Offshoring and Skill Overlap: An empirical investigation

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Abstract

Conventional international trade theory predicts that bilateral offshoring flows would be highest when two countries are most different regarding factor endowments while the New trade theory contends that offshoring would be most substantial between two similar countries. This paper empirically tests the relationship between offshoring and skill overlap and finds alternative evidence that there is an inverted U-shape relationship. Our empirical results predict that the accumulation of more educational attainment in China will drive U.S. multinationals to send their tasks to China in the short-run, however, it will re-shore production tasks from China back to the U.S. in the long-run.

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

JEL Code: F14, F23, J24.

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1 Introduction

There are two contrasting theories of the relationship between the amount of offshoring and the skill overlap between two countries. In the traditional Heckscher-Ohlin-Vanek (HOV) model and the Feenstra and Hanson (1996) model, trade and offshoring would be greatest when factor endowments are most different. Standing in contrast to these models are Helpman (1987), who examines intra-industry trade, Markusen (1995), who examines foreign direct investment, and Markusen and Venables (2000), who examine multinational activities. They note that the share of intra-industry trade, foreign direct investment, multinational activities, respectively, are more likely to exist when two countries have similar factor endowments. The first theoretical prediction implies that trade and offshoring flows would be most significant between developed countries like the U.S. and developing countries like Malawi, while the second theoretical prediction suggests that the flows would be highest among developed countries.

However, the U.S. is shifting most of its production activities to countries like Brazil, China, Mexico, and India, whose skill distributions have some skill overlaps with the U.S. The U.S. is sending abroad manufacturing tasks to countries that are not very poor (no skill overlap) or not too advanced (complete skill overlap) but that are middle-income with an intermediate level of skill overlap with the U.S (moderate skill overlap). The existing theories fail to explain the observed pattern of multinational activities. Some may challenge this view by insisting that after controlling for other confounding factors such as institution, the relationship between the amount of offshoring and the skill overlap between two countries would still be linear, either increasing or decreasing, which supports traditional views.

In this paper, we set up a formal empirical specification to uncover the relationship between the amount of offshoring and the skill overlap between the two countries. We find compelling evidence that there is an inverted U-shape relation between offshoring and skill overlap between two countries. Based on the estimated hump-shaped pattern, we predict that more educational attainment in China will drive 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 nudge the U.S. multinationals to re-shore their production tasks from China back to the U.S.

2 Empirical Analysis

We set up a gravity equation, similar to the specification in Carr, Markusen and Maskus (2001),[1] that includes the skill overlap index, the square of the skill overlap index, and other standard control variables. We employ Silva and Tenreyro (2006)'s method of a Poisson pseudo-maximum-likelihood (PPML) to estimate the offshoring gravity equation to uncover the relationship between skill overlap and offshoring.[2]

2.1 Data Description

2.1.1 Volume of Offshoring

For a dependent variable, we propose three different measures to capture the volume of offshoring. First, we draw data from the U.S. Bureau of Economic Analysis Direct Investment & Multinational Enterprises (MNEs), which reports employment by U.S. multinationals in the year 2010 at the country level and the country-industry level. In the analysis, we further decompose these multinationals into all foreign affiliates and majority-owned foreign affiliates.

The second measure of the volume of offshoring is drawn from Ramondo, Rodríguez-Clare and Tintelnot (2015)'s Multinational production dataset, which presents the bilat-

[1] 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.

[2] As pointed out by Silva and Tenreyro (2006), the standard OLS method yields biased estimates of coefficients of the log-linearized gravity equation model under heteroskedasticity. Moreover, taking logs of the dependent variable leaves out many zeros of bilateral trade (or offshoring).

eral activities, and especially the values of affiliate sales and the number of affiliates, of multinational firms across country pairs. The primary dataset, originally from UNCTAD (the Investment and Enterprise Program, FDI Statistics, and FDI Country Profiles), contains 59 countries that entail 3,422 (58 $\times$ 59) country pairs averaged over 1996 to 2001. In the analysis, we use affiliate sales imputed by FDI stocks, M&A transactions, and raw affiliate sales by UNCTAD.

