impact of offshoring under cross-country differences in manager distribution

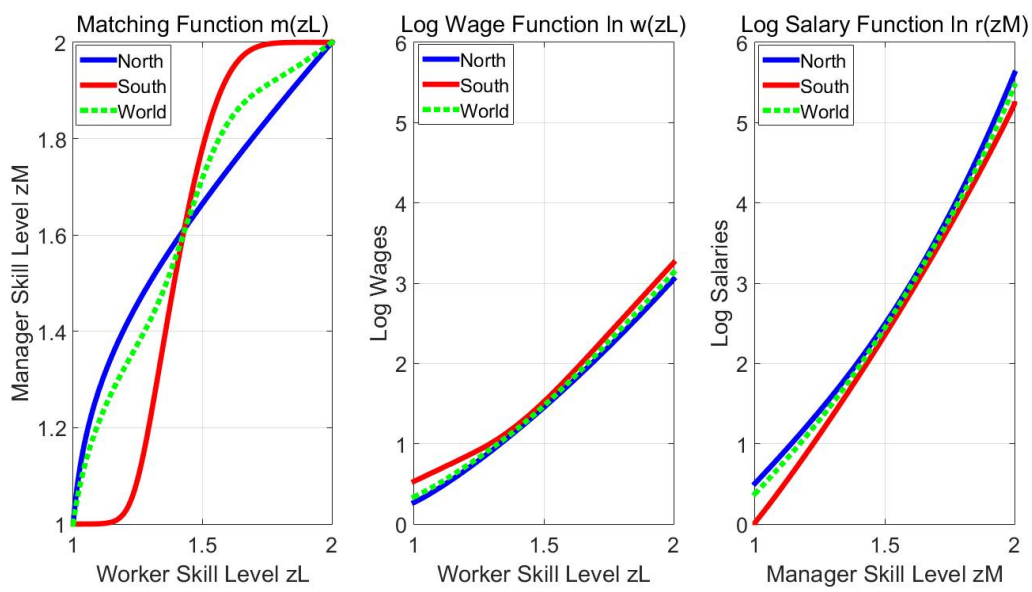


8.2.4 Numerical Simulations for Proposition 7

Table 4: Sets of parameter values for Proposition 7

Parameter	Description	North	South	World
M	Number of managers	100	100	200
$\bar{L}$	Number of workers	1,000	1,000	2,000
$\mathcal{M}$	Set of manager skill levels	[1,2]	[1,2]	[1,2]
$\mathcal{L}$	Set of worker skill levels	[1,2]	[1,2]	[1,2]
μ_M	Mean parameter for manager skill distribution	1.5	1.5	1.5
μ_L	Mean parameter for worker skill distribution	1.5	1.5	1.5
σ_M	Variance parameter for manager skill distribution	0.3	0.3	0.3
σ_L	Variance parameter for worker skill distribution	**0.6**	**0.1**	$\sigma_{\mathbf{L}} \in (\mathbf{0.1}, \mathbf{0.6})$
β	Sensitivity to manager skill level	1.2	1.2	1.2
γ	Span of control	0.65	0.65	0.65

Figure 4: The impact of offshoring under cross-country differences in worker distribution

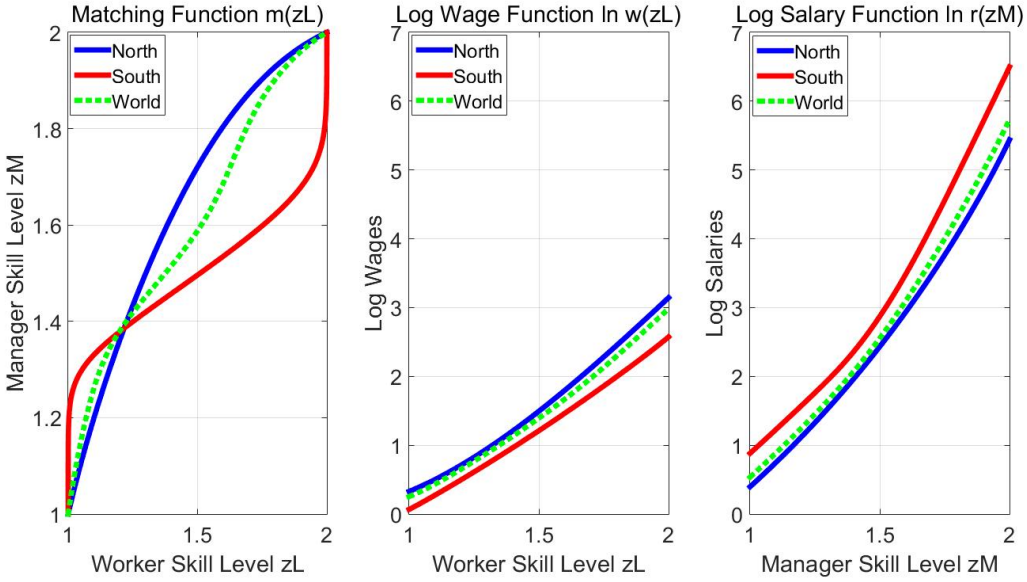


8.2.5 Numerical Simulations for Proposition 8

Table 5: Sets of parameter values for Proposition 8

Parameter	Description	North	South	World
M	Number of managers	100	100	200
$\bar{L}$	Number of workers	1,000	1,000	2,000
$\mathcal{M}$	Set of manager skill levels	[1,2]	[1,2]	[1,2]
$\mathcal{L}$	Set of worker skill levels	[1,2]	[1,2]	[1,2]
μ_M	Mean parameter for manager skill distribution	1.5	1.5	1.5
μ_L	Mean parameter for worker skill distribution	1.5	1.5	1.5
σ_M	Variance parameter for manager skill distribution	**0.6**	**0.1**	$\sigma_{\mathbf{M}} \in (\mathbf{0.1}, \mathbf{0.6})$
σ_L	Variance parameter for worker skill distribution	0.3	0.3	0.3
β	Sensitivity to manager skill level	1.2	1.2	1.2
γ	Span of control	0.65	0.65	0.65

Figure 5: The impact of offshoring under cross-country differences in manager distribution

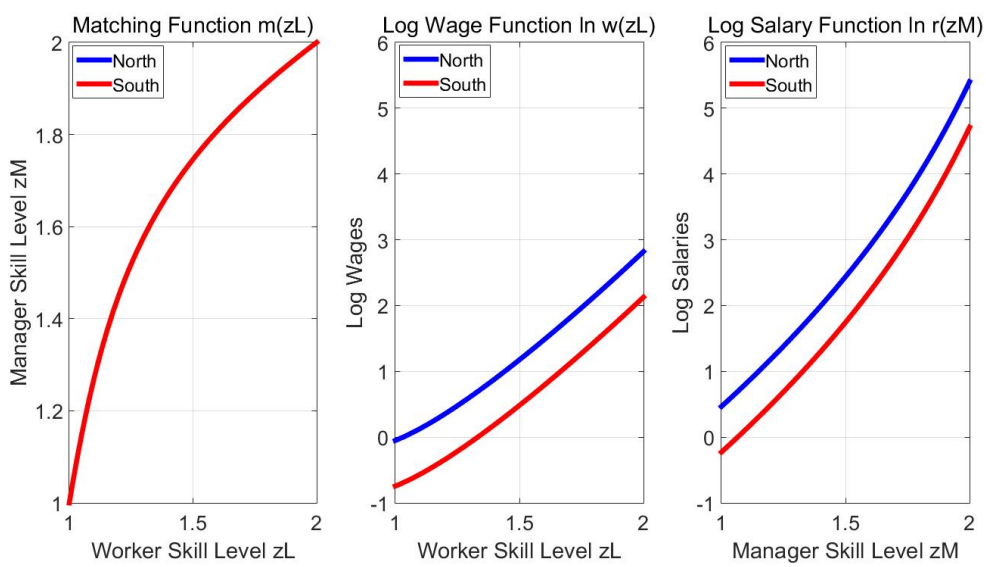


8.2.6 Numerical Simulations for Proposition 9

Table 6: Sets of parameter values for Proposition 9

Parameter	Description	Value (North)	Value (South)
M	Number of managers	100	100
$\bar{L}$	Number of workers	1,000	1,000
$\mathcal{M}$	Set of manager skill levels	[1,2]	[1,2]
$\mathcal{L}$	Set of worker skill levels	[1,2]	[1,2]
k_M	Shape parameter for manager skill distribution	2	2
k_L	Shape parameter for worker skill distribution	2	2
α	Hicks-neutral technology	**0.8**	**0.4**
β	Sensitivity to manager skill level	1.2	1.2
γ	Span of control	0.65	0.65

