Offshoring and Skill Overlap: An Empirical Investigation

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Abstract

Conventional international trade theory predicts that bilateral offshoring flows will be highest when two countries have very different relative factor endowments. In contrast, the new trade theory contends that offshoring is more likely to exist when countries' relative factor endowments are similar. Using the Barro and Lee (2013) dataset, this paper empirically tests the relationship between offshoring and relative factor endowments, measured by the skill overlap index between two countries and finds evidence that there is an inverted U-shape relationship. Our empirical results predict that the rise in educational attainment in China will motivate U.S. multinationals to send their tasks to China in the short run; over the long run, however, they will re-shore production tasks from China back to the United States. This finding sheds new light on the current trade tensions between the United States and China and has implications for trade policy.

Keywords: Offshoring; Human capital; Multinational activities; Re-shoring.
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1 Introduction

There are two contrasting theories about the relationship between the amount of offshoring and the relative factor endowments between two countries. In the traditional Heckscher-Ohlin-Vanek (HOV) model and the Feenstra and Hanson (1996) model, international trade and offshoring will be greatest when countries' relative factor endowments are most different. In contrast, Helpman (1987), who examines intra-industry trade, Markusen (1995), who examines foreign direct investment, and Markusen and Venables (2000), who examine multinational activities, note that the share of intra-industry trade, foreign direct investment, and multinational activities, respectively, are more likely to exist when two countries have similar relative factor endowments.[1] The first theoretical prediction implies that international trade and offshoring flows will be most significant between developed countries like the United States and developing countries like Malawi; the second theoretical prediction suggests that flows will be highest between developed countries.

Kremer and Maskin (1996, 2006) propose a matching model of production by workers of different skill levels that rebuts the first theoretical prediction. If the skill levels in two countries are sufficiently different, then it is inefficient for workers in the skill-abundant country to match with workers in the skill-scarce country. Hence, the model predicts that there will be little offshoring between developed countries and developing countries. With respect to the second theoretical prediction, the matching model of Kremer and Maskin (1996, 2006) neither supports nor refutes the idea that workers in skill-abundant countries are more likely to match with workers in other skill-abundant countries.

However, when we turn our attention to observed offshoring flows in the U.S. data, we see that the United States shifts most of its production activities to countries such as Brazil,

[1] Throughout this paper we use the term "relative factor endowment" to mean the relative supply of high-skilled workers to low-skilled workers, as in Feenstra and Hanson (1996). In the Heckscher-Ohlin-Vanek (HOV), Helpman (1987), Markusen (1995), and Markusen and Venables (2000) models, the factors of production are labor and capital, but their predictions can easily extend to the case where the factors of production are defined as high-skilled workers and low-skilled workers.

China, Mexico, and India, whose relative factor endowments are not too similar or not too disparate. The existing theories fail to explain this observed pattern of multinational activity. Some may challenge this view by maintaining that, after controlling for other confounding factors such as quality of institutions, the relationship between the amount of offshoring and the relative factor endowments between two countries would still be linear, either increasing or decreasing, which supports the traditional view. Others may disagree with this view because U.S. offshoring cannot be generalized to global offshoring flows.

In this paper, we set up a formal empirical specification to uncover the relationship between the amount of offshoring and relative factor endowments, measured by the skill overlap between two countries. The major challenge in estimating this relationship is the limited data. Unlike for international trade flows, there are few available data sources that capture bilateral offshoring flows.[2] We overcome the data limitation by using two different data sources, both of which are relatively new and unexploited, to capture bilateral offshoring flows: Ramondo, Rodríguez-Clare, and Tintelnot (2015)'s multinational production dataset, and the U.S. Bureau of Economic Analysis Direct Investment & Multinational Enterprises (MNEs) dataset. Both measures are based on multinational activities and are more appropriate objects to capture offshoring than the foreign direct investment (FDI) flow measures that are commonly used in the literature, such as the OECD's Foreign Direct Investment Statistics.[3] The advantage of the Ramondo, Rodríguez-Clare, and Tintelnot (2015)'s multinational production dataset is its comprehensive coverage of 59 countries with 3,422 (58×59) possible bilateral observations. The U.S. BEA dataset is larger, covering 199 countries, but is limited to observations that are bilateral with the

[2] Blonigen and Piger (2014) note that there are not many reliable measures of foreign direct investment (FDI). In addition, because there is no common source for FDI data, prior studies have used a number of different measures of FDI.

[3] Ramondo, Rodríguez-Clare, and Tintelnot (2015) argue that their multinational production dataset better captures many of the questions in the field of international trade than the FDI dataset because the importance of a subsidiary relies on the magnitude of its production activity rather than financing activity.

United States.[4]

We develop a novel measure, the skill overlap index, using the Barro and Lee (2013) Educational Attainment Dataset, to proxy for the relative factor endowment variable. The Barro and Lee (2013) dataset provides data for 146 countries on the distribution of educational attainment of the population over age 15 at seven levels of schooling—no formal education, incomplete primary, complete primary, lower secondary, upper secondary, incomplete tertiary, and complete tertiary. For all country pairs, we calculate the overlapping area of two skill distributions, using a range from 0 (for no skill overlap) to 1 (for complete skill overlap). The newly developed skill overlap index provides a more precise measure of the relative factor endowment difference between two countries than the average-years-of-schooling difference that is widely used in the literature. Suppose, for example, that the skill distributions of two countries have the same average but different variances. If researchers measure the skill difference between the two countries based on the average years of schooling, the two countries will be shown to have the same skill level. However, the skill-overlap index yields different skill levels for two countries, which captures beyond the first moment of the distribution.

In this study, we adopt a structural gravity model of FDI developed by Head and Ries (2008).[5] The theoretically based gravity model of FDI yields an equation for bilateral FDI as a function of source country fixed effects, host country fixed effects, and a vector of pair-specific variables such as distance, contiguity, language, and colonial link.[6] We base our estimation framework on Head and Ries (2008) and incorporate the newly developed skill overlap index and its squared term into the equation to test the relation between bilateral offshoring flows and relative factor endowments. We then employ Silva and Tenreyro (2006)'s method of Poisson pseudo-maximum-likelihood (PPML) to estimate

[4] We also use U.S. BEA data at the country-industry level (56 countries $\times$ 14 industries = 784 observations) to overcome the small-sample issue in the U.S. BEA dataset.

[5] Head and Ries (2008) provide an analytical structure on which to base estimations of bilateral FDI.

[6] The source and host country fixed effects are analogous to the exporter and importer fixed effects that capture the multilateral resistance terms in different theoretical international trade gravity models.

the offshoring gravity equation.[7]

We first specify a linear fitting between offshoring and skill overlap using Ramondo, Rodríguez-Clare, and Tintelnot (2015)'s multinational production dataset and find that the coefficients of interest are not statistically significant. This result implies that neither the conventional trade theory nor the new trade theory can explain the relation. Then we set up a quadratic relation and find compelling evidence that there is an inverted U-shape relation between offshoring and skill overlap between two countries. Next we analyze the relationship using the U.S. BEA data and still find an inverted U-shape relation. This result stands up to several robustness checks.

Based on the estimated hump-shaped pattern, we ask whether U.S. multinationals are more or less likely to send their tasks to China in the future, given that China is used to being blamed for taking away U.S. jobs. Our empirical results predict that more educational attainment in China will motivate U.S. multinationals to send more tasks to China in the short run. However, in the long-run, more human capital accumulation in China will encourage U.S. multinationals to re-shore their production tasks from China back to the United States. Admittedly, the prediction is based on the assumption that everything remains unchanged except the relative factor endowment difference, which narrows between the United States and China.

Our empirical offshoring gravity model is related to important early work that uses the gravity equation to investigate the determinants of FDI. Carr, Markusen, and Maskus (2001) present a "knowledge-capital model" of multinationals and estimate multinational activity between countries as a function of country characteristics. Bergstrand and Egger (2007) add physical capital to the "knowledge-capital model" and test their propositions using gravity equations for FDI flows. Although the main focus of their studies is not the relation between offshoring and relative factor endowments, their empirical gravity equation estimation results reveal that the relation between FDI flows and skilled-labor

[7] Head and Ries (2008) also consider the Poisson pseudo-maximum-likelihood (PPML) results to be the preferred specification.

abundance between two countries is positive. We extend these earlier studies to incorporate the squared term of the skill overlap index into the gravity equation and find that the relationship is an inverted U-shape. Also, we expand our dataset to cover a larger number of country pairs than the previous studies,[8] and use a more precise measure of the relative factor endowment between two countries.

2 Background

Throughout the 2016 U.S. presidential election campaign, candidate Donald Trump appealed to U.S. voters by saying he would "bring back U.S. jobs" that had been outsourced to foreign countries such as China. After his election, in early 2018 the United States placed tariffs on products produced outside the United States, such as solar panels, steel, and aluminum, with the aim of making imported goods more expensive and bringing back manufacturing to the United States that had been outsourced to China and other countries. Trade tension between the United States and China is an ongoing issue, and whether a protectionism policy is the best way to restore U.S. jobs is also the topic of heated debate. From an academic perspective, multinationals' shifting of tasks from the United States to other countries—i.e., offshoring—is also an interesting research topic. To investigate this topic further, it is instructive to outline the regional distribution of the total employment of foreign affiliates by U.S. multinationals in the year 2010.[9]

Table 1 lists the 20 highest outward offshoring countries among U.S. multinationals, showing those countries' characteristics, such as average years of schooling, skill overlap index,[10] population, and GDP per capita. U.S. multinationals (manufacturing and non-

[8] Carr, Markusen, and Maskus (2001) use data for 36 countries with a bilateral relationship with the U.S. We use U.S. BEA data for 130 countries. Bergstrand and Egger (2007) utilize data for the 17 most developed OECD countries for 11 years. Their FDI gravity equation, including a skilled-labor abundance variable, covers 254 country pairs. We use Ramondo, Rodríguez-Clare, and Tintelnot (2015)'s multinational production dataset, which encompasses 2,409 country pairs.

[9] Although the U.S. BEA dataset is available through the year 2016, we utilize the year 2010 because our key variable, the skill overlap index, is available only until 2010.

[10] See Section 4.2, Measuring Skill Overlap, for a more detailed explanation of the construction of the skill

manufacturing firms) employ 13,474 people worldwide. China ranks first; 12.2 percent of employment by U.S. multinationals are Chinese workers. It is thus understandable that China is often blamed for taking away U.S. jobs.