The third measure of offshoring comes from the World Input-Output Database (WIOD). It contains an annual global input-output table for 40 countries and 35 industries over the 1995-2011 period. Following Blanchard, Bown and Johnson (2016), we use the WIOD dataset to construct the national origin of the value-added content embodied in the final goods that each country produces in each industry. For instance, we compute the amount of Korean value-added embodied in the U.S. production of transport equipment. In the analysis, we construct a panel dataset of value-added content covering 1,560 (39 $\times$ 40) country pairs and 35 industries in the years 1995, 2000, 2005, and 2010.

2.1.2 Skill Overlap

We use the Barro and Lee (2013) dataset for constructing a skill overlap index. The dataset, which covers for 146 countries in 5-year intervals from 1950 to 2010, contains education attainment for population aged 15 and over. More specifically, for each country in each year, the dataset contains the average years of schooling, the percentage of no schooling, the percentage of primary education, the percentage of secondary education, and the percentage of tertiary education. Using these data, we propose a skill overlap index between country i and country j as follows:

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

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 in country i. This index captures the overlapped area for two skill distributions and can range from 0 (no skill overlap) to 1 (a complete skill overlap). The upper panel of Figure 1 plots distributions of education level for the U.S. and Niger; the skill overlap index is 0.104. The lower panel of Figure 1 plots distributions of education level for the U.S. and Russian Federation; the skill overlap index is 0.918. Figure 2 shows a scatter plot of the average years of schooling against the skill overlap index[3]; there is a high positive relationship between two. Because the average years of schooling of the U.S. was the largest in the world in 2010, the higher the average years of education, the higher the skill overlap index.

2.1.3 Other Control Variables

We include several control variables, such as real GDP, real GDP per capita, population, distance, contiguity, language, colony, and the investment impediment index. 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. Lastly, 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 the institution.

[3]Skill overlap index is calculated between the U.S. and other countries.

2.2 Empirical Context

We outline the regional distribution of the total employment of foreign affiliates by U.S. multinationals in the year 2010. Table 1 lists the top 20 countries that have the highest employment and those country's characteristics, such as average years of schooling, skill overlap index, population, and GDP per capita. A total of 13,474 thousand people are employed in the world by U.S. multinationals, which include both manufacturing and non-manufacturing companies. The employment is concentrated in a few countries: the top 5 countries' share is 46.6%; the top 10 countries' share is 66.3%; the top 15 countries' share is 74.1%; and the top 20 countries' share is 80.0%. Among the 199 countries listed in the U.S. BEA data, 89 countries - most of them low-income countries - report less than one thousand employees. This implies that U.S. multinationals are less likely to send their tasks to low-income countries. Are U.S. multinationals, then, more likely to send their tasks to high-income countries than to mid-income countries? Based on the top 20 countries that comprise of 80% of total employment, six countries (China, Mexico, India, Brazil, Thailand, and the Philippines) classified as mid-income countries (using the World Bank Atlas Method) occupy 35.3% of total employment. If we confine our analysis to the manufacturing sector, the mid-income country share becomes larger.

2.3 Empirical Specification

Following Silva and Tenreyro (2006) and Cameron and Trivedi (2013), we specify the poisson regression model for the offshoring gravity equation. The dependent variable, $\mathit{Offshoring}_{ij}$, is the volume of offshoring between country i and country j, and x is the set of controls that includes GDP$_i$, GDP$_j$, Distance$_{ij}$, Contiguity$_{ij}$, Language$_{ij}$, Colony$_{ij}$, Investment$_j$, and, most importantly, Skill Overlap$_{ij}$ and the square of Skill Overlap$_{ij}$. Given x, the poisson regression model of $\mathit{Offshoring}_{ij}$ can be formulated as:

$$\mathit{Offshoring}_{ij} = \exp(\mathbf{x}'\boldsymbol{\beta}) + \epsilon_{ij}$$

where $\textit{Offshoring}_{ij} \geq 0$ and $\mathbb{E}[\epsilon_{ij}|\mathbf{x}] = 0$. Also, the exponential mean function, $\mathbb{E}[\textit{Offshoring}_{ij}|\mathbf{x}]$ can be expressed as:

$$\begin{aligned}\mathbb{E}[\textit{Offshoring}_{ij}|\mathbf{x}] = \exp(\mathbf{x}'\boldsymbol{\beta}) = \exp[&\ln\beta_0 + \beta_1\text{Skill Overlap}_{ij} + \beta_2(\text{Skill Overlap}_{ij})^2 \\ &+ \beta_3\text{lnGDP}_i + \beta_4\text{lnGDP}_j + \beta_5\text{lnDistance}_{ij} + \beta_6\text{Contiguity}_{ij} \\ &+ \beta_7\text{Language}_{ij} + \beta_8\text{Colony}_{ij} + \beta_9\text{InvestmentFriction}_j].\end{aligned}$$

The Poisson maximum likelihood estimator based on the above poisson regression model is the solution to the following first-order conditions:[4]

$$\sum_i \sum_j \left[\textit{Offshoring}_{ij} - \exp(\mathbf{x_{ij}}'\boldsymbol{\beta})\right] \mathbf{x_{ij}} = \mathbf{0}. \quad (2)$$

2.4 Empirical Results

In Table 2 we begin our empirical analysis by running a country-level Poisson regression model of the offshoring gravity equation. The first dataset is limited to the U.S. multinationals. Thus, this analysis uncovers whether the skill overlap between the U.S. and other countries determines the U.S. multinational's location choice. In column (1) of Table 2, we find that the relationship between the U.S. multinational's total employment abroad and the measure of skill overlap is indeed an inverted U-shape. The estimated coefficient on skill overlap, $\hat{\beta}_1$, is 9.854 and the squared of skill overlap, $\hat{\beta}_2$, is -8.914. Both are statistically

[4]The assumption of a poisson distribution data generating process for $\textit{Offshoring}_{ij}$ is stronger than necessary. Gourieroux, Monfort and Trognon (1984) noted that if the conditional expectation function, $\mathbb{E}[\textit{Offshoring}_{ij}|\mathbf{x}]$, is correctly specified, then the estimator based on the equation (2) is consistent. Thus, the data generating process for $\textit{Offshoring}_{ij}$ need not to be a possion distribution. Furthermore, $\textit{Offshoring}_{ij}$ need not to be an integer, and $\textit{Offshoring}_{ij} \geq 0$ 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 (2) is a poisson pseudo-maximum-likelihood (PPML) estimator. Throughout the analysis, we use the PPML estimator to uncover the relationship between the volume of offshoring and the skill overlap between country i and country j.

significant at the 1% 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 for U.S. multinationals offshoring is maximized at the skill overlap index of 0.553 Figure 3 shows a partial scatterplot for column (1) of Table 2. The inverted U-shape relationship that we identify is consistent with our model's prediction. In Figure 3, Brazil (0.554) is the closest to the skill overlap index of 0.553, which is the maximum value. China (0.505), India (0.531), and Mexico (0.627), countries where U.S. multinationals actively operate, have skill overlap indexes close to the maximized value of 0.553. Niger (0.104), Mozambique (0.107), and Senegal (0.144) have the lowest skill overlaps with the U.S. The U.S. multinationals have a very low level of employment in these countries.

Other standard gravity control variables in column (1) of Table 2 also have expected signs. Real GDP, contiguity, language link, colonial relationship, and investment environment are positively related to the offshoring while distance is negatively associated with the offshoring. Acemoglu, Gallego and Robinson (2014) argue that once they control for the historical determinants of institutions and human capital, the estimates of the effect of human capital on long-run development decline significantly. Based on this insight, we include in column (2) of Table 2 an additional control variable, the rule of law index. Reassuringly, the result is still robust. In columns (3) and (4) of Table 2, instead of real GDP, we include per capita GDP and population as control variables, both of which have positive and significant effects on offshoring. The central coefficients (i.e., skill overlap coefficients) still show an inverted U-shape under this specification. We repeat these regressions in columns from (5) to (8) of Table 2, but now we use majority-owned affiliates that are owned more than 50 percent by their U.S. parents. Note that the signs and significance are the same as in columns (1) through (4) of Table 2.