Figure 6: The distributional impact of Hicks-neutral technology transfer

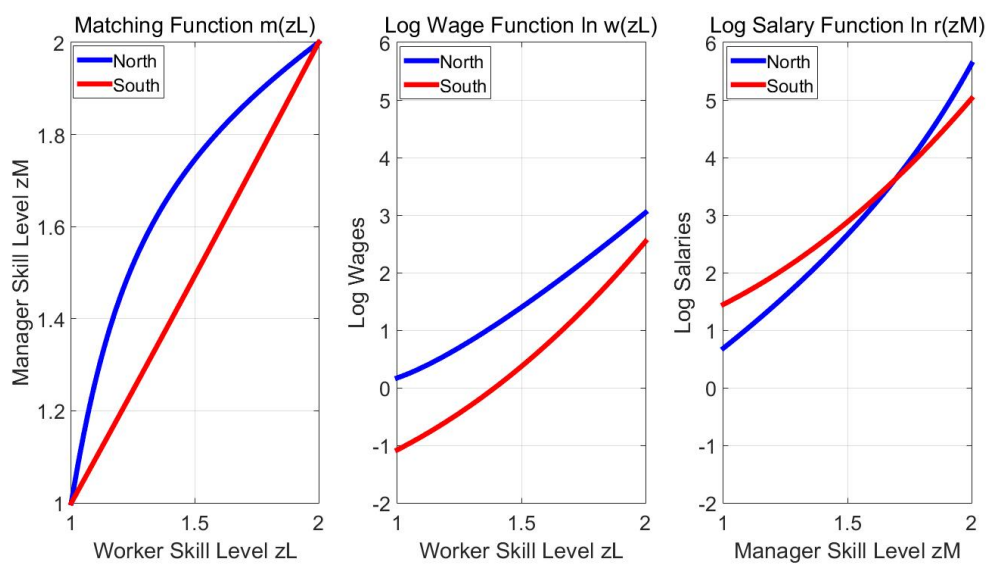


8.2.7 Numerical Simulations for Proposition 10

Table 7: Sets of parameter values for Proposition 10

Parameter	Description	Value (North)	Value (South)
M	Number of managers	100	100
$\bar{L}$	Number of workers	1,000	1,000
$\mathcal{M}$	Set of manager skill levels	[1,2]	[1,2]
$\mathcal{L}$	Set of worker skill levels	[1,2]	[1,2]
k_M	Shape parameter for manager skill distribution	2	2
k_L	Shape parameter for worker skill distribution	2	2
α	Hicks-neutral technology	1	1
β	Sensitivity to manager skill level	1.2	1.2
γ	Span of control	**0.65**	**0.45**

Figure 7: The distributional impact of improvement in management technology

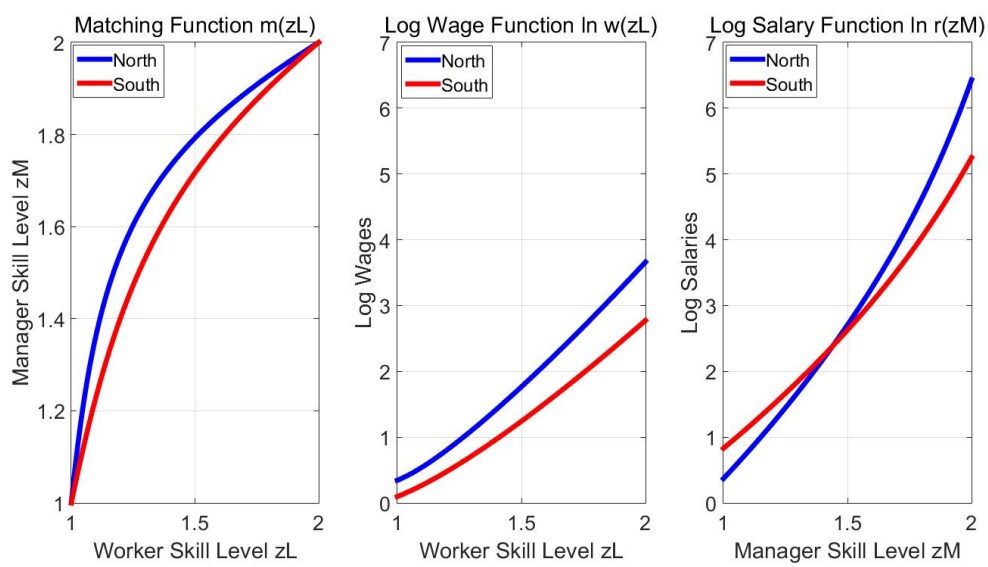


8.2.8 Numerical Simulations for Proposition 11

Table 8: Sets of parameter values for Proposition 11

Parameter	Description	Value (North)	Value (South)
M	Number of managers	100	100
$\bar{L}$	Number of workers	1,000	1,000
$\mathcal{M}$	Set of manager skill levels	[1,2]	[1,2]
$\mathcal{L}$	Set of worker skill levels	[1,2]	[1,2]
k_M	Shape parameter for manager skill distribution	2	2
k_L	Shape parameter for worker skill distribution	2	2
α	Hicks-neutral technology	1	1
β	Sensitivity to manager skill level	**1.4**	**1.1**
γ	Span of control	0.65	0.65

Figure 8: The distributional impact of manager-biased technical change



8.3 Tables

Table 9: Industry Categories

INDNAICS	BEA Code	Description
331M1	3111, 3112	Animal food, grain and oilseed milling
3113	3113	Sugar and confectionery products
3114	3114	Fruit and vegetable preserving and specialty foods
3115	3115	Dairy products
3116	3116	Animal slaughtering and processing
311811	3118	Retail bakeries
3118Z	3118	Bakeries, except retail
311M2	3117, 3119	Seafood and other miscellaneous foods, n.e.c.
3121	3121	Beverage
3122	3122	Tobacco
3131	3130	Fiber, yarn, and thread mills
3132Z	3130	Fabric mills, except knitting
3133	3130	Textile and fabric finishing and coating mills
31411	3140	Carpets and rugs
314Z	3140	Textile product mills except carpets and rugs
3152	3150	Cut and sew apparel
3159	3150	Apparel accessories and other apparel
3162	3160	Footwear
316M	3160	Leather tanning and products, except footwear
3211	3210	Sawmills and wood preservation
3212	3210	Veneer, plywood, and engineered wood products
32199M	3210	Prefabricated wood buildings and mobile homes
3219ZM	3210	Miscellaneous wood products
3221	3221	Pulp, paper, and paperboard mills
32221	3222	Paperboard containers and boxes
3222M	3222	Miscellaneous paper and pulp products
323	3231	Printing and related support activities
32411	3242	Petroleum refining
3241M	3243, 3244	Miscellaneous petroleum and coal products
3252	3252	Resin, synthetic rubber and fibers, and filaments
3253	3253	Agricultural chemicals
3254	3254	Pharmaceuticals and medicines
3255	3255	Paint, coating, and adhesives
3256	3256	Soap, cleaning compound, and cosmetics
325M	3251, 3259	Industrial and miscellaneous chemicals
3261	3261	Plastics products
32621	3262	Tires
3262M	3262	Rubber products, except tires
32711	3271	Pottery, ceramics, and related products
32712	3271	Structural clay products
3272	3272	Glass and glass products
327M	3273, 3274	Cement, concrete, lime, and gypsum products
3279	3279	Miscellaneous nonmetallic mineral products
331M	3311, 3312	Iron and steel mills and steel products
3313	3313	Aluminum production and processing
3314	3314	Nonferrous metal, except aluminum, production and processing

Notes: The industry classification of American Community Survey is INDNAICS, which is based on the North America Industry Classification System (NAICS). The Bureau of Economic Analysis (BEA) code also is based on the 4-digit NAICS industry classification.