Aside from China, there are several other notable patterns reflected by the location choices of U.S. multinationals. First, employment is concentrated in a few countries: the top 5 countries' share is 46.6 percent; the top 10 countries' share is 66.3 percent; the top 15 countries' share is 74.1 percent; and the top 20 countries' share is 80.0 percent. Second, U.S. multinationals are less likely to hire workers in low-income countries or countries where the average years of schooling is low. Although not listed in Table 1, among the 199 countries listed in the U.S. BEA data, 89 countries—most of them low-income countries—U.S. multinationals report fewer than 1,000 employees. Third, middle-income countries occupy a sizable share of employment by U.S. multinationals. Of the top 20 countries that comprise 80% of total employment, six countries (China, Mexico, India, Brazil, Thailand, and the Philippines) are classified as middle-income countries (using the World Bank Atlas Method) and represent 35.3% of total employment by U.S. multinationals.[11] Fourth, U.S. multinationals do not appear to favor high-income countries over middle-income countries.

We further investigate the pattern of location choices of U.S. multinationals by creating scatter plots of offshoring against the average years of schooling and log of GDP per capita. Figure 1 reconfirms that there are many countries where U.S. multinationals have no offshoring, especially those with low GDP per capita and low average years of schooling. Another noteworthy feature is that there is no linear relation between offshoring and GDP per capita (or average years of schooling). It appears that a quadratic function may better capture the pattern between offshoring and GDP per capita (or average years of schooling): that is, U.S. multinationals are more likely to send their tasks to

overlap index. Skill overlap is the similarity between any two countries' skill distributions, ranging from 0 (no skill overlap) to 1 (complete skill overlap).

[11] If we confine our analysis to the manufacturing sector, the middle-income country share is larger.

middle-income (or moderate-level-of-schooling) countries. Admittedly, there are many other confounding variables (other than the GDP per capita and years of schooling) that might affect the location decisions of U.S. multinationals.

Motivated by the non-linear relation in Figure 1, we use the gravity equation to formally uncover the relationship between the volume of offshoring by U.S. multinationals and relative factor endowments between two countries. We begin by analyzing the relationship using Ramondo, Rodríguez-Clare, and Tintelnot (2015)'s global bilateral multinational data, rather than confining our study to U.S. multinationals. In this way we contribute to the literature by testing competing theories in the international trade that we discussed previously. Then we use the U.S. multinational data to check the validity of the result.

In addition, our research can reasonably predict the direction of the volume of offshoring from the U.S. to China. As China catches up with the U.S. in human capital (i.e., as educational attainment in China rises), the difference between relative factor endowments between the two countries is predicted to become narrower. Based on our regression estimates, we can then predict whether the U.S. is more likely to send tasks to China than in the baseline year. In this way, we can evaluate current U.S. trade policy and its effort to "bring back U.S. jobs."

3 Empirical Specification

First, we set up a bilateral offshoring gravity equation as in Head and Ries (2008) to test the relation between offshoring and relative factor endowment between two countries. In addition to source country fixed effects, host country fixed effects, and standard bilateral gravity controls (as measured in Head and Ries (2008)), we incorporate the skill overlap index and the square of the skill overlap index into the equation. The skill overlap index is a proxy for the relative factor endowment difference between two countries. Second, we focus on the location decisions of U.S. multinationals by specifying a one-way offshoring gravity equation similar to the specification in Carr, Markusen, and Maskus (2001). In their empirical model, the volume of the production of foreign affiliates is a function of particular characteristics of those countries, including size, size differences, relative endowment differences, trade and investment costs, and certain interactions among these variables. Again, we add the skill overlap index and the square of the skill overlap index to the one-way offshoring gravity equation.

We then employ Silva and Tenreyro (2006)'s method of Poisson pseudo-maximum-likelihood (PPML) to estimate the offshoring gravity equations to uncover the relationship between offshoring and skill overlap. The reason we adopt the PPML technique is that, as is well known in the literature, the standard ordinary least squares (OLS) estimation yields biased estimates of coefficients of the log-linearized gravity equation model in the presence of heteroskedasticity. Moreover, taking logs of the dependent variable leaves out many countries. This problem is more severe for offshoring than for trade because there are more countries with which U.S. multinationals have no bilateral offshoring flows (Head and Ries, 2008).

3.1 Two-Way Gravity Specification

Following Head and Ries (2008), we specify the Poisson regression model for the bilateral offshoring gravity equation:

$$y_{ij} = \exp(\mathbf{x_{ij}}'\boldsymbol{\beta}) + \epsilon_{ij}$$

where the dependent variable, $y_{ij} \geq 0$, is the amount of offshoring between country i and country j, and $\mathbf{x_{ij}}$ is a set of controls that includes source country fixed effects (Source$_i$), host country fixed effects (Host$_j$), Distance$_{ij}$, Contiguity$_{ij}$, Language$_{ij}$, Colony$_{ij}$, and, most importantly, Skill Overlap$_{ij}$ and the square of Skill Overlap$_{ij}$. The source and host country fixed effects are multilateral resistance terms, which correspond to exporter and importer fixed effects, respectively, in the international trade gravity equation. The inclusion of multilateral resistance terms (MRT) alleviates a concern that unobserved heterogeneity might be confounded with the skill overlap index and lead to biased estimates of our main interest of coefficients. The exponential mean function, $\mathbb{E}[y_{ij}|\mathbf{x_{ij}}]$, can be expressed as follows:

$$\mathbb{E}[y_{ij}|\mathbf{x_{ij}}] = \exp(\mathbf{x_{ij}}'\boldsymbol{\beta}) = \exp[\ln\beta_0 + \beta_1 \text{Skill Overlap}_{ij} + \beta_2(\text{Skill Overlap}_{ij})^2 + \beta_3 \ln\text{Distance}_{ij} + \beta_4 \text{Contiguity}_{ij} + \beta_5 \text{Language}_{ij} + \beta_6 \text{Colony}_{ij} + \text{Source}_i + \text{Host}_j].$$

The Poisson pseudo-maximum-likelihood estimator (PPML) based on the Poisson regression model is the solution to the following first-order conditions:[12]

$$\sum_i \sum_j \left[y_{ij} - \exp(\mathbf{x_{ij}}'\boldsymbol{\beta})\right] \mathbf{x_{ij}} = \mathbf{0}. \quad (1)$$

3.2 One-Way Gravity Specification

Next, similar to Carr, Markusen, and Maskus (2001), we specify the following Poisson regression model for the one-way offshoring gravity equation:

$$y_i = \exp(\mathbf{x_i}'\boldsymbol{\beta}) + \epsilon_i$$

where the dependent variable, $y_i \geq 0$, is the volume of offshoring between country i and the U.S., and $\mathbf{x_i}$ are a set of host country characteristics such as GDP$_i$, InvestmentFriction$_i$, and RuleOfLaw$_i$ and a set of bilateral characteristics between country i and the U.S. such as Distance$_i$, Contiguity$_i$, Language$_i$, Colony$_i$, Skill Overlap$_i$ and the square of Skill

[12] The assumption of a Poisson distribution data generating process for y_{ij} is stronger than necessary. Gourieroux, Monfort, and Trognon (1984) noted that, if the conditional expectation function $\mathbb{E}[y_{ij}|\mathbf{x}]$ is correctly specified, then the estimator based on the equation (1) is consistent. Thus, the data-generating process for y_{ij} need not to be a Possion distribution. Furthermore, y_{ij} need not to be an integer, and $y_{ij} \geq 0$ is sufficient. If the conditional expectation function is correctly specified and the data generating-process is not Poisson, the estimator defined by the solution to the equation (1) is a Poisson pseudo-maximum-likelihood (PPML) estimator.

Overlap$_i$. The exponential mean function, $\mathbb{E}[y_i|\mathbf{x_i}]$ can be expressed as follows:[13]

$$\begin{aligned}\mathbb{E}[y_i|\mathbf{x_i}] = \exp(\mathbf{x_i}'\boldsymbol{\beta}) = \exp[&\ln\beta_0 + \beta_1\text{Skill Overlap}_i + \beta_2(\text{Skill Overlap}_i)^2 \\ &+ \beta_3\ln\text{GDP}_i + \beta_4\text{InvestmentFriction}_i + \beta_5\text{RuleOfLaw}_i \\ &+ \beta_6\ln\text{Distance}_i + \beta_7\text{Contiguity}_i + \beta_8\text{Language}_i + \beta_9\text{Colony}_i].\end{aligned}$$

Admittedly, the one-way gravity specification is a less preferred approach than the two-way gravity equation because the multilateral resistance terms (MRT) cannot be included in the specification. However, the one-way gravity specification has its own merits. First, if the relation between offshoring and skill overlap exhibits a certain pattern for global dyadic flows, we would still expect the relation in the two-way specification to hold using the one-way dataset—i.e., U.S. multinational data. It would therefore be a good exercise to check the validity of our finding in the two-way specification. Second, the bilateral dataset covers 59 countries with 3,422 (58 $\times$ 59) possible observations. For each country, the maximum number of trading partners is 58. However, in the U.S. BEA data, there are 199 countries. Since our analysis uses the relative factor endowment difference between two countries as a key source of variation, expanding the number of countries increases the source of variation, especially in the U.S. Last, we try to evaluate the current trade tension between the U.S. and China from the perspective of U.S. trade policy. The U.S. data provide a better picture of the relation between offshoring and skill overlap from the U.S. perspective and thus suggest more accurate policy implications.

[13] We also check the robustness by including the squared of log of GDP, population, and GDP per capita. As in the two-way case, the Poisson pseudo-maximum-likelihood estimator (PPML) is the solution to the following first-order conditions:

$$\sum_i [y_i - \exp(\mathbf{x_i}'\boldsymbol{\beta})]\,\mathbf{x_i} = \mathbf{0}.$$

4 Data

4.1 Measuring Volume of Offshoring

For a dependent variable, we propose two different measures to capture the volume of offshoring between two countries. First, we use Ramondo, Rodríguez-Clare, and Tintelnot (2015)'s Multinational Production dataset, which presents bilateral multinational production activity. The dataset, originally from UNCTAD (the Investment and Enterprise Program, FDI Statistics, and FDI Country Profiles), contains 59 countries and entails 3,422 (58×59) possible country pairs. Each observation is a summation over nonfinancial industries, averaged over the period from 1996 to 2001.

We use sales by affiliates of foreign firms as a proxy measure of bilateral offshoring.[14] There are three different measures of bilateral sales of affiliates in Ramondo, Rodríguez-Clare, and Tintelnot (2015)'s Multinational Production dataset: UNCTAD raw data, bilateral sales of affiliates imputed by merger and acquisitions (M&A) transactions, and FDI stocks. A major problem with the UNCTAD raw data on bilateral sales of affiliates is that there are many missing values. A total of 2,311 values are reported: 590 observations with positive numbers and 1,721 observations with a value of zero. Ramondo, Rodríguez-Clare, and Tintelnot (2015) exploit the Thomson and Reuters M&A transaction dataset and FDI stocks from UNCTAD to estimate missing and zero values.[15] The data on bilateral sales of affiliates imputed by M&A contain 2,694 non-missing values with 1,215 positive observations and 1,479 observations with a value of zero; the data imputed by FDI stocks have 2,730 observations with 1,251 positive observations and 1,479 observations with a value of zero. In the empirical analysis, we utilize all three measures as a dependent variable.