Based on the estimated coefficients, we ask whether the U.S. multinationals have more incentives to send their manufacturing tasks to China. Given that China is catching up with the U.S. with regard to educational attainment, the skill overlap index between the U.S. and China, which is 0.505 in 2010, is more likely to rise in the future. 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 0.553. However, we predict that over the long run, the accumulation of more educational attainment in China will deter U.S. multinationals from sending their manufacturing tasks once the skill overlap index reaches the maximum point.

In Table 3, we repeat the exercise from Table 2, but rather than using a dependent variable we use a more detailed dataset on employment by country-industry level from the Bureau of Economic Analysis. Now the dataset records total employment of U.S. multinationals not only by countries but by industry-country level. In columns (1) through (8) of Table 3 we consistently find evidence of an inverted U-shape relationship between the volume of offshoring and skill overlap. The estimated coefficients, $\hat{\beta}_1$ and $\hat{\beta}_2$, are still expected signs and they are statistical significant. The dependent variable is maximized at the skill overlap index of 0.621 in column (1) of Table 3 and 0.605 in column (5) of Table 3, which are similar to the levels of the country-level analysis. Moreover, all the signs and significance of the coefficients of other control variables remain unchanged, which suggests that the result is quite robust under the more detailed dataset.

In Table 4, we separate industries into two major categories, (a) Manufacturing and (b) Other Industries, and we re-run the regressions. In both cases, the inverted U-shape relationship is identified. Interestingly, offshoring is maximized at the skill overlap index of 0.61 for manufacturing and 0.63 for non-manufacturing. This suggests that unlike non-manufacturing tasks, which are sent to more developed countries, the U.S. is shifting its manufacturing tasks to less developed countries, as defined by the skill overlap index.

2.5 Robustness Checks

We now check the validity of our findings using alternative measures of offshoring. To this end, we analyze the relationship between the volume of offshoring and skill overlap using Ramondo, Rodríguez-Clare and Tintelnot (2015)'s multinational production data as a dependent variable. The previous analysis was confined to U.S. multinationals. Here we expand the scope of analysis to a more general setting in which 2,970 (54×55) country pairs' dyadic offshoring flows can be investigated.[5] Reassuringly, Table 5 confirms that in this more general setting the relationship between the volume of offshoring and skill overlap is still an inverted U-shape and the model's prediction can be extended to global offshoring flows. In column (1) of Table 5, where affiliate revenue is imputed from M&A data supplied by Thomson and Reuters, the estimated coefficients of interest, $\hat{\beta}_1$ and $\hat{\beta}_2$, are expected signs, and they are statistically significant. The affiliate revenue is maximized at the skill overlap index of 0.834. In Column (3) and Column (5) of Table 5, where affiliate sales are imputed from FDI stocks and raw data are taken from UNCTAD, respectively, we find evidence of the U-shape. In these columns the volumes of offshoring are maximized at the skill overlap index of 0.810 and 0.807, respectively. In columns (2), (4), and (6) we add the rule of law index into the baseline specifications. We find that the inverted U-shape relation becomes weaker even though the estimated coefficients of interest, $\hat{\beta}_1$ and $\hat{\beta}_2$, show expected signs. This finding supports Acemoglu, Gallego and Robinson (2014)'s argument that the institution is a compounding factor that weakens the impacts of human capital on economic outcomes. Lastly, we use value-added content embodied in the final goods that each country produces in each industry (constructed from the World Input-Ouput Database (WIOD)) as a measure of the volume of offshoring in order to analyze the relationship between the volume of offshoring and skill overlap. The data covers 1,560 (39×40) country pairs and 35 industries during the years 1995, 2000,

[5]Three countries, Belarus, Lebanon, and Turkmenistan, are missing in Barro and Lee (2013) dataset and Cuba is missing in Feenstra, Inklaar and Timmer (2015)'s Penn World Table 8.1 dataset. Thus, the number of countries that we can analyze in this set-up is reduced to 54 countries.

2005, and 2010, which extends the scope of the analysis from a cross-section to a panel framework. Table 6 presents the result of the panel analysis. We also find that the skill overlap coefficients are expected signs and statistically significant even when we extend the analysis to a panel framework.