Table 10: Industry Categories (continued)

INDNAICS	BEA Code	Description
3315	3315	Foundries
3321	3321	Metal forgings and stampings
3322	3322	Cutlery and hand tools
332M	3323, 3324	Structural metals, and tank and shipping containers
3327	3327	Machine shops; turned products; screws, nuts and bolts
3328	3328	Coating, engraving, heat treating and allied activities
33299M	3329	Ordnance
332MZ	3325, 3326	Miscellaneous fabricated metal products
33311	3331	Agricultural implements
3331M	3331	Construction mining and oil field machinery
3333	3333	Commercial and service industry machinery
3335	3335	Metalworking machinery
3336	3336	Engines, turbines, and power transmission equipment
333M	3332, 3334, 3339	Machinery, n.e.c.
3341	3341	Computer and peripheral equipment
334M1	3342, 3343	Communications, audio, and video equipment
3345	3345	Navigational, measuring, electromedical, and control instruments
334M2	3344, 3346	Electronic components and products, n.e.c.
3352	3352	Household appliances
335M	3351, 3353, 3359	Electrical machinery, equipment, and supplies, n.e.c.
336M	3361, 3362, 3363	Motor vehicles and motor vehicle equipment
33641M1	3364	Aircraft and parts
33641M2	3364	Aerospace products and parts
3365	3365	Railroad rolling stock
3366	3366	Ship and boat building
3369	3369	Other transportation equipment
337	3370	Furniture and fixtures
3391	3391	Medical equipment and supplies
3399M	3399	Toys, amusement, and sporting goods
3399ZM	3399	Miscellaneous manufacturing, n.e.c.

Notes: The industry classification of American Community Survey is INDNAICS, which is based on the North America Industry Classification System (NAICS). The Bureau of Economic Analysis (BEA) code also is based on the 4-digit NAICS industry classification.

Table 11: Broad Occupation Categories

Code	Title
000-200	Managerial and Professional
000-022	Executive, Administrative, and Managerial Occupations
023-037	Management Related Occupations
038-200	Professional Specialty Occupations
201-400	Technical, Sales, and Administrative
401-470	Service
471-500	Farming, Forestry, and Fishing
501-700	Precision Production, Craft, and Repairers
701-900	Operatives and Laborers

Table 12: Trends in manufacturing employment in the U.S, 2002-2013

Year	(a) U.S. multinationals $\rightarrow$ Foreign employees	(b) Foreign multinationals $\rightarrow$ U.S. employees	(c) Total U.S. employees		$(d \equiv \frac{a}{c})$ *Offshoring*	$(e \equiv \frac{b}{c})$ *Inshoring*
2002	4.29	2.24	14.95		28.7%	15.0%
2003	4.22	2.12	14.78		28.5%	14.3%
2004	4.32	2.00	14.30		30.2%	14.0%
2005	4.45	2.00	14.26		31.2%	14.0%
2006	4.60	2.06	14.19		32.4%	14.5%
2007	4.64	2.05	13.96		33.3%	14.7%
2008	4.55	2.15	13.66		33.3%	15.8%
2009	4.54	1.96	12.44		36.5%	15.8%
2010	4.65	2.01	11.49		40.5%	17.5%
2011	4.79	2.10	11.61		41.3%	18.1%
2012	4.77	2.20	11.87		40.2%	18.5%
2013	4.89	2.31	11.98		40.8%	19.3%
Growth rate 2002-2013	13.8%	3.5%	-19.8%		12.1%p	4.4%p

Notes: The employment counts are based on millions of people. The table only includes manufacturing sectors. (a) is defined as the number of foreign employees working abroad for U.S. multinationals (from BEA data). (b) is defined as the number of U.S. employees who work for foreign multinationals (from BEA data). (c) is the total number of U.S. employees in the U.S. according to BLS data. (a) and (c) are mutually exclusive while (b) is a subset of (c). *Offshoring*, $(d \equiv \frac{a}{c})$, is defined as the the number of foreign employees who work abroad for U.S. multinationals divided by the total number of U.S. employees. *Inshoring*, $(e \equiv \frac{b}{c})$, is defined as the number of U.S. employees who work for foreign multinationals divided by the total number of U.S. employees.
Source: Bureau of Economic Analysis (BEA) and Bureau of Labor Statistics (BLS)

Table 13: Industries with the Highest and Lowest *Offshoring* in the U.S., 2002-2013

Description	BEA Code	*Offshoring* (%) 2002 ($a \equiv \frac{c}{e}$)	2013 ($b \equiv \frac{d}{f}$)	Diff (%p) (b-a)	U.S. multinationals → Foreign employees 2002 (c)	2013 (d)	Diff (d-c)	Total U.S. employees 2002 (e)	2013 (f)	Diff (f-e)
Panel A: Top 10 Industries by Changes in *Offshoring*										
Tobacco products	3122	155.4	678.7	523.3	50,800	92,100	41,300	32,680	13,570	- 19,110
Computers and peripheral equipment	3341	49.7	166.0	116.3	117,600	256,300	138,700	236,750	154,440	- 82,310
Household appliances	3352	71.2	133.7	62.4	68,000	75,000	7,000	95,440	56,110	- 39,330
Sugar and confectionery products	3113	42.0	101.3	59.3	39,400	69,300	29,900	93,840	68,430	- 25,410
Motor vehicle parts	3363	74.9	127.2	52.3	547,400	641,600	94,200	730,450	504,210	-226,240
Paints, coatings, and adhesives	3255	43.0	92.0	49.0	30,400	52,800	22,400	70,650	57,370	- 13,280
Grain and oilseed milling	3112	69.0	112.0	43.1	42,700	66,400	23,700	61,910	59,270	- 2,640
Semiconductors and other electronic components	3344	57.7	92.5	34.8	286,900	348,000	61,100	497,110	376,040	-121,070
Clay products and refractories	3271	25.3	57.9	32.7	17,900	23,000	5,100	70,840	39,690	- 31,150
Soap, cleaning compounds, and toilet preparations	3256	104.0	136.2	32.2	123,900	141,300	17,400	119,120	103,720	- 15,400
Panel B: Bottom 10 Industries by Changes in *Offshoring*										
Electric lighting equipment	3351	55.1	35.5	-19.6	38,700	16,300	- 22,400	70,250	45,950	- 24,300
Seafood product preparation and packaging	3117	19.7	0.6	-19.1	7,500	200	- 7,300	38,040	33,660	- 4,380
Communications equipment	3342	74.5	62.9	-11.5	123,900	65,300	- 58,600	166,410	103,780	- 62,630
Audio and video equipment	3343	97.6	90.4	-7.2	40,100	17,000	- 23,100	41,080	18,810	- 22,270
Magnetic and optical media	3346	21.4	14.7	-6.6	11,900	2,700	- 9,200	55,710	18,350	- 37,360
Foundries	3315	8.7	2.4	-6.2	15,000	3,100	- 11,900	172,960	127,310	- 45,650
Fruit and vegetable preserving and specialty foods	3114	25.3	19.9	-5.4	45,900	33,100	- 12,800	181,590	166,550	- 15,040
Iron and steel mills and ferroalloys	3311	24.1	20.6	-3.5	26,100	18,800	- 7,300	108,200	91,190	- 17,010
Forging and stamping	3321	15.2	11.7	-3.5	16,600	11,500	- 5,100	109,420	98,190	- 11,230
Bakeries and tortillas	3118	11.4	8.0	-3.4	34,300	22,800	- 11,500	299,860	284,920	- 14,940

Notes: The employment counts are based on the number of people. The table only includes manufacturing sectors. (c) and (d) are defined as the number of foreign employees working abroad for U.S. multinationals (from BEA data). (e) and (f) are defined as the total number of U.S. employees in the U.S. according to BLS data.