Second, we use data from the U.S. Bureau of Economic Analysis Direct Investment &

[14] A foreign affiliate is defined as a firm with 10 percent or more of its share owned by a foreigner. The data on sales include both domestic sales and exports.

[15] See Ramondo, Rodríguez-Clare, and Tintelnot (2015) for the detailed extrapolation procedure.

Multinational Enterprises (MNEs), which reports the number of foreign affiliate workers employed by U.S. multinationals in the year 2010 at the country level and the country-industry level.[16] We further decompose all affiliates and majority-owned affiliates (those that are more than 50 percent owned by their U.S. parent). At the country level, we identify 199 countries in which there are 152 positive observations and 47 observations with a value of zero. At the country-industry level, there are 56 countries and 14 industries that entail 784 (56×14) observations, of which there are 708 positive observations and 76 observations with a value of zero.

4.2 Measuring Skill Overlap

Next we use the Barro and Lee (2013) dataset to construct a skill overlap index to proxy for relative factor endowment differences between two countries. The dataset, which covers 146 countries at 5-year intervals from 1950 to 2010, includes educational attainment for the population aged 15 and over.[17] More specifically, for each country in each year, the dataset contains the average years of schooling, the percentage of the population with no schooling, the percentage with a primary education, the percentage with a secondary education, and the percentage with a tertiary education. Using these data, we propose a skill overlap index between country i and country j as follows:

$$\text{Skill Overlap I}_{ij} = \frac{\sum_{k=1}^{4} \min\{educ_{i,k}, educ_{j,k}\}}{100}$$

where k denotes the highest education level attained, ranging from 1 (no schooling) to 4 (tertiary education), and $educ_{i,k}$ is the percent of population aged 15 and over in group k

[16] A foreign affiliate is a foreign business enterprise in which a U.S. person or parent firm owns 10 percent or more of the voting securities or the equivalent. Note also that although the U.S. BEA dataset is available through the year 2016, we utilize the year 2010 because our key variable, the skill overlap index, is available only until 2010.

[17] We use the year 2000 to link the skill overlap index to Ramondo, Rodríguez-Clare, and Tintelnot (2015)'s dataset in the two-way gravity equation, and the year 2010 to connect the skill overlap index to the U.S. BEA dataset in the one-way gravity equation.

in country i.

The education categories in the Barro and Lee (2013) dataset are further decomposed into seven levels of schooling: no formal education, incomplete primary, complete primary, lower secondary, upper secondary, incomplete tertiary, and complete tertiary. We propose an alternative measure of the skill overlap index between country i and j as follows:

$$\text{Skill Overlap II}_{ij} = \frac{\sum_{k=1}^{7} \min\{educ_{i,k}, educ_{j,k}\}}{100}$$

where k denotes the highest education level attained, ranging from 1 (no schooling) to 7 (complete tertiary education).

The skill overlap index captures the overlapping area for two skill distributions and can range from 0 (no skill overlap) to 1 (complete skill overlap). If the two skill distributions are similar for two countries, then the skill overlap index is higher. Because the new index utilizes all the information contained in the two distributions, it has an advantage over other measures (such as the difference in average years of schooling between two countries) to proxy for the relative factor difference between two countries. Average years of schooling is based solely on the first moment of distribution and therefore cannot capture differences in higher moments of skill distribution; our proposed index can capture higher moments of two skill distributions, such as the difference between two distributions with the same mean and unequal variance.

The upper panel of Figure 2 plots distributions of the education level for the U.S. and Niger with four levels of schooling; the skill overlap index I is 0.104. The lower panel of Figure 2 plots distributions of the education level for the U.S. and the Russian Federation with four levels of schooling; the skill overlap index I is 0.918. Figure 3 shows a scatter plot of the average years of schooling against the skill overlap index I[18]; there is a high positive relationship between the two. Because the average years of schooling in the United States was the highest in the world in 2010, the higher the average years of

[18] The skill overlap index is calculated between the U.S. and other countries.

education in another country, the higher the skill overlap index.

4.3 Other Control Variables

We include several control variables, such as real GDP, real GDP per capita, population, distance, contiguity, language, colony, the investment impediment index, and the rule of law. Data on real GDP, real GDP per capita, and population come from Feenstra, Inklaar, and Timmer (2015)'s Penn World Table 8.1. Data on trade frictions, such as the distance between country i and country j, binary land contiguity between i and j, the binary common ethnic language between i and j, and the binary colonial relationship between i and j, are taken from Mayer and Zignago (2011). Information about the investment impediment index is taken from the World Bank Group's Doing Business Index. Last, we use the rule of law index from the Worldwide Governance Indicators that Kaufmann, Kraay, and Mastruzzi (2011) provide as a proxy for the quality of institutions.

4.4 Summary Statistics

We report summary statistics in Table 2 for the three data sets: Panel A. Dyadic flows data from Ramondo, Rodríguez-Clare, and Tintelnot (2015); Panel B. Country-level data from the U.S. BEA; and Panel C. Country-Industry level data from the U.S. BEA.

Panel A of Table 2 shows summary statistics for the dyadic flow data. We drop three countries (Belarus, Lebanon, and Turkmenistan) from Ramondo, Rodríguez-Clare, and Tintelnot (2015)'s dataset because the Barro and Lee (2013) data do not include those countries; our observations are therefore reduced from 3,422 (58×59) to 3,080 (55×56).[19] Without those three countries, non-missing values for affiliates' sales (M&A based), affiliates' sales (FDI stocks based), and UNCTAD raw data are 2,369, 2,409, and 1,982. The average affiliate sales revenue (M&A based) is \$U.S. 3,001 million with a standard deviation of \$U.S. 19,907 million. There are 1,200 non-zero and 1,169 zero observations. Japan

[19] See Table 3 for a list of countries.

(source) - U.S. (host) bilateral affiliate revenue has a maximum value of $U.S. 430,225 million. The skill overlap index I has a mean value of 0.73 and a standard deviation of 0.14. The index ranges from 0.20 (Czech Republic and Guatemala) to 0.99 (Poland and Slovakia), which gives us enough variations to work with.

Panel B of Table 2 shows summary statistics for the country level data. There are 130 countries that we can match consistently across different data sources.[20] We start with the U.S. BEA dataset that contains 199 countries and the Barro and Lee (2013) dataset that has 146 countries. We drop two countries (Reunion Island and the U.S) from the Barro and Lee (2013) dataset because the U.S. BEA dataset does not include them. Of the remaining 144 countries, we drop 14 countries[21] because they are not included in the Penn World Table 8.1. data, the World Bank Group's Doing Business Index data, the Worldwide Governance data, and the CEPII data. The average number of employees by U.S. multinational firms at the country level is 102,468. The country with the most workers employed by U.S. multinationals is China, with 1,637,500 employees. The skill overlap index ranges from 0.10 (Niger) to 0.92 (Russian Federation).

In Panel C of Table 2, we report summary statistics for the country-industry-level data. The original U.S. BEA dataset covers 784 (56 countries $\times$ 14 industries) observations, but data for four countries countries[22] are not available from Barro and Lee (2013), Penn World Table 8.1. data, the World Bank Group's Doing Business Index, Worldwide Governance, and CEPII. The total number of observations is 728 (52 countries $\times$ 14 industries).[23] The average number of employees at the country-industry level is 34,139. The skill overlap index ranges from 0.41 (Honduras) to 0.92 (Russian Federation).

[20] See Table 3 for a list of countries.

[21] The 14 countries are Afghanistan, Algeria, Barbados, Cuba, French Guiana, Haiti, Libya, Macau, Malta, Myanmar, Nicaragua, Papua New Guinea, Tonga, and United Arab Emirates.

[22] Barbados, Bermuda, Nigeria, and United Arab Emirates.

[23] See Table 3 for a list of countries.

5 Empirical Results

5.1 Two-Way Gravity Result

In Table 5, we begin our empirical analysis by running a Poisson regression model of the bilateral offshoring gravity equation using Ramondo, Rodríguez-Clare, and Tintelnot (2015)'s multinational production data as a dependent variable. The estimators are obtained from the solution to the first-order condition in equation (1). We use two-way cluster-robust standard errors that control for both sources of clustering—i.e., source country and host country—because errors can be expected to be correlated within the source country as well as within the host country.

In column (1) of Table 5, where affiliate revenue is imputed from M&A data supplied by Thomson and Reuters, we test whether a linear fit can represent the relation between offshoring (measured by affiliate revenue) and the skill overlap.[24] The estimated coefficient on skill overlap, $\hat{\beta}_1$, is 1.530 with no statistical significance. The result implies that neither the conventional trade theory nor the new trade theory can explain the relation. In column (2) of Table 5, we include the square of Skill Overlap$_{ij}$ in the empirical specification and find that the relationship between offshoring and the relative factor endowment is indeed an inverted U-shape. The estimated coefficient on skill overlap, $\hat{\beta}_1$, is 6.664 and the square of skill overlap, $\hat{\beta}_2$, is -3.606. . Both are statistically significant at the 1 percent level. Moreover, the volume of offshoring is maximized at:

$$\text{Skill Overlap} = \left| \frac{\hat{\beta}_1}{2 \times \hat{\beta}_2} \right|.$$

Using the estimated coefficients, $\hat{\beta}_1$ and $\hat{\beta}_2$, to apply the maximum value formula of a quadratic function, we find that the bilateral offshoring is maximized at the skill overlap index of 0.92. As the Skill Overlap I index ranges from 0.20 to 0.99 with the average value

[24] We drop the square of Skill Overlap$_{ij}$ in this specification.

of 0.73, the positive relation is observed for a relatively long interval, from 0.20 to 0.92, while the negative relation is detected for a short interval, from 0.92 to 0.99.

In columns (3) and (4) of Table 5, where affiliate sales are imputed from FDI stocks, we still find evidence of the inverted U-shape. The linear fitting fails to explain the relation in column (3), while the inverted U-shape stands out in column (4). The volume of offshoring is maximized at the skill overlap index of 0.90 in column (4). Last, we use raw data from UNCTAD in columns (5) and (6) of Table 5, and find the same patterns. The volume of offshoring is maximized at the skill overlap index of 0.86 in column (6).