3 Conclusion

In this paper, we provide new empirical evidence of the relationship between offshoring and skill overlap, which is an inverted U-shape. This finding challenges the work of earlier researchers, who tended to predict that the relationship between the two is linear, either increasing or decreasing. Our finding has significant consequences for the broader domain of international trade policy debate. Will U.S. multinationals bring back jobs into the U.S.? Given that China is catching up with the U.S. concerning educational attainment, we can reasonably conjecture that the skill overlap index between the U.S. and China will increase. Then, the U.S. multinationals will send their tasks to China in the short-run, however, it will re-shore production tasks from China back to the U.S. in the long-run, ceteris paribus.

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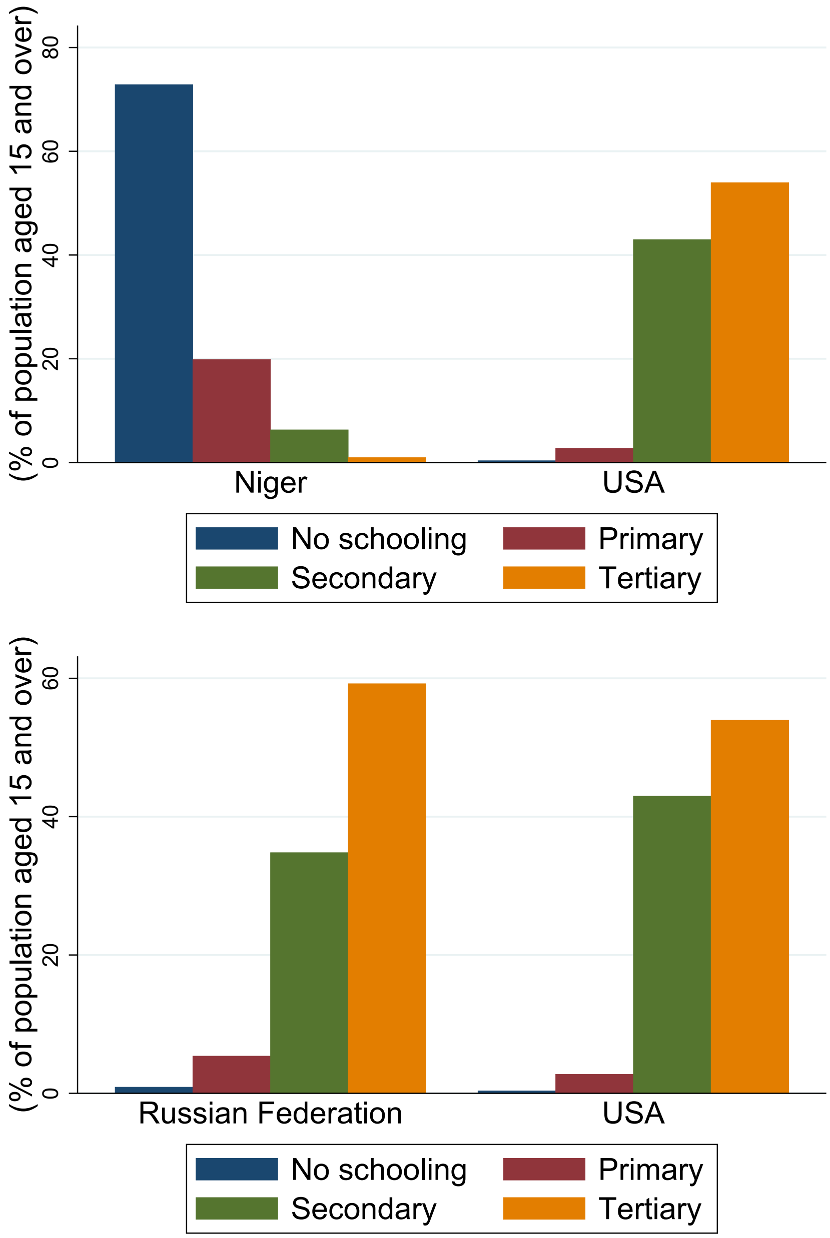
4 Appendix