Table 14: Industries with the Highest and Lowest *Inshoring* in the U.S., 2002-2013

Description	BEA Code	*Inshoring* (%) 2002 ($a \equiv \frac{c}{e}$)	2013 ($b \equiv \frac{d}{f}$)	Diff (%p) (b-a)	Foreign multinationals → U.S. employees 2002 (c)	2013 (d)	Diff (d-c)	Total U.S. employees 2002 (e)	2013 (f)	Diff (f-e)
Panel A: Top 10 Industries by Changes in *Inshoring*										
Iron and steel mills and ferroalloys	3311	16.1	66.6	50.5	17,400	60,700	43,300	108,200	91,190	- 17,010
Electrical equipment	3353	15.4	54.1	38.7	25,600	78,100	52,500	166,690	144,450	- 22,240
Steel products from purchased steel	3312	11.5	34.4	22.9	6,900	20,100	13,200	60,010	58,450	- 1,560
Basic chemicals	3251	33.1	55.8	22.8	55,100	80,200	25,100	166,710	143,620	- 23,090
Rubber products	3262	47.8	69.0	21.2	86,300	90,400	4,100	180,590	131,020	- 49,570
Motor vehicle parts	3363	26.5	47.2	20.7	193,400	237,800	44,400	730,450	504,210	-226,240
Aerospace products and parts	3364	9.5	28.5	19.0	42,900	143,500	100,600	451,790	502,740	50,950
Animal slaughtering and processing	3116	1.3	19.4	18.0	6,900	93,700	86,800	521,540	484,130	- 37,410
Industrial machinery	3332	20.4	36.3	16.0	25,900	38,600	12,700	127,230	106,300	- 20,930
Hardware	3325	25.4	41.2	15.9	10,200	9,400	- 800	40,210	22,800	- 17,410
Panel B: Bottom 10 Industries by Changes in *Inshoring*										
Medical equipment and supplies	3391	40.6	17.8	-22.8	124,600	54,400	- 70,200	306,580	305,280	- 1,300
Resins and synthetic rubber, fibers, and filaments	3252	35.5	13.3	-22.2	39,800	12,100	- 27,700	111,980	91,000	- 20,980
Glass and glass products	3272	34.5	12.5	-22.0	42,300	10,100	- 32,200	122,460	80,850	- 41,610
Electric lighting equipment	3351	29.2	8.1	-21.1	20,500	3,700	- 16,800	70,250	45,950	- 24,300
Forging and stamping	3321	25.7	5.0	-20.7	28,100	4,900	- 23,200	109,420	98,190	- 11,230
Magnetic and optical media	3346	21.4	1.6	-19.7	11,900	300	- 11,600	55,710	18,350	- 37,360
Commercial and service industry machinery	3333	26.1	6.7	-19.4	32,200	5,900	- 26,300	123,580	88,110	- 35,470
Agriculture, construction, and mining machinery	3331	30.3	13.8	-16.5	58,000	34,600	- 23,400	191,560	250,400	58,840
Nonferrous metal (except aluminum)	3314	20.9	10.5	-10.4	16,200	6,500	- 9,700	77,670	62,040	- 15,630
Other food products	3119	22.2	15.4	-6.9	33,800	27,400	- 6,400	152,090	178,490	26,400

Notes: The employment counts are based on the number of people. The table only includes manufacturing sectors. (c) and (d) are defined as the number of U.S. employees who work for foreign multinationals (from BEA data). (e) and (f) are defined as the total number of U.S. employees in the U.S. according to BLS data.

Table 15: The Average Effects of Exposure to Offshoring, 2002-2011
Dependent variable: Log real yearly income

	I. Baseline				II. Narrow Workers			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Offshoring$_{t-1}$, γ_A	-0.076*	-0.060*	-0.051*	-0.044*	-0.076	-0.059	-0.049	-0.042
	(0.044)	(0.033)	(0.027)	(0.025)	(0.048)	(0.037)	(0.031)	(0.029)
Inshoring$_{t-1}$, γ_B	0.061*	0.033	0.033	0.028	0.030	0.003	0.002	-0.007
	(0.036)	(0.027)	(0.023)	(0.024)	(0.041)	(0.033)	(0.028)	(0.029)
Male	0.378***	0.379***	0.380***	0.377***	0.335***	0.333***	0.334***	0.332***
	(0.009)	(0.009)	(0.009)	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)
Age	0.112***	0.113***	0.113***	0.111***	0.110***	0.110***	0.110***	0.108***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age^2	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
White	0.137***	0.141***	0.142***	0.143***	0.107***	0.109***	0.110***	0.111***
	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
College or more	0.336***	0.351***	0.351***	0.343***	0.332***	0.345***	0.345***	0.337***
	(0.012)	(0.011)	(0.011)	(0.010)	(0.012)	(0.011)	(0.011)	(0.011)
$ManagerN$	0.630***	0.625***	0.625***	0.625***	0.722***	0.722***	0.721***	0.721***
	(0.016)	(0.017)	(0.017)	(0.017)	(0.017)	(0.018)	(0.018)	(0.018)
Capital Intensity$_{t-1}$		-0.114***	-0.087***	-0.091***		-0.113***	-0.088***	-0.093***
		(0.037)	(0.025)	(0.024)		(0.036)	(0.025)	(0.023)
TFP$_{t-1}$		0.013	-0.006	-0.009		0.032	0.009	0.006
		(0.027)	(0.024)	(0.021)		(0.030)	(0.028)	(0.025)
Fixed effects:								
Industry	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Region	Yes	Yes	No	No	Yes	Yes	No	No
Year	Yes	Yes	No	No	Yes	Yes	No	No
Region-Year	No	No	Yes	Yes	No	No	Yes	Yes
Industry-Region	No	No	No	Yes	No	No	No	Yes
p-value: Test of $\gamma_A = \gamma_B = 0$	[0.197]	[0.200]	[0.160]	[0.218]	[0.255]	[0.181]	[0.171]	[0.192]
p-value: Test of $\gamma_A = \gamma_B$	[0.072]	[0.091]	[0.064]	[0.099]	[0.202]	[0.318]	[0.331]	[0.501]
Observations	707,232	618,100	618,094	617,962	529,803	463,297	463,285	463,139
R-squared	0.410	0.412	0.414	0.423	0.443	0.446	0.448	0.457

Notes: Individual data are taken from ACS samples from 2002 to 2011. Baseline specifications, columns (1)-(4), include a broad definition of workers (501 $\leq$ occ1990 $\leq$ 900). In columns (5)-(8), we include a narrow definition of workers (701 $\leq$ occ1990 $\leq$ 900). In all specifications, managers are defined by narrow criteria (000 $\leq$ occ1990 $\leq$ 037). Estimation is done by OLS weighted by person (perwt) in ACS. Clustered robust standard errors are in parentheses. Errors are clustered at industry and five-year periods. *** p<0.01, ** p<0.05, * p<0.1.