In Table 6, we use an alternative measure of relative factor difference, the Skill Overlap II, to test the relation. In columns (1), (3), and (5) of Table 6, we report estimates in the absence of the squared term of the skill overlap index. In all cases, the coefficients of the skill overlap are not statistically significant, which confirms that the linear fitting cannot explain the relationship between offshoring and skill overlap. In columns (2), (4), and (6), the estimated coefficients, $\hat{\beta}_1$ and $\hat{\beta}_2$, are statistically significant and have the same signs as the benchmark case. The volumes of offshoring are maximized at the skill overlap index of 0.75 (M&A based), 0.69 (Stock based), and 0.67 (Raw data), respectively, all of which are lower than those of the benchmark cases.

5.2 One-Way Gravity Result (Country Level)

Having established the inverted U-shape relationship between offshoring and skill overlap using the bilateral offshoring gravity equation, we use the U.S. BEA data to validate the relationship and to evaluate current U.S. trade policy and its efforts to "bring back U.S. jobs." Although we cannot use the two-way fixed effects (source and host countries) in the gravity equation, one advantage of using the U.S. BEA data is its coverage of countries. There are 130 countries in the sample, excluding the United States.

Table 7 reports all the pairwise correlation coefficients between the two variables that are used in the analysis. The first column of Table 7 shows the correlation between the employment[25] (the dependent variable) and the control variables. The correlation between employment and skill overlap is 0.25 and is statistically significant at the 1 percent level. Also, the dependent variable is positively correlated with GDP, GDP per capita, population, contiguity, investment impediment index, and the rule of law; it is negatively correlated with distance.[26] Note, however, that the positive correlation between employment and skill overlap does not necessarily imply a positive linear relationship. We now investigate the relationship between offshoring and skill overlap more precisely, controlling for standard gravity country-specific variables.

In Table 8 we begin our empirical analysis by running a country-level Poisson regression model using the one-way offshoring gravity equation. Because the dataset is limited to U.S. multinationals, this analysis reveals whether the skill overlap between the United States and other countries determines U.S. multinationals' location choice. In column (1) of Table 8, we find that the relationship between U.S. multinationals' total employment abroad and the measure of skill overlap is an inverted U-shape, which reconfirms the two-way gravity result. The estimated coefficient on skill overlap, $\hat{\beta}_1$, is 9.238 and the square of skill overlap, $\hat{\beta}_2$, is -8.625. Both are statistically significant at the 5 percent level. Using the estimated coefficients, $\hat{\beta}_1$ and $\hat{\beta}_2$, to apply the maximum value formula of a quadratic function, we find that for U.S. multinationals offshoring is maximized at the skill overlap index of 0.536. Other standard gravity control variables in column (1) of Table 8 also have expected signs. Real GDP, contiguity, language link, colonial relationship, and investment environment are positively related to the offshoring, and distance is negatively associated with offshoring. Acemoglu, Gallego, and Robinson (2014) argue that, once they control for the historical determinants of the quality of institutions, estimates of the effect of human capital on long-run development decline significantly. Based on this insight, we include an additional control variable, the rule of law index in column

[25] The dependent variable, employment, is taken from the U.S. Bureau of Economic Analysis and is calculated as total employment by U.S. multinational enterprises in each country.

[26] The skill overlap index is positively correlated with GDP, GDP per capita, contiguity, investment impediment index, and the rule of law; it is negatively correlated with distance.

(1) of Table 8. The coefficient of the rule of law index is positive, but is not statistically significant. Even after controlling for the rule of law index, the impact of the skill overlap index is still significant on offshoring.

In columns (2), (3), and (4) of Table 8, instead of real GDP, we include different control variables: real GDP and its squared term in column (2), GDP per capita and population in column (3), and GDP per captia, its squared term and population in column (4). The main coefficients (i.e., skill overlap coefficients) still show an inverted U-shape under these specifications.[27] We repeat these regressions in columns from (5) to (8) of Table 8, but now we use majority-owned affiliates that are more than 50 percent owned by their U.S. parents. Note that the signs and significance are the same as in columns (1) through (4) of Table 8.[28] In Table 9, we repeat the regression analysis in Table 8 using an alternative measure of the skill overlap index, the Skill Overlap II. Reassuringly, the results are similar to those shown in Table 8.

Based on the estimated coefficients, we ask whether U.S. multinationals have more incentives to send their manufacturing tasks to China. This question is closely related to asking whether a U.S. trade policy of restoring jobs to the United States that have been offshored to China is the best option for the U.S. To this end, in Figure 4, we first draw a partial scatter plot for column (1) of Table 8. As is visible, there is an inverted U-shape relationship pattern. Offshoring is maximized at the skill overlap index of 0.536. China (0.505), India (0.531), Brazil (0.554), and Mexico (0.627), countries where U.S. multinationals operate, have skill overlap indexes close to the maximized value of 0.536. Niger (0.104), Mozambique (0.107), and Senegal (0.144) have the lowest skill overlaps with the United States. U.S. multinationals have a very low level of employment in those countries.

Given that China is catching up with the U.S. in educational attainment, the skill overlap index between the U.S. and China, which is 0.505 in 2010, is likely to rise in the fu-

[27] The volumes of offshoring are maximzed at 0.568, 0.566, and 0.547, respectively.

[28] The volumes of offshoring are maximzed at 0.560 0.575, 0.593, and 0.583, respectively.

ture.[29] We predict that the skill overlap factor will induce U.S. multinationals to send their tasks to China in the short run until it reaches the skill overlap index of 0.536. Over the long run, however, we predict that the accumulation of higher educational attainment in China will deter U.S. multinationals from sending their manufacturing tasks once the skill overlap index reaches the maximum point. This result has clear policy implications for trade relations between the U.S. and China. Our result suggests that as China catches up with the U.S. in human capital accumulation, U.S. multinationals will have fewer incentives to send their tasks to China over the long run. As a result, a policy to "bring back U.S. jobs" would not be optimal for U.S. multinationals because it would only distort the profit-maximizing behavior of U.S. multinationals.

5.3 One-Way Gravity Result (Country-Industry Level)

We expand the sample size of the country-level data from the U.S. BEA by using U.S. multinational activity at the country-industry level, which allows us to increase the number of observations from 130 to 728 (= 52 countries $\times$ 14 industries).[30] This alleviates concern that a small sample size might reduce the reliability of the estimation results. To this end, we use the country-industry data and augment the one-way gravity specification with industry fixed effects. Then, we use two-way cluster-robust standard errors that control for both sources of clustering—i.e., country and industry—because errors can be expected to be correlated within a country as well as within an industry.

In Table 10, we repeat the exercise from Table 8 using a more detailed dataset on employment by country-industry level from the Bureau of Economic Analysis. In columns (1) through (8) of Table 10 we consistently find evidence of an inverted U-shape relationship between offshoring and skill overlap. The estimated coefficients, $\hat{\beta}_1$ and $\hat{\beta}_2$, still have the expected signs and are statistical significant. The dependent variable is maximized at

[29]We assume that all other variables stay the same in the U.S. and China.

[30]See Table 3 for a list of countries and Table 4 for a list of industries.

the skill overlap index of 0.582 in column (1) of Table 10 and 0.550 in column (5) of Table 10, which are similar to the levels of the country-level analysis. Moreover, the signs and significance of the coefficients of other control variables remain unchanged, which suggests that the results are robust under the more detailed dataset. In Table 11, we separate industries into two major categories, (a) Manufacturing and (b) Other Industries,[31] and we re-run the regressions. In both cases, an inverted U-shape relationship is identified.

6 Conclusion

In this paper, we provide new empirical evidence of the relationship between offshoring and skill overlap, which is shown as an inverted U shape. We obtain the result by running an offshoring gravity equation using Ramondo, Rodríguez-Clare, and Tintelnot (2015)'s multinational production dataset and the U.S. Bureau of Economic Analysis Direct Investment & Multinational Enterprises (MNEs) dataset. We link those datasets to a novel skill overlap index that we constructed using the Barro and Lee (2013) Educational Attainment Dataset.

The new finding challenges the work of earlier researchers who predicted that the relationship between the two would be linear, either increasing or decreasing. Our finding also has significant consequences for the broader domain of international trade policy: Are U.S. multinationals more or less likely to send their tasks to China in the future? We provide a novel answer to that question. Given that educational attainment in China is catching up to that in the U.S., we can reasonably conjecture that the skill overlap index between the United States and China will increase in the future. From the inverted U-shape relation, we can find the value of the skill overlap index at which offshoring is maximized. China is located slightly to the left of the maximum value. This suggests that U.S. multinationals will send their tasks to China in the short run but will return

[31] See Table 4 for a list of industries.

production tasks to the U.S. from China in the long-run, ceteris paribus.

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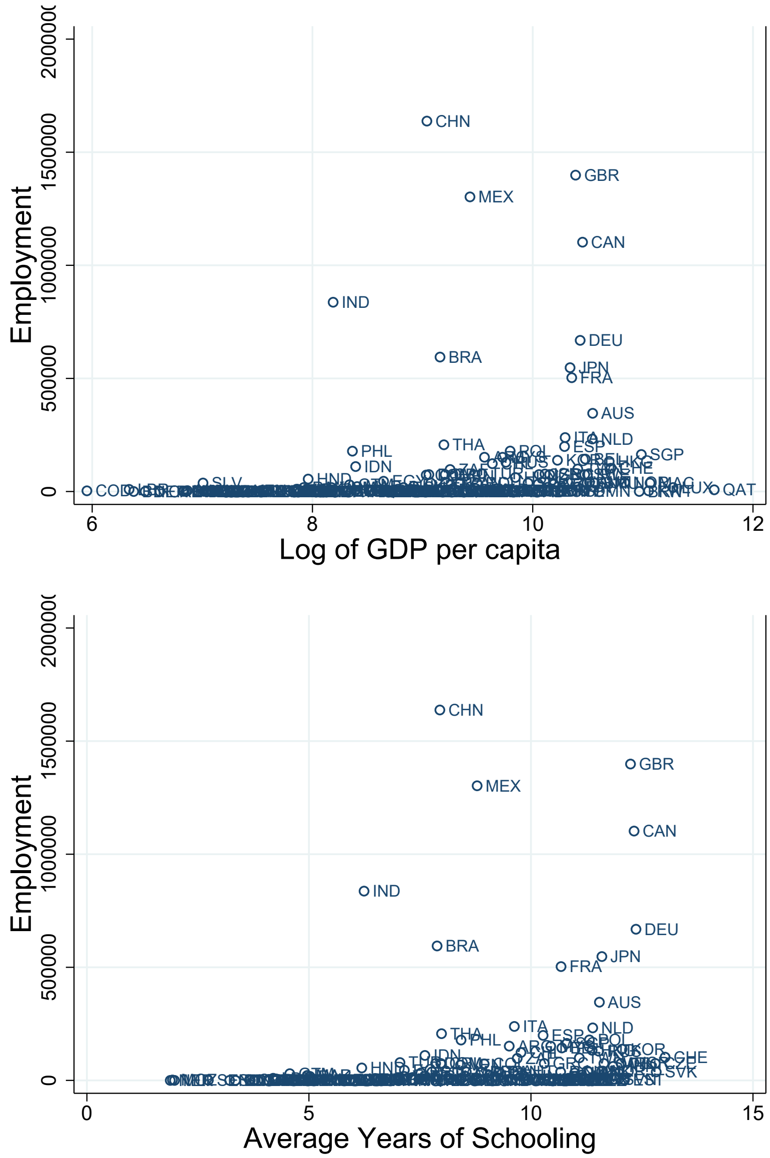
7 Appendix

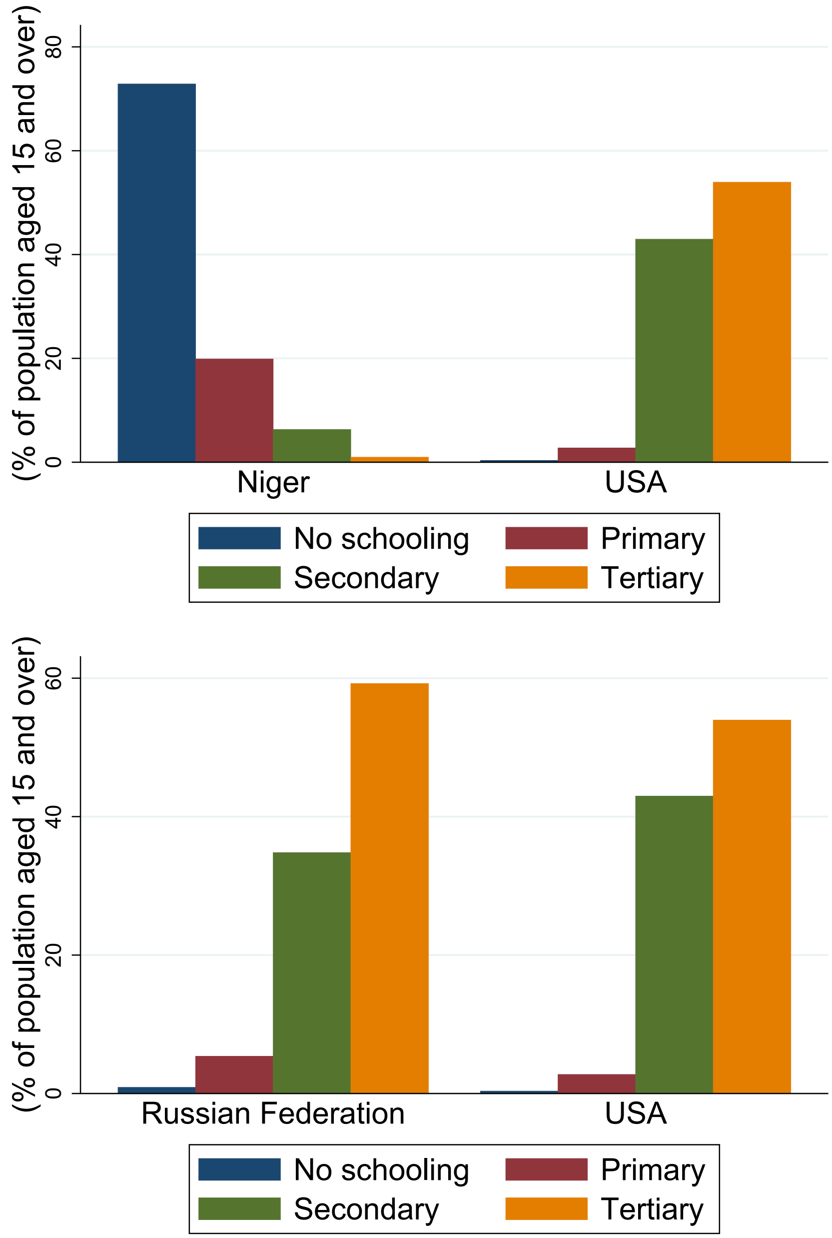
7.1 Figures

Figure 1: Scatter plot of offshoring against GDP per capita and years of schooling



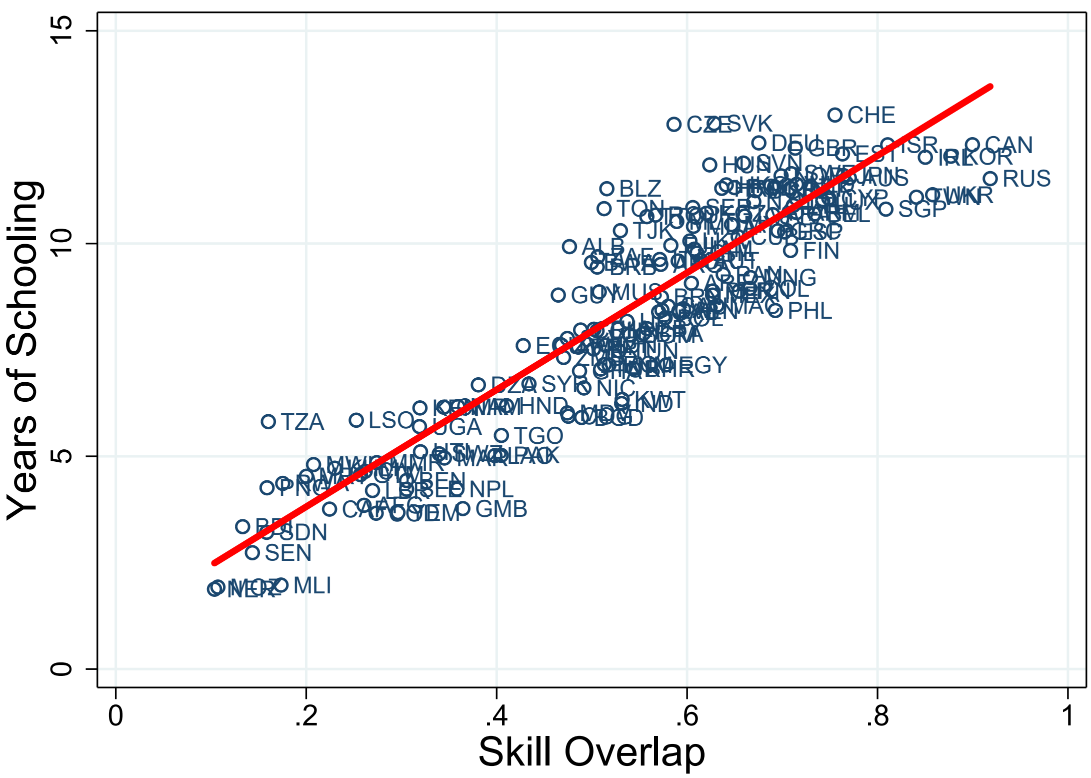
Notes: In both panels, the y-axis denotes the number of workers who work for U.S. multinationals in the year 2010. The x-axis in the upper panel represents the log of GDP per capita and the one in the lower panel indicates the average years of schooling in the year 2010.
Source: Bureau of Economic Analysis (BEA), Barro and Lee (2013) and Feenstra, Inklaar, and Timmer (2015).

Figure 2: Educational attainment of the total population aged 15 and over



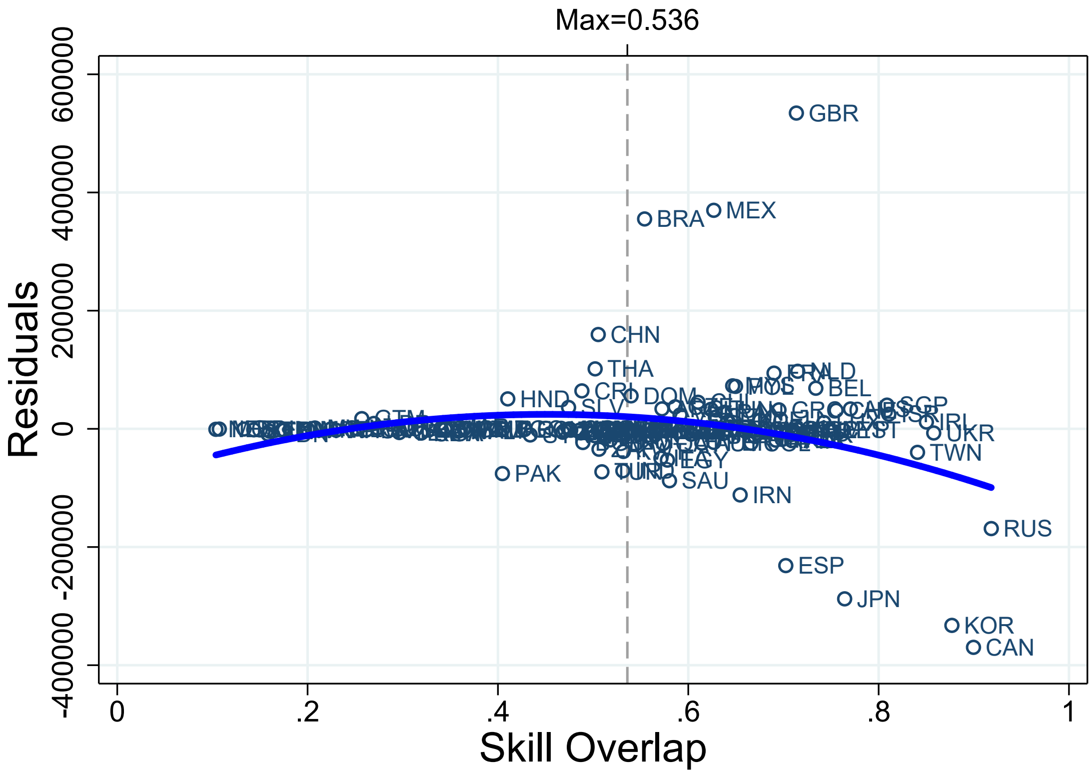
Notes: The figure denotes the highest education level attained for Niger, Russian Federation, and the U.S. in the year 2010.
Source: Barro and Lee (2013).

Figure 3: Scatter plot of years of schooling against skill overlap, country level, 2010



Notes: The skill overlap index is based on equation (4.2), and the U.S. is the reference country.
Source: Barro and Lee (2013).

Figure 4: Partial scatter plot of offshoring against skill overlap, country level, 2010



Notes: This scatter plot is drawn from the specification of column (1) of Table 8. The Y-axis denotes residuals of employment regressed on independent variables except for skill overlap. The blue line is fitted quadratic line of residuals regressed on skill overlap index. The dashed vertical line denotes the skill overlap index that maximizes the volume of offshoring, 0.536, in column (1) of Table 8.