Table 16: Heterogeneous Effects of Exposure to Offshoring, 2002-2011
Dependent variable: Log real yearly income

	I. Baseline				II. Narrow Workers			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Offshoring$_{t-1}$	-0.111***	-0.091***	-0.081***	-0.073***	-0.125***	-0.102***	-0.090***	-0.081***
$\times\ Worker,\ \gamma_1$	(0.041)	(0.031)	(0.026)	(0.024)	(0.043)	(0.034)	(0.029)	(0.027)
Offshoring$_{t-1}$	0.026	0.033	0.039	0.049	0.026	0.029	0.035	0.045
$\times\ ManagerN,\ \gamma_2$	(0.073)	(0.064)	(0.059)	(0.055)	(0.075)	(0.065)	(0.060)	(0.057)
Inshoring$_{t-1}$	0.133***	0.102***	0.100***	0.092***	0.135**	0.104**	0.101**	0.085*
$\times\ Worker,\ \gamma_3$	(0.043)	(0.035)	(0.032)	(0.030)	(0.058)	(0.051)	(0.048)	(0.047)
Inshoring$_{t-1}$	-0.160**	-0.175**	-0.172**	-0.170**	-0.165**	-0.185**	-0.183**	-0.181**
$\times\ ManagerN,\ \gamma_4$	(0.076)	(0.076)	(0.077)	(0.073)	(0.076)	(0.077)	(0.077)	(0.076)
Male	0.377***	0.378***	0.379***	0.376***	0.333***	0.332***	0.333***	0.331***
	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)
Age	0.112***	0.113***	0.112***	0.111***	0.109***	0.110***	0.109***	0.108***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age^2	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
White	0.136***	0.141***	0.142***	0.143***	0.106***	0.109***	0.110***	0.110***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
College or more	0.335***	0.349***	0.349***	0.341***	0.329***	0.343***	0.343***	0.335***
	(0.012)	(0.011)	(0.010)	(0.010)	(0.012)	(0.011)	(0.011)	(0.010)
$ManagerN$	0.628***	0.624***	0.625***	0.622***	0.716***	0.721***	0.722***	0.718***
	(0.019)	(0.022)	(0.021)	(0.020)	(0.021)	(0.023)	(0.023)	(0.022)
Capital Intensity$_{t-1}$		-0.114***	-0.087***	-0.092***		-0.112***	-0.088***	-0.093***
		(0.036)	(0.024)	(0.023)		(0.035)	(0.023)	(0.022)
TFP$_{t-1}$		0.004	-0.014	-0.017		0.021	0.000	-0.003
		(0.026)	(0.023)	(0.021)		(0.029)	(0.027)	(0.025)
Fixed effects:								
Industry	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Region	Yes	Yes	No	No	Yes	Yes	No	No
Year	Yes	Yes	No	No	Yes	Yes	No	No
Region-Year	No	No	Yes	Yes	No	No	Yes	Yes
Industry-Region	No	No	No	Yes	No	No	No	Yes
p-value: Test of $\gamma_1 = \gamma_2$	[0.022]	[0.035]	[0.042]	[0.023]	[0.018]	[0.034]	[0.043]	[0.028]
p-value: Test of $\gamma_1 = \gamma_3$	[0.002]	[0.002]	[0.001]	[0.001]	[0.006]	[0.009]	[0.007]	[0.014]
p-value: Test of $\gamma_2 = \gamma_4$	[0.147]	[0.075]	[0.064]	[0.042]	[0.143]	[0.070]	[0.057]	[0.042]
p-value: Test of $\gamma_3 = \gamma_4$	[0.005]	[0.009]	[0.006]	[0.007]	[0.026]	[0.037]	[0.042]	[0.049]
Observations	707,232	618,100	618,094	617,962	529,803	463,297	463,285	463,139
R-squared	0.410	0.412	0.415	0.423	0.443	0.447	0.449	0.457

Notes: Individual data are taken from ACS samples from 2002 to 2011. Baseline specifications, columns (1)-(4), include a broad definition of workers (501 $\leq$ occ1990 $\leq$ 900). In columns (5)-(8), we include a narrow definition of workers (701 $\leq$ occ1990 $\leq$ 900). In all specifications, managers are defined by narrow criteria (000 $\leq$ occ1990 $\leq$ 037). Estimation is done by OLS weighted by person (perwt) in ACS. Clustered robust standard errors are in parentheses. Errors are clustered at industry and five-year periods. *** p<0.01, ** p<0.05, * p<0.1.

Table 17: Heterogeneous Effects of Exposure to Offshoring, 2002-2011
Dependent variable: Log real yearly income

	I. Baseline				II. Narrow Workers			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Offshoring$_{t-1}$	-0.110***	-0.090***	-0.080***	-0.072***	-0.124***	-0.100***	-0.088***	-0.079***
$\times\ Worker,\ \gamma_1$	(0.041)	(0.032)	(0.026)	(0.024)	(0.043)	(0.035)	(0.030)	(0.028)
Offshoring$_{t-1}$	-0.152**	-0.135**	-0.129**	-0.108**	-0.185***	-0.175***	-0.168***	-0.148***
$\times\ ManagerN \times Noncol, \gamma_2$	(0.062)	(0.054)	(0.050)	(0.048)	(0.067)	(0.059)	(0.055)	(0.053)
Offshoring$_{t-1}$	0.119	0.122*	0.127*	0.135**	0.141*	0.143*	0.149**	0.157**
$\times\ ManagerN \times College, \gamma_3$	(0.080)	(0.072)	(0.067)	(0.062)	(0.083)	(0.074)	(0.070)	(0.065)
Inshoring$_{t-1}$	0.138***	0.106***	0.104***	0.096***	0.142**	0.111**	0.107**	0.091*
$\times\ Worker,\ \gamma_4$	(0.043)	(0.035)	(0.031)	(0.030)	(0.058)	(0.051)	(0.047)	(0.046)
Inshoring$_{t-1}$	-0.150**	-0.168**	-0.165**	-0.164**	-0.149**	-0.172**	-0.171**	-0.171**
$\times\ ManagerN,\ \gamma_5$	(0.070)	(0.072)	(0.073)	(0.069)	(0.071)	(0.072)	(0.073)	(0.072)
Male	0.377***	0.378***	0.378***	0.376***	0.333***	0.332***	0.332***	0.330***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)
Age	0.112***	0.113***	0.112***	0.111***	0.109***	0.110***	0.109***	0.108***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age^2	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
White	0.137***	0.141***	0.142***	0.143***	0.106***	0.109***	0.110***	0.110***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
College or more	0.274***	0.286***	0.286***	0.282***	0.237***	0.244***	0.245***	0.241***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.014)	(0.015)	(0.015)	(0.015)
$ManagerN$	0.660***	0.659***	0.660***	0.654***	0.763***	0.773***	0.774***	0.767***
	(0.018)	(0.021)	(0.021)	(0.020)	(0.021)	(0.023)	(0.023)	(0.022)
Capital Intensity$_{t-1}$		-0.115***	-0.088***	-0.093***		-0.114***	-0.090***	-0.095***
		(0.036)	(0.024)	(0.023)		(0.034)	(0.023)	(0.022)
TFP$_{t-1}$		-0.003	-0.021	-0.024		0.011	-0.010	-0.013
		(0.025)	(0.023)	(0.021)		(0.028)	(0.026)	(0.024)
Fixed effects:								
Industry	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Region	Yes	Yes	No	No	Yes	Yes	No	No
Year	Yes	Yes	No	No	Yes	Yes	No	No
Region-Year	No	No	Yes	Yes	No	No	Yes	Yes
Industry-Region	No	No	No	Yes	No	No	No	Yes
p-value: Test of $\gamma_1 = \gamma_3$	[0.001]	[0.002]	[0.003]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
p-value: Test of $\gamma_2 = \gamma_3$	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
p-value: Test of $\gamma_1 = \gamma_4$	[0.002]	[0.002]	[0.001]	[0.001]	[0.005]	[0.007]	[0.005]	[0.012]
p-value: Test of $\gamma_4 = \gamma_5$	[0.002]	[0.003]	[0.004]	[0.003]	[0.006]	[0.008]	[0.010]	[0.012]
Observations	707,232	618,100	618,094	617,962	529,803	463,297	463,285	463,139
R-squared	0.411	0.413	0.416	0.424	0.444	0.448	0.450	0.458

Notes: Individual data are taken from ACS samples from 2002 to 2011. Baseline specifications, columns (1)-(4), include a broad definition of workers (501 $\leq$ occ1990 $\leq$ 900). In columns (5)-(8), we include a narrow definition of workers (701 $\leq$ occ1990 $\leq$ 900). In all specifications, managers are defined by narrow criteria (000 $\leq$ occ1990 $\leq$ 037). Estimation is done by OLS weighted by person (perwt) in ACS. Clustered robust standard errors are in parentheses. Errors are clustered at industry and five-year periods. *** p<0.01, ** p<0.05, * p<0.1.