7.2 Tables

Table 1: Countries with the top 20 Highest *Outward Offshoring* by U.S. multinationals, 2010

Rank	Country Name	Country Code	Employment Total	Employment MFG	Share (%)	Cumulative Share (%)	Average Schooling	Skill Overlap	Population	PCGDP
1	China	CHN	1,638	667	12.2	12.2	7.9	50.5	1,318,170	8,426
2	U.K.	GBR	1,399	381	10.4	22.5	12.2	71.4	62,036	32,503
3	Mexico	MEX	1,302	728	9.7	32.2	8.8	62.7	113,423	12,459
4	Canada	CAN	1,102	307	8.2	40.4	12.3	90.0	34,017	34,623
5	India	IND	837	162	6.2	46.6	6.2	53.1	1,224,614	3,597
6	Germany	DEU	668	374	5.0	51.5	12.4	67.5	82,302	33,889
7	Brazil	BRA	594	331	4.4	56.0	7.9	55.4	194,946	9,491
8	Japan	JPN	547	154	4.1	60.0	11.6	76.4	126,536	30,916
9	France	FRA	503	207	3.7	63.8	10.7	69.0	64,731	31,387
10	Australia	AUS	346	72	2.6	66.3	11.5	77.0	22,268	37,955
11	Italy	ITA	239	110	1.8	68.1	9.6	57.1	60,551	29,565
12	Netherlands	NLD	232	90	1.7	69.8	11.4	71.5	16,613	37,837
13	Thailand	THA	207	126	1.5	71.3	8.0	50.2	69,122	9,832
14	Spain	ESP	199	103	1.5	72.8	10.3	70.2	46,077	29,400
15	Poland	POL	179	80	1.3	74.1	11.3	65.0	38,277	17,950
16	Philippines	PHL	178	63	1.3	75.5	8.4	69.3	93,261	4,285
17	Singapore	SGP	164	65	1.2	76.7	10.8	80.9	5,086	59,056
18	Argentina	ARG	152	51	1.1	77.8	9.5	57.2	40,412	14,211
19	Malaysia	MYS	151	103	1.1	78.9	10.4	64.7	28,401	16,748
20	Belgium	BEL	143	70	1.1	80.0	10.7	73.4	10,712	35,519
	Total		13,474		100.0	100.0				

Notes: The table includes all sectors, both manufacturing and non-manufacturing. MFG denotes manufacturing. Share (%) and Cumulative Share (%) are based on total employment. The employment and population counts are thousands of people. Average Schooling is the average years of schooling. PCGDP is per capita GDP in US dollars.
Sources: Bureau of Economic Analysis (BEA), Barro and Lee (2013), and Feenstra, Inklaar, and Timmer (2015).

Table 2: Summary Statistics

Variables	Mean	SD	Min	Max	Obs	Format	Source
Panel A. Dyadic flows data							
Affiliate Revenues, in millions USD:							
(M&A)	3,001	19,907	0	430,225	2,369	Level	Ramondo et al. (2015)
(Stocks)	2,885	19,726	0	430,225	2,409	Level	Ramondo et al. (2015)
(Raw)	3,377	21,708	0	430,225	1,982	Level	UNCTAD
Skill Overlap I	0.73	0.14	0.20	0.99	3,080	Index	Barro and Lee (2013)
Skill Overlap II	0.67	0.13	0.20	0.95	3,080	Index	Barro and Lee (2013)
Distance	8.56	1.01	4.09	9.89	3,080	Log	CEPII
Contiguity	0.04	0.19	0	1	3,080	Binary	CEPII
Language	0.11	0.31	0	1	3,080	Binary	CEPII
Colony	0.01	0.07	0	1	3,080	Binary	CEPII
Panel B. Country level data							
Employment:							
(All)	102,468	262,661	0	1,637,500	130	Level	BEA
(Majority-owned)	86,255	216,965	0	1,213,000	130	Level	BEA
Skill Overlap I	0.53	0.19	0.10	0.92	130	Index	Barro and Lee (2013)
Skill Overlap II	0.48	0.20	0.10	0.86	130	Index	Barro and Lee (2013)
GDP	11.42	1.85	7.72	16.22	130	Log	PWT
PCGDP	8.99	1.27	5.95	11.65	130	Log	PWT
Population	2.43	1.57	-1.17	7.18	130	Log	PWT
Distance	8.99	0.48	6.31	9.69	130	Log	CEPII
Contiguity	0.02	0.12	0.00	1.00	130	Binary	CEPII
Language	0.40	0.49	0.00	1.00	130	Binary	CEPII
Colony	0.01	0.09	0.00	1.00	130	Binary	CEPII
DoingBusiness	60.72	13.18	27.50	91.79	130	Index	World Bank
Rule of Law	0.03	1.00	-1.81	1.98	130	Index	WGI
Panel C. Country-Industry level data							
Employment:							
(All)	15,113	34,139	0	363,100	728	Level	BEA
(Manufacturing)	10,532	20,143	0	168,800	364	Level	BEA
(Other Industries)	19,694	43,431	0	363,100	364	Level	BEA
(Majority-owned)	13,398	33,651	0	363,100	728	Level	BEA
Skill Overlap I	0.65	0.12	0.41	0.92	728	Index	Barro and Lee (2013)
Skill Overlap II	0.60	0.14	0.30	0.86	728	Index	Barro and Lee (2013)
GDP	13.04	1.26	9.99	16.22	728	Log	PWT
PCGDP	9.84	0.76	7.96	11.27	728	Log	PWT
Population	3.20	1.46	-0.68	7.18	728	Log	PWT
Distance	8.85	0.58	6.31	9.69	728	Log	CEPII
Contiguity	0.04	0.19	0.00	1.00	728	Binary	CEPII
Language	0.48	0.50	0.00	1.00	728	Binary	CEPII
Colony	0.02	0.14	0.00	1.00	728	Binary	CEPII
DoingBusiness	69.22	11.29	36.72	91.79	728	Index	World Bank
Rule of Law	0.67	1.01	-1.64	1.98	728	Index	WGI

Notes: The baseline year in the Panel A is 2000; The Panels B and C are based on the year 2010.

Table 3: List of Countries

	Country	Code	Dyadic	US BEA I	US BEA II		Country	Code	Dyadic	US BEA I	US BEA II
1	Albania	ALB		✓		68	Lesotho	LSO		✓	
2	Argentina	ARG	✓	✓	✓	69	Liberia	LBR		✓	
3	Armenia	ARM		✓		70	Libya	LBY	✓		
4	Australia	AUS	✓	✓	✓	71	Lithuania	LTU	✓	✓	
5	Austria	AUT	✓	✓	✓	72	Luxembourg	LUX		✓	✓
6	Bahrain	BHR		✓		73	Malawi	MWI		✓	
7	Bangladesh	BGD		✓		74	Malaysia	MYS	✓	✓	✓
8	Belgium	BEL	✓	✓	✓	75	Maldives	MDV		✓	
9	Belize	BLZ		✓		76	Mali	MLI		✓	
10	Benin	BEN		✓		77	Mauritania	MRT		✓	
11	Bolivia	BOL		✓		78	Mauritius	MUS		✓	
12	Botswana	BWA		✓		79	Mexico	MEX	✓	✓	✓
13	Brazil	BRA	✓	✓	✓	80	Moldova	MDA		✓	
14	Brunei	BRN		✓		81	Mongolia	MNG		✓	
15	Bulgaria	BGR	✓	✓		82	Morocco	MAR		✓	
16	Burundi	BDI		✓		83	Mozambique	MOZ		✓	
17	Cambodia	KHM		✓		84	Namibia	NAM		✓	
18	Cameroon	CMR		✓		85	Nepal	NPL		✓	
19	Canada	CAN	✓	✓	✓	86	Netherlands	NLD	✓	✓	✓
20	Central African Rep.	CAF		✓		87	New Zealand	NZL	✓	✓	✓
21	Chile	CHL	✓	✓	✓	88	Niger	NER		✓	
22	China	CHN	✓	✓	✓	89	Norway	NOR	✓	✓	✓
23	Colombia	COL	✓	✓	✓	90	Pakistan	PAK		✓	
24	Congo	COG		✓		91	Panama	PAN		✓	✓
25	Costa Rica	CRI	✓	✓	✓	92	Paraguay	PRY		✓	
26	Cote D'Ivoire	CIV		✓		93	Peru	PER		✓	✓
27	Croatia	HRV	✓	✓		94	Philippines	PHL		✓	✓
28	Cyprus	CYP		✓		95	Poland	POL	✓	✓	✓
29	Czech Republic	CZE	✓	✓	✓	96	Portugal	PRT	✓	✓	✓
30	Congo	COD		✓		97	Qatar	QAT		✓	
31	Cuba	CUB	✓			98	Romania	ROU	✓	✓	
32	Denmark	DNK	✓	✓	✓	99	Russia	RUS	✓	✓	✓
33	Dominican Republic	DOM	✓	✓	✓	100	Rwanda	RWA		✓	
34	Ecuador	ECU		✓	✓	101	Saudi Arabia	SAU	✓	✓	✓
35	Egypt	EGY		✓	✓	102	Senegal	SEN		✓	
36	El Salvador	SLV	✓	✓		103	Serbia	SER		✓	
37	Estonia	EST		✓		104	Sierra Leone	SLE		✓	
38	Fiji	FJI		✓		105	Singapore	SGP	✓	✓	✓
39	Finland	FIN	✓	✓	✓	106	Slovakia	SVK	✓	✓	
40	France	FRA	✓	✓	✓	107	Slovenia	SVN		✓	
41	Gabon	GAB		✓		108	South Africa	ZAF	✓	✓	✓
42	Gambia	GMB		✓		109	Spain	ESP	✓	✓	✓
43	Germany	DEU	✓	✓	✓	110	Sri Lanka	LKA		✓	
44	Ghana	GHA		✓		111	Sudan	SDN		✓	
45	Greece	GRC	✓	✓	✓	112	Swaziland	SWZ		✓	
46	Guatemala	GTM	✓	✓		113	Sweden	SWE	✓	✓	✓
47	Honduras	HND		✓	✓	114	Switzerland	CHE	✓	✓	✓
48	Hong Kong	HKG		✓	✓	115	Syria	SYR		✓	
49	Hungary	HUN	✓	✓	✓	116	Taiwan	TWN		✓	✓
50	Iceland	ISL		✓		117	Tajikistan	TJK		✓	
51	India	IND	✓	✓	✓	118	Tanzania	TZA		✓	
52	Indonesia	IDN	✓	✓	✓	119	Thailand	THA	✓	✓	✓
53	Iran	IRN	✓	✓		120	Togo	TGO		✓	
54	Iraq	IRQ		✓		121	Trinidad & Tob.	TTO		✓	
55	Ireland	IRL	✓	✓	✓	122	Tunisia	TUN	✓	✓	
56	Israel	ISR	✓	✓	✓	123	Turkey	TUR	✓	✓	✓
57	Italy	ITA	✓	✓	✓	124	Uganda	UGA		✓	
58	Jamaica	JAM		✓		125	Ukraine	UKR		✓	
59	Japan	JPN	✓	✓	✓	126	United Kingdom	GBR	✓	✓	✓
60	Jordan	JOR		✓		127	United States	USA	✓		
61	Kazakhstan	KAZ		✓		128	Uruguay	URY	✓	✓	
62	Kenya	KEN		✓		129	Venezuela	VEN	✓	✓	✓
63	Korea, Republic of	KOR	✓	✓	✓	130	Vietnam	VNM		✓	
64	Kuwait	KWT		✓		131	Yemen	YEM		✓	
65	Kyrgyzstan	KGZ		✓		132	Zambia	ZMB		✓	
66	Laos	LAO		✓		133	Zimbabwe	ZWE		✓	
67	Latvia	LVA		✓							

Notes: Dyadic (56 countries) refers to the Ramondo et al. (2015) data, US BEA I (130 countries) denotes the country level sample, and US BEA II (52 countries) indicates the country-industry level data.

Table 4: Industry Categories

Code	Description
ind1	Mining
ind2	Food
ind3	Chemicals
ind4	Primary and fabricated metals
ind5	Machinery
ind6	Computers and electronic products
ind7	Electrical equipment, appliances, and components
ind8	Transportation Equipment
ind9	Wholesale Trade
ind10	Retail Trade
ind11	Information
ind12	Finance and insurance
ind13	Professional, scientific, and technical services
ind14	Other Industries not specified

Source: Bureau of Economic Analysis

Table 5: Offshoring and skill overlap, dyadic flows
Dependent variable: Affiliate Revenues

	Revenues (M&A)		Revenues (Stocks)		Revenues (Raw)	
	(1)	(2)	(3)	(4)	(5)	(6)
Skill Overlap I	1.530	6.664***	1.222	5.878**	1.149	6.720***
	(0.980)	(2.291)	(1.023)	(2.315)	(1.131)	(2.265)
$(\text{Skill Overlap I})^2$		-3.606***		-3.256**		-3.894***
		(1.364)		(1.342)		(1.481)
Distance	-0.291**	-0.315***	-0.289**	-0.310***	-0.205*	-0.227**
	(0.120)	(0.116)	(0.122)	(0.118)	(0.120)	(0.114)
Contiguity	0.536**	0.541**	0.566**	0.574**	0.735***	0.752***
	(0.213)	(0.216)	(0.222)	(0.226)	(0.231)	(0.238)
Language	0.373**	0.368**	0.363**	0.353**	0.319*	0.299*
	(0.162)	(0.165)	(0.171)	(0.175)	(0.164)	(0.171)
Colony	-0.020	-0.026	-0.068	-0.076	0.616	0.589*
	(0.195)	(0.183)	(0.205)	(0.195)	(0.389)	(0.329)
Fixed effects:						
Source Country	Yes	Yes	Yes	Yes	Yes	Yes
Host Country	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,369	2,369	2,409	2,409	1,982	1,982
Pseudo R-squared	0.947	0.948	0.945	0.946	0.954	0.955

Notes: The dependent variable, affiliate revenue, is taken from Ramondo, Rodríguez-Clare, and Tintelnot (2015)'s multinational production data, which is averaged over 1996 to 2001. Affiliate revenue in columns (1) and (2) is extrapolated from M&A transactions from Thomson and Reuters. In columns (3) and (4), affiliate revenue is imputed from FDI stocks from UNCTAD. Columns (5) and (6) present raw affiliate revenue from UNCTAD. Standard errors in parentheses are two-way clustered on source country and host country as in Cameron, Gelbach, and Miller (2012). *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 6: Robustness Check: Offshoring and skill overlap, dyadic flows
Dependent variable: Affiliate Revenues

	Revenues (M&A)		Revenues (Stocks)		Revenues (Raw)	
	(1)	(2)	(3)	(4)	(5)	(6)
Skill Overlap II	0.561	4.953**	0.153	4.469*	-0.032	5.953***
	(1.027)	(2.431)	(1.105)	(2.310)	(1.269)	(1.461)
(Skill Overlap II)^2		-3.283**		-3.223**		-4.460***
		(1.516)		(1.418)		(0.810)
Distance	-0.298**	-0.298**	-0.299**	-0.298**	-0.220*	-0.214*
	(0.118)	(0.117)	(0.120)	(0.119)	(0.118)	(0.114)
Contiguity	0.554**	0.598**	0.588**	0.634***	0.753***	0.825***
	(0.227)	(0.238)	(0.232)	(0.242)	(0.244)	(0.254)
Language	0.387**	0.447***	0.371**	0.430**	0.332**	0.412**
	(0.165)	(0.161)	(0.173)	(0.173)	(0.168)	(0.170)
Colony	-0.072	-0.008	-0.126	-0.063	0.513	0.662**
	(0.187)	(0.189)	(0.199)	(0.196)	(0.364)	(0.306)
Fixed effects:						
Source Country	Yes	Yes	Yes	Yes	Yes	Yes
Host Country	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,369	2,369	2,409	2,409	1,982	1,982
Pseudo R-squared	0.946	0.944	0.945	0.943	0.953	0.952

Notes: The dependent variable, affiliate revenue, is taken from Ramondo, Rodríguez-Clare, and Tintelnot (2015)'s multinational production data, which is averaged over 1996 to 2001. Affiliate revenue in columns (1) and (2) is extrapolated from M&A transactions from Thomson and Reuters. In columns (3) and (4), affiliate revenue is imputed from FDI stocks from UNCTAD. Columns (5) and (6) present raw affiliate revenue from UNCTAD. Standard errors in parentheses are two-way clustered on source country and host country as in Cameron, Gelbach, and Miller (2012). *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Pairwise Correlations, country level, 2010

	Empl-oyment	Skill Overlap	GDP	PCGDP	Popul-ation	Distance	Conti-guity	Lang-uage	Colony	Doing Business	Rule of Law
Empl-oyment	1.00										
Skill Overlap	0.25	1.00									
	(0.00)										
GDP	0.59	0.53	1.00								
	(0.00)	(0.00)									
PCGDP	0.23	0.79	0.55	1.00							
	(0.01)	(0.00)	(0.00)								
Popul-ation	0.50	-0.02	0.74	-0.16	1.00						
	(0.00)	(0.87)	(0.00)	(0.07)							
Distance	-0.23	-0.22	-0.04	-0.18	0.10	1.00					
	(0.01)	(0.01)	(0.68)	(0.05)	(0.26)						
Conti-guity	0.53	0.15	0.18	0.09	0.14	-0.46	1.00				
	(0.00)	(0.08)	(0.04)	(0.28)	(0.12)	(0.00)					
Lang-uage	0.10	-0.01	-0.06	-0.08	-0.00	-0.19	0.15	1.00			
	(0.26)	(0.93)	(0.51)	(0.34)	(0.99)	(0.03)	(0.08)				
Colony	0.03	0.07	0.07	-0.04	0.12	0.10	-0.01	0.11	1.00		
	(0.77)	(0.40)	(0.42)	(0.62)	(0.18)	(0.27)	(0.90)	(0.22)			
Doing Business	0.24	0.68	0.45	0.78	-0.10	-0.14	0.11	0.08	-0.04	1.00	
	(0.01)	(0.00)	(0.00)	(0.00)	(0.24)	(0.12)	(0.20)	(0.39)	(0.63)		
Rule of Law	0.24	0.61	0.40	0.79	-0.17	-0.13	0.07	-0.05	-0.05	0.83	1.00
	(0.01)	(0.00)	(0.00)	(0.00)	(0.05)	(0.13)	(0.41)	(0.55)	(0.54)	(0.00)	

Notes: N=130. The sample comes from the country level data as in Panel B of Table 2. The table displays all the pairwise correlation coefficients between the variables. The significance levels of correlation coefficients are in parenthesis. The employment variable is based on "All" multinationals instead of "Majority-owned" multinationals. The Skill Overlap is based on the Skill Overlap Index I.

Table 8: Offshoring and Skill Overlap, country level, 2010
Dependent variable: Employment

	All				Majority-owned			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Skill Overlap I	9.238**	11.401***	11.143***	9.328**	10.373***	11.533***	12.907***	11.492***
	(3.675)	(3.743)	(3.984)	(4.220)	(3.811)	(3.932)	(4.056)	(4.273)
(Skill Overlap I)^2	-8.625***	-10.044***	-9.843***	-8.526***	-9.259***	-10.020***	-10.880***	-9.856***
	(2.645)	(2.682)	(2.851)	(3.033)	(2.761)	(2.805)	(2.921)	(3.068)
GDP	1.022***	0.000			0.984***	0.436		
	(0.042)	(0.712)			(0.043)	(0.876)		
(GDP)^2		0.037				0.020		
		(0.026)				(0.032)		
PCGDP			0.855***	3.388			0.766***	2.663
			(0.183)	(2.561)			(0.191)	(2.799)
(PCGDP)^2				-0.137				-0.102
				(0.136)				(0.149)
Population			1.017***	1.003***			0.978***	0.967***
			(0.043)	(0.041)			(0.043)	(0.042)
Distance	-0.337**	-0.336**	-0.359**	-0.308*	-0.342**	-0.343**	-0.370**	-0.332*
	(0.153)	(0.147)	(0.163)	(0.172)	(0.157)	(0.155)	(0.168)	(0.174)
Continuity	0.835**	0.877***	0.819**	0.879**	0.884***	0.905***	0.866**	0.910***
	(0.331)	(0.317)	(0.337)	(0.348)	(0.336)	(0.332)	(0.343)	(0.352)
Language	0.579***	0.607***	0.523***	0.548***	0.589***	0.604***	0.518***	0.535***
	(0.148)	(0.155)	(0.165)	(0.165)	(0.164)	(0.173)	(0.183)	(0.182)
Colony	1.061***	1.074***	0.945***	1.008***	1.156***	1.164***	1.002***	1.051***
	(0.187)	(0.189)	(0.202)	(0.208)	(0.195)	(0.199)	(0.213)	(0.223)
DoingBusiness	0.020*	0.020*	0.025*	0.022	0.013	0.013	0.019	0.017
	(0.012)	(0.012)	(0.014)	(0.015)	(0.012)	(0.013)	(0.015)	(0.017)
Rule of Law	0.157	0.158	0.178	0.290	0.261**	0.261**	0.290**	0.373**
	(0.124)	(0.122)	(0.126)	(0.179)	(0.121)	(0.121)	(0.125)	(0.186)
Observations	130	130	130	130	130	130	130	130
Pseudo R-squared	0.926	0.928	0.927	0.928	0.916	0.916	0.917	0.918