Table 18: Robustness Check: Heterogeneous Effects of Exposure to Offshoring Without Global Financial Crisis, 2002-2007
Dependent variable: Log real yearly income

	I. Baseline				II. Narrow Workers			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Offshoring$_{t-1}$	-0.056**	-0.045*	-0.045*	-0.033	-0.064*	-0.049	-0.050	-0.036
$\times\ Worker,\ \gamma_1$	(0.025)	(0.025)	(0.025)	(0.023)	(0.036)	(0.037)	(0.036)	(0.033)
Offshoring$_{t-1}$	-0.126**	-0.124**	-0.126**	-0.099*	-0.158**	-0.168**	-0.170**	-0.146**
$\times\ ManagerN \times Noncol, \gamma_2$	(0.061)	(0.062)	(0.063)	(0.057)	(0.064)	(0.065)	(0.066)	(0.061)
Offshoring$_{t-1}$	0.190**	0.172**	0.171*	0.180**	0.230**	0.208**	0.206**	0.214**
$\times\ ManagerN \times College, \gamma_3$	(0.088)	(0.086)	(0.086)	(0.081)	(0.091)	(0.089)	(0.090)	(0.085)
Inshoring$_{t-1}$	0.081**	0.066**	0.070**	0.055*	0.076	0.064	0.068	0.043
$\times\ Worker,\ \gamma_4$	(0.032)	(0.031)	(0.030)	(0.028)	(0.053)	(0.052)	(0.051)	(0.049)
Inshoring$_{t-1}$	-0.171*	-0.179**	-0.173*	-0.174*	-0.169*	-0.178*	-0.172*	-0.171*
$\times\ ManagerN,\ \gamma_5$	(0.088)	(0.090)	(0.090)	(0.089)	(0.089)	(0.090)	(0.090)	(0.089)
Male	0.396***	0.395***	0.395***	0.392***	0.350***	0.348***	0.348***	0.345***
	(0.010)	(0.009)	(0.009)	(0.009)	(0.010)	(0.009)	(0.008)	(0.008)
Age	0.117***	0.117***	0.117***	0.116***	0.114***	0.114***	0.113***	0.112***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age^2	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
White	0.139***	0.144***	0.145***	0.146***	0.107***	0.109***	0.110***	0.110***
	(0.007)	(0.008)	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)
College or more	0.262***	0.276***	0.277***	0.274***	0.219***	0.228***	0.228***	0.227***
	(0.014)	(0.012)	(0.012)	(0.012)	(0.014)	(0.015)	(0.015)	(0.015)
$ManagerN$	0.650***	0.656***	0.656***	0.649***	0.755***	0.773***	0.773***	0.765***
	(0.022)	(0.025)	(0.025)	(0.024)	(0.027)	(0.029)	(0.029)	(0.028)
Capital Intensity$_{t-1}$		-0.054**	-0.040	-0.052**		-0.041	-0.028	-0.036
		(0.024)	(0.025)	(0.024)		(0.028)	(0.033)	(0.033)
TFP$_{t-1}$		-0.101*	-0.106**	-0.115**		-0.124	-0.133*	-0.140**
		(0.057)	(0.052)	(0.052)		(0.075)	(0.071)	(0.069)
Fixed effects:								
Industry	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Region	Yes	Yes	No	No	Yes	Yes	No	No
Year	Yes	Yes	No	No	Yes	Yes	No	No
Region-Year	No	No	Yes	Yes	No	No	Yes	Yes
Industry-Region	No	No	No	Yes	No	No	No	Yes
p-value: Test of $\gamma_1 = \gamma_3$	[0.010]	[0.020]	[0.021]	[0.016]	[0.005]	[0.010]	[0.011]	[0.009]
p-value: Test of $\gamma_2 = \gamma_3$	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
p-value: Test of $\gamma_1 = \gamma_4$	[0.009]	[0.032]	[0.022]	[0.059]	[0.079]	[0.153]	[0.132]	[0.285]
p-value: Test of $\gamma_4 = \gamma_5$	[0.021]	[0.024]	[0.027]	[0.031]	[0.052]	[0.056]	[0.061]	[0.085]
Observations	366,129	316,171	316,169	316,027	273,940	236,350	236,344	236,188
R-squared	0.400	0.403	0.404	0.415	0.430	0.435	0.436	0.447

Notes: Individual data are taken from ACS samples from 2002 to 2007. Baseline specifications, columns (1)-(4), include broad definition of workers (501 $\leq$ occ1990 $\leq$ 900). In columns (5)-(8), we include narrow definition of workers (701 $\leq$ occ1990 $\leq$ 900). In all specifications, managers are defined as narrow criteria (000 $\leq$ occ1990 $\leq$ 037). Estimation is done by OLS weighted by person (perwt) in ACS. Clustered robust standard errors are in parentheses. Errors are clustered at industry and five-year period. *** p<0.01, ** p<0.05, * p<0.1.

Table 19: Robustness Check: Heterogeneous Effects of Exposure to Offshoring With Broad Measure of Managers, 2002-2011
Dependent variable: Log real yearly income

	I. Baseline				II. Narrow Workers			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Offshoring$_{t-1}$	-0.115***	-0.092***	-0.081***	-0.073***	-0.129***	-0.100***	-0.088***	-0.078***
$\times\ Worker,\ \gamma_1$	(0.039)	(0.030)	(0.025)	(0.023)	(0.040)	(0.033)	(0.028)	(0.026)
Offshoring$_{t-1}$	-0.128**	-0.110**	-0.103**	-0.088**	-0.156**	-0.145***	-0.137***	-0.121**
$\times\ ManagerB \times Noncol, \gamma_2$	(0.059)	(0.051)	(0.046)	(0.044)	(0.063)	(0.055)	(0.049)	(0.048)
Offshoring$_{t-1}$	0.082	0.089	0.095	0.095	0.096	0.103	0.109*	0.112*
$\times\ ManagerB \times College, \gamma_3$	(0.077)	(0.068)	(0.062)	(0.058)	(0.077)	(0.069)	(0.062)	(0.058)
Inshoring$_{t-1}$	0.172***	0.140***	0.139***	0.128***	0.189***	0.159***	0.156***	0.138***
$\times\ Worker,\ \gamma_4$	(0.047)	(0.039)	(0.035)	(0.033)	(0.064)	(0.057)	(0.054)	(0.051)
Inshoring$_{t-1}$	-0.101	-0.124*	-0.123*	-0.121*	-0.089	-0.116*	-0.117*	-0.117*
$\times\ ManagerB,\ \gamma_5$	(0.062)	(0.063)	(0.064)	(0.061)	(0.060)	(0.062)	(0.062)	(0.061)
Male	0.356***	0.354***	0.355***	0.352***	0.314***	0.310***	0.311***	0.309***
	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)
Age	0.114***	0.114***	0.114***	0.113***	0.111***	0.112***	0.112***	0.111***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age^2	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
White	0.132***	0.136***	0.137***	0.138***	0.104***	0.105***	0.106***	0.108***
	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.006)
College or more	0.276***	0.286***	0.286***	0.282***	0.246***	0.250***	0.251***	0.248***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.012)	(0.014)	(0.014)	(0.013)
$ManagerB$	0.594***	0.596***	0.597***	0.591***	0.696***	0.711***	0.712***	0.704***
	(0.018)	(0.020)	(0.020)	(0.019)	(0.022)	(0.022)	(0.023)	(0.021)
Capital Intensity$_{t-1}$		-0.114***	-0.087***	-0.091***		-0.114***	-0.089***	-0.092***
		(0.034)	(0.022)	(0.021)		(0.033)	(0.021)	(0.020)
TFP$_{t-1}$		-0.003	-0.026	-0.026		0.005	-0.022	-0.022
		(0.023)	(0.021)	(0.018)		(0.025)	(0.023)	(0.020)
Fixed effects:								
Industry	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Region	Yes	Yes	No	No	Yes	Yes	No	No
Year	Yes	Yes	No	No	Yes	Yes	No	No
Region-Year	No	No	Yes	Yes	No	No	Yes	Yes
Industry-Region	No	No	No	Yes	No	No	No	Yes
p-value: Test of $\gamma_1 = \gamma_3$	[0.003]	[0.006]	[0.007]	[0.005]	[0.002]	[0.004]	[0.005]	[0.003]
p-value: Test of $\gamma_2 = \gamma_3$	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
p-value: Test of $\gamma_1 = \gamma_4$	[0.001]	[0.000]	[0.000]	[0.000]	[0.001]	[0.002]	[0.001]	[0.003]
p-value: Test of $\gamma_4 = \gamma_5$	[0.002]	[0.003]	[0.004]	[0.003]	[0.007]	[0.009]	[0.010]	[0.012]
Observations	800,751	705,347	705,341	705,219	623,322	550,544	550,534	550,404
R-squared	0.432	0.434	0.436	0.444	0.466	0.470	0.472	0.479

Notes: Individual data are taken from ACS samples from 2002 to 2011. Baseline specifications, columns (1)-(4), include a broad definition of workers (501 $\leq$ occ1990 $\leq$ 900). In columns (5)-(8), we include a narrow definition of workers (701 $\leq$ occ1990 $\leq$ 900). In all specifications, managers are defined by broad criteria (000 $\leq$ occ1990 $\leq$ 200). Estimation is done by OLS weighted by person (perwt) in ACS. Clustered robust standard errors are in parentheses. Errors are clustered at industry and five-year periods. *** p<0.01, ** p<0.05, * p<0.1.

Table 20: Robustness Check: Heterogeneous Effects of Exposure to Offshoring With Industry-Specific and Region-Specific Time Trends, 2002-2011
Dependent variable: Log real yearly income

	I. Baseline			II. Narrow Workers		
	(1)	(2)	(3)	(4)	(5)	(6)
Offshoring$_{t-1}$	-0.051**	0.055*	-0.056**	-0.057*	0.038	-0.070*
$\times Worker,\ \gamma_1$	(0.023)	(0.033)	(0.027)	(0.032)	(0.035)	(0.035)
Offshoring$_{t-1}$	-0.091**	-0.051	-0.107**	-0.132***	-0.091**	-0.153***
$\times ManagerN \times Noncol,\ \gamma_2$	(0.045)	(0.035)	(0.051)	(0.049)	(0.036)	(0.057)
Offshoring$_{t-1}$	0.160**	0.210***	0.148**	0.184**	0.226***	0.163**
$\times ManagerN \times College,\ \gamma_3$	(0.064)	(0.055)	(0.072)	(0.070)	(0.057)	(0.078)
Inshoring$_{t-1}$	0.080**	0.321***	0.072**	0.083	0.355***	0.078
$\times Worker,\ \gamma_4$	(0.032)	(0.079)	(0.035)	(0.054)	(0.087)	(0.056)
Inshoring$_{t-1}$	-0.199***	0.132	-0.192**	-0.204***	0.131	-0.194**
$\times ManagerN,\ \gamma_5$	(0.075)	(0.122)	(0.076)	(0.075)	(0.118)	(0.076)
Male	0.407***	0.388***	0.378***	0.357***	0.337***	0.332***
	(0.009)	(0.010)	(0.008)	(0.008)	(0.009)	(0.008)
Age	0.126***	0.115***	0.112***	0.123***	0.111***	0.110***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age^2	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
White	0.162***	0.151***	0.142***	0.128***	0.116***	0.110***
	(0.006)	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)
College or more	0.303***	0.310***	0.286***	0.259***	0.270***	0.245***
	(0.012)	(0.014)	(0.011)	(0.016)	(0.018)	(0.015)
$ManagerN$	0.695***	0.682***	0.659***	0.816***	0.793***	0.775***
	(0.021)	(0.025)	(0.021)	(0.024)	(0.027)	(0.024)
Capital Intensity$_{t-1}$	-0.049*	0.089***	-0.040**	-0.046*	0.082***	-0.036*
	(0.025)	(0.027)	(0.017)	(0.027)	(0.025)	(0.020)
TFP$_{t-1}$	0.030	0.041	0.008	-0.003	0.047*	-0.026
	(0.052)	(0.030)	(0.058)	(0.057)	(0.026)	(0.064)
Fixed effects:						
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Region	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Industry time trends	Yes	No	Yes	Yes	No	Yes
Region time trends	No	Yes	Yes	No	Yes	Yes
p-value: Test of $\gamma_1 = \gamma_3$	[0.002]	[0.015]	[0.032]	[0.001]	[0.007]	[0.002]
p-value: Test of $\gamma_2 = \gamma_3$	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
p-value: Test of $\gamma_1 = \gamma_4$	[0.011]	[0.006]	[0.024]	[0.073]	[0.002]	[0.073]
p-value: Test of $\gamma_4 = \gamma_5$	[0.003]	[0.045]	[0.005]	[0.008]	[0.033]	[0.012]
Observations	618,100	618,100	618,100	463,297	463,297	463,297
R-squared	0.357	0.405	0.415	0.395	0.441	0.450

Notes: Individual data are taken from ACS samples from 2002 to 2011. Baseline specifications, columns (1)-(3), include a broad definition of workers (501 $\leq$ occ1990 $\leq$ 900). In columns (4)-(6), we include a narrow definition of workers (701 $\leq$ occ1990 $\leq$ 900). In all specifications, managers are defined by narrow criteria (000 $\leq$ occ1990 $\leq$ 037). Estimation is done by OLS weighted by person (perwt) in ACS. Clustered robust standard errors are in parentheses. Errors are clustered at industry and five-year periods. *** p<0.01, ** p<0.05, * p<0.1.

Table 21: Robustness Check: Dynamic Effects of Exposure to Offshoring, 2002-2011
Dependent variable: Log real yearly income

	I. Baseline				II. Narrow Workers			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Offshoring_{t-1}$	-0.072***				-0.079***			
$\times Worker$	(0.024)				(0.028)			
$Offshoring_{t-1}$	-0.108**				-0.148***			
$\times ManagerN \times Noncol$	(0.047)				(0.052)			
$Offshoring_{t-1}$	0.135**				0.157**			
$\times ManagerN \times College$	(0.061)				(0.064)			
$Inshoring_{t-1}$	0.096***				0.091*			
$\times Worker$	(0.030)				(0.047)			
$Inshoring_{t-1}$	-0.164**				-0.171**			
$\times ManagerN$	(0.072)				(0.075)			
$Offshoring_{t-2}$		-0.047***				-0.041*		
$\times Worker$		(0.017)				(0.023)		
$Offshoring_{t-2}$		-0.081*				-0.112**		
$\times ManagerN \times Noncol$		(0.042)				(0.045)		
$Offshoring_{t-2}$		0.168***				0.204***		
$\times ManagerN \times College$		(0.055)				(0.056)		
$Inshoring_{t-2}$		0.081**				0.116***		
$\times Worker$		(0.031)				(0.044)		
$Inshoring_{t-2}$		-0.150**				-0.135**		
$\times ManagerN$		(0.063)				(0.064)		
$Offshoring_{t-3}$			-0.032*				-0.042*	
$\times Worker$			(0.018)				(0.024)	
$Offshoring_{t-3}$			-0.064*				-0.103**	
$\times ManagerN \times Noncol$			(0.038)				(0.041)	
$Offshoring_{t-3}$			0.187***				0.213***	
$\times ManagerN \times College$			(0.054)				(0.052)	
$Inshoring_{t-3}$			0.054*				0.082**	
$\times Worker$			(0.029)				(0.040)	
$Inshoring_{t-3}$			-0.143**				-0.132**	
$\times ManagerN$			(0.060)				(0.062)	
$Offshoring_{t-4}$				-0.016				-0.021
$\times Worker$				(0.016)				(0.022)
$Offshoring_{t-4}$				-0.061				-0.096**
$\times ManagerN \times Noncol$				(0.040)				(0.042)
$Offshoring_{t-4}$				0.204***				0.234***
$\times ManagerN \times College$				(0.054)				(0.056)
$Inshoring_{t-4}$				0.054*				0.073*
$\times Worker$				(0.029)				(0.039)
$Inshoring_{t-4}$				-0.136**				-0.128**
$\times ManagerN$				(0.061)				(0.062)
Observations	617,962	583,002	543,261	460,410	463,139	437,269	407,570	345,756
R-squared	0.424	0.429	0.431	0.435	0.458	0.464	0.467	0.471