Notes: The dependent variable, employment, is taken from the U.S. Bureau of Economic Analysis and is calculated as total employment of the U.S. multinational enterprises in each country. All variables are in logarithms, except employment, the skill overlap indices, the doingbusiness index, the rule of law index, and the binary variables, such as contiguity, language and colony. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 9: Robustness Check: Offshoring and Skill Overlap, country level, 2010
Dependent variable: Employment

	All				Majority-owned			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Skill Overlap II	6.421**	9.499***	8.412***	7.105**	8.070***	10.210***	10.650***	9.631***
	(3.028)	(2.996)	(3.252)	(3.325)	(3.039)	(3.121)	(3.219)	(3.243)
(Skill Overlap II)^2	-6.619**	-8.892***	-8.089***	-6.984***	-7.759***	-9.341***	-9.667***	-8.812***
	(2.599)	(2.501)	(2.633)	(2.710)	(2.614)	(2.538)	(2.591)	(2.612)
GDP	1.033***	-0.333			1.000***	0.041		
	(0.050)	(0.756)			(0.052)	(0.927)		
(GDP)^2		0.050*				0.035		
		(0.028)				(0.034)		
PDGDP			0.812***	3.633			0.716***	2.812
			(0.209)	(2.488)			(0.217)	(2.731)
(PCGDP)^2				-0.153				-0.114
				(0.132)				(0.145)
Population			1.034***	1.014***			1.000***	0.986***
			(0.050)	(0.049)			(0.052)	(0.051)
Distance	-0.269	-0.259	-0.294	-0.244	-0.270	-0.264	-0.300	-0.265
	(0.171)	(0.166)	(0.179)	(0.183)	(0.175)	(0.174)	(0.184)	(0.187)
Contiguity	0.823**	0.935**	0.847**	0.892**	0.911**	0.986**	0.943**	0.973**
	(0.407)	(0.390)	(0.410)	(0.411)	(0.413)	(0.408)	(0.415)	(0.417)
Languague	0.524***	0.563***	0.449**	0.476**	0.535***	0.562***	0.441**	0.459**
	(0.174)	(0.178)	(0.195)	(0.197)	(0.186)	(0.193)	(0.206)	(0.205)
Colony	0.905***	0.909***	0.771***	0.824***	0.991***	0.996***	0.818***	0.861***
	(0.149)	(0.144)	(0.188)	(0.187)	(0.145)	(0.144)	(0.195)	(0.198)
DoingBusiness	0.020	0.020	0.028*	0.024	0.012	0.012	0.022	0.019
	(0.013)	(0.013)	(0.016)	(0.017)	(0.013)	(0.013)	(0.016)	(0.018)
Rule of Law	0.162	0.154	0.194	0.317*	0.261*	0.255*	0.301**	0.391**
	(0.141)	(0.139)	(0.138)	(0.181)	(0.137)	(0.137)	(0.135)	(0.187)
Observations	130	130	130	130	130	130	130	130
Pseudo R-squared	0.920	0.923	0.921	0.923	0.911	0.912	0.913	0.914

Notes: The dependent variable, employment, is taken from the U.S. Bureau of Economic Analysis and is calculated as total employment of the U.S. multinational enterprises in each country. All variables are in logarithms, except employment, the skill overlap indices, the doingbusiness index, the rule of law index, and the binary variables, such as contiguity, language and colony. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Offshoring and skill overlap, country-industry level, 2010
Dependent variable: Employment

	All				Majority-owned			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Skill Overlap I	10.883***	14.158***	12.324***	11.966***	8.441	9.579	10.328**	10.056**
	(4.081)	(4.289)	(4.059)	(4.093)	(6.031)	(6.005)	(5.138)	(5.130)
(Skill Overlap I)^2	-9.351***	-11.499***	-10.257***	-9.926***	-7.672*	-8.419**	-8.861**	-8.589**
	(2.790)	(2.836)	(2.741)	(2.738)	(4.171)	(4.052)	(3.595)	(3.590)
GDP	0.948***	-0.450			0.942***	0.464		
	(0.063)	(1.064)			(0.071)	(1.322)		
(GDP)^2		0.050				0.017		
		(0.039)				(0.048)		
PCGDP			0.832***	3.547			0.797***	3.197
			(0.218)	(3.114)			(0.198)	(2.788)
(PCGDP)^2				-0.146				-0.130
				(0.168)				(0.146)
Population			0.943***	0.940***			0.936***	0.934***
			(0.063)	(0.061)			(0.051)	(0.050)
Distance	-0.253*	-0.250*	-0.272*	-0.233*	-0.249	-0.248	-0.275**	-0.239**
	(0.134)	(0.133)	(0.139)	(0.127)	(0.176)	(0.176)	(0.120)	(0.113)
Contiguity	0.860**	0.923***	0.838**	0.880**	0.934***	0.953***	0.901***	0.940***
	(0.351)	(0.351)	(0.452)	(0.356)	(0.320)	(0.323)	(0.275)	(0.267)
Languague	0.466***	0.485**	0.426**	0.449**	0.595***	0.602***	0.543***	0.563***
	(0.182)	(0.192)	(0.200)	(0.198)	(0.212)	(0.221)	(0.135)	(0.130)
Colony	0.929***	0.888***	0.836***	0.903***	1.050***	1.035***	0.934**	0.987**
	(0.083)	(0.316)	(0.149)	(0.082)	(0.210)	(0.169)	(0.387)	(0.412)
DoingBusiness	0.018	0.017	0.022	0.019	0.004	0.004	0.001	0.007
	(0.103)	(0.011)	(0.014)	(0.015)	(0.014)	(0.014)	(0.011)	(0.011)
Rule of Law	0.144	0.149	0.152	0.262	0.340**	0.341**	0.345**	0.445***
	(0.125)	(0.123)	(0.128)	(0.177)	(0.135)	(0.135)	(0.138)	(0.118)
Fixed effects:								
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	728	728	728	728	728	728	728	728
Pseudo R-squared	0.707	0.709	0.706	0.711	0.640	0.641	0.640	0.643

Notes: The dependent variable, employment, is taken from the U.S. Bureau of Economic Analysis and is calculated as total employment of the U.S. multinational enterprises in each country and each industry. There are 14 industries (See Table 3). Manufacturing industry is composed of "Food (2)," "Chemicals (3)," "Primary and fabricated metals (4)," "Machinery (5)," "Computers and electronic products (6)," "Electrical equipment, appliances, and components (7)," and "Transportation Equipment (8)." Other industries is composed of "Mining (1)," "Wholesale Trade (9)," "Retail Trade (10)," "Information (11)," "Finance and insurance (12)," "Professional, scientific, and technical services (13)," and "Other Industries (14)." To control for time-invariant industry-level unobserved heterogeneity, we use industry fixed effect. All variables are in logarithms, except employment, the skill overlap indices, the doingbusiness index, the rule of law index, and the binary variables, such as contiguity, language and colony. Standard errors in parentheses are two-way clustered on industry and country as in Cameron, Gelbach, and Miller (2012). *** p<0.01, ** p<0.05, * p<0.1.

Table 11: Offshoring and skill overlap, country-industry level, 2010
Dependent variable: Employment (Manufacturing and Others)

	Manufacturing				Other Industries			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Skill Overlap I	15.928**	17.224***	16.292**	15.470**	8.720***	13.870***	10.859***	10.749***
	(7.566)	(5.629)	(7.308)	(7.365)	(2.036)	(3.436)	(2.286)	(2.207)
(Skill Overlap I)^2	-12.918**	-13.763***	-13.148**	-12.390**	-7.846***	-11.227***	-9.190***	-9.091***
	(5.324)	(3.924)	(5.082)	(5.085)	(1.365)	(2.235)	(1.693)	(1.603)
GDP	0.879***	0.239			0.987***	-1.053		
	(0.062)	(1.113)			(0.066)	(0.957)		
(GDP)^2		0.023				0.073*		
		(0.040)				(0.035)		
PCGDP			0.850***	7.805**			0.815***	1.536
			(0.244)	(3.875)			(0.249)	(3.214)
(PCGDP)^2				-0.373*				-0.039
				(0.210)				(0.170)
Population			0.878***	0.872***			0.979***	0.978***
			(0.063)	(0.059)			(0.066)	(0.065)
Distance	-0.313	-0.308*	-0.318	-0.239	-0.219*	-0.219*	-0.245**	-0.234**
	(0.270)	(0.175)	(0.258)	(0.259)	(0.114)	(0.114)	(0.113)	(0.103)
Contiguity	0.909**	0.944***	0.904**	0.967**	0.855*	0.938**	0.824*	0.837*
	(0.383)	(0.338)	(0.377)	(0.390)	(0.450)	(0.437)	(0.439)	(0.465)
Languague	-0.017	-0.014	-0.027	0.038	0.705***	0.742***	0.645***	0.651***
	(0.153)	(0.124)	(0.157)	(0.135)	(0.181)	(0.186)	(0.201)	(0.209)
Colony	0.411***	0.393	0.387***	0.596	1.184***	1.123***	1.048***	1.064***
	(0.121)	(0.428)	(0.127)	(0.457)	(0.371)	(0.369)	(0.401)	(0.414)
DoingBusiness	0.023	0.023*	0.024	0.018	0.015	0.014	0.021	0.020
	(0.016)	(0.012)	(0.017)	(0.017)	(0.011)	(0.011)	(0.016)	(0.017)
Rule of Law	-0.113	-0.112	-0.111	0.140	0.283*	0.291*	0.292*	0.323*
	(0.175)	(0.137)	(0.176)	(0.238)	(0.155)	(0.149)	(0.158)	(0.195)
Fixed effects:								
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	364	364	364	364	364	364	364	364
Pseudo R-squared	0.660	0.660	0.660	0.673	0.729	0.737	0.728	0.729

Notes: The dependent variable, employment, is taken from the U.S. Bureau of Economic Analysis and is calculated as total employment of the U.S. multinational enterprises in each country and each industry. We use all multinationals, instead of majority-owned multinationals. Manufacturing industry is composed of "Food (2)," "Chemicals (3)," "Primary and fabricated metals (4)," "Machinery (5)," "Computers and electronic products (6)," "Electrical equipment, appliances, and components (7)," and "Transportation Equipment (8)." Other industries is composed of "Mining (1)," "Wholesale Trade (9)," "Retail Trade (10)," "Information (11)," "Finance and insurance (12)," "Professional, scientific, and technical services (13)," and "Other Industries (14)." To control for time-invariant industry-level unobserved heterogeneity, we use industry fixed effect. All variables are in logarithms, except employment, the skill overlap indices, the doingbusiness index, the rule of law index, and the binary variables, such as contiguity, language and colony. Standard errors in parentheses are two-way clustered on industry and country as in Cameron, Gelbach, and Miller (2012). *** p<0.01, ** p<0.05, * p<0.1.