Notes: Individual data are taken from ACS samples from 2002 to 2011. Baseline specifications, columns (1)-(4), include a broad definition of workers (501 $\leq$ occ1990 $\leq$ 900). In columns (5)-(8), we include a narrow definition of workers (701 $\leq$ occ1990 $\leq$ 900). In all specifications, managers are defined by broad criteria (000 $\leq$ occ1990 $\leq$ 200). Other control variables include male, age, age squared, race, college degree, manager, capital intensity, TFP. Region-year fixed effects and industry-region fixed effects are included. Estimation is done by OLS weighted by person (perwt) in ACS. Clustered robust standard errors are in parentheses. Errors are clustered at industry and five-year periods. *** p<0.01, ** p<0.05, * p<0.1.

Table 22: Heterogeneous Effects of Exposure to Offshoring and Chinese Import Competition across Tasks, 2002-2011
Dependent variable: Log real yearly income

	I. Baseline			II. Narrow Workers		
	(1)	(2)	(3)	(4)	(5)	(6)
Offshoring$_{t-1}$	-0.096***	-0.085***	-0.078***	-0.106***	-0.094***	-0.085***
$\times\ Worker,\ \gamma_1$	(0.032)	(0.027)	(0.025)	(0.035)	(0.030)	(0.028)
Offshoring$_{t-1}$	-0.072*	-0.066*	-0.042	-0.086*	-0.079*	-0.057
$\times\ ManagerN \times Noncol,\ \gamma_2$	(0.043)	(0.039)	(0.038)	(0.046)	(0.043)	(0.041)
Offshoring$_{t-1}$	0.066	0.072	0.077*	0.072	0.078*	0.083**
$\times\ ManagerN \times College,\ \gamma_3$	(0.051)	(0.048)	(0.044)	(0.047)	(0.044)	(0.041)
Inshoring$_{t-1}$	0.092***	0.092***	0.085***	0.093**	0.090**	0.076*
$\times\ Worker,\ \gamma_4$	(0.031)	(0.028)	(0.027)	(0.044)	(0.041)	(0.041)
Inshoring$_{t-1}$	-0.175***	-0.172**	-0.170***	-0.185***	-0.183***	-0.182***
$\times\ ManagerN,\ \gamma_5$	(0.065)	(0.067)	(0.064)	(0.065)	(0.067)	(0.066)
ln *Chinese Import*$_{t-1}$	0.006	0.004	0.004	0.004	0.004	0.003
$\times\ Worker,\ \vartheta_1$	(0.006)	(0.005)	(0.004)	(0.006)	(0.006)	(0.005)
ln *Chinese Import*$_{t-1}$	0.026***	0.023***	0.022**	0.025**	0.023**	0.021**
$\times\ ManagerN \times Noncol,\ \vartheta_2$	(0.010)	(0.009)	(0.008)	(0.010)	(0.009)	(0.009)
ln *Chinese Import*$_{t-1}$	0.041***	0.039***	0.037***	0.050***	0.048***	0.047***
$\times\ ManagerN \times College,\ \vartheta_3$	(0.010)	(0.009)	(0.008)	(0.010)	(0.009)	(0.009)
Other Controls						
Individual Observables:						
Male, Age, Age^2, White College or more, $ManagerN$	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year Confounders:						
Capital Intensity$_{t-1}$	Yes	Yes	Yes	Yes	Yes	Yes
TFP$_{t-1}$	Yes	Yes	Yes	No	Yes	Yes
Fixed effects:						
Industry	Yes	Yes	No	Yes	Yes	No
Region	Yes	No	No	Yes	No	No
Year	Yes	No	No	Yes	No	No
Region-Year	No	Yes	Yes	No	Yes	Yes
Industry-Region	No	No	Yes	No	No	Yes
p-value: Test of $\vartheta_1 = \vartheta_2$	[0.011]	[0.013]	[0.011]	[0.011]	[0.013]	[0.010]
p-value: Test of $\vartheta_1 = \vartheta_3$	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
p-value: Test of $\vartheta_2 = \vartheta_3$	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Observations	616,022	616,015	615,885	461,698	461,685	461,541
R-squared	0.414	0.416	0.425	0.449	0.452	0.460

Notes: Individual data are taken from ACS samples from 2002 to 2011. Baseline specifications, columns (1)-(3), include a broad definition of workers (501 $\leq$ occ1990 $\leq$ 900). In columns (4)-(6), we include a narrow definition of workers (701 $\leq$ occ1990 $\leq$ 900). In all specifications, managers are defined by narrow criteria (000 $\leq$ occ1990 $\leq$ 037). Estimation is done by OLS weighted by person (perwt) in ACS. Clustered robust standard errors are in parentheses. Errors are clustered at industry and five-year periods. *** p<0.01, ** p<0.05, * p<0.1.

Table 23: Contribution of the Offshoring to the Change in Income Inequality, 2002-2011

	I. Baseline				II. Narrow Workers			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Offshoring								
Offshoring	11.7	10.9	12.1	12.1	18.0	18.0	19.3	19.2
Other Controls	6.7	15.9	84.4	83.5	1.1	8.0	85.2	84.9
Residuals	81.5	73.1	3.5	4.4	81.0	74.0	-4.5	-4.0
Panel B. Inshoring								
Inshoring	0.8	0.9	0.0	0.1	2.5	2.2	1.1	1.1
Other Controls	17.6	26.0	96.4	83.5	16.6	23.8	103.5	102.9
Residuals	81.5	73.1	3.5	4.4	81.0	74.0	-4.5	-4.0
Panel C. Total Offshoring								
Total Offshoring	12.1	11.6	12.0	12.1	20.5	20.5	20.7	20.6
Other Controls	6.4	15.3	84.5	83.5	-1.5	5.5	83.8	83.4
Residuals	81.5	73.1	3.5	4.4	81.0	74.0	-4.5	-4.0
Other Controls								
Individual Observables:								
Male, Age, Age^2, White College or more, $ManagerN$	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year Confounders:								
Capital Intensity$_{t-1}$	No	Yes	Yes	Yes	No	Yes	Yes	Yes
TFP$_{t-1}$	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Fixed effects:								
Industry	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Region	Yes	Yes	No	No	Yes	Yes	No	No
Year	Yes	Yes	No	No	Yes	Yes	No	No
Region-Year	No	No	Yes	Yes	No	No	Yes	Yes
Industry-Region	No	No	No	Yes	No	No	No	Yes
Growth rate in var$(\ln w_{ijt})$	7.3	7.8	7.8	7.8	6.8	6.9	6.9	6.9

Notes: All entries are percentage. The decomposition in each column corresponds to the specification in each column in Table 17. Baseline specifications, columns (1)-(4), include a broad definition of workers (501 $\leq$ occ1990 $\leq$ 900). In columns (5)-(8), we include a narrow definition of workers (701 $\leq$ occ1990 $\leq$ 900). In all specifications, managers are defined by narrow criteria (000 $\leq$ occ1990 $\leq$ 037).

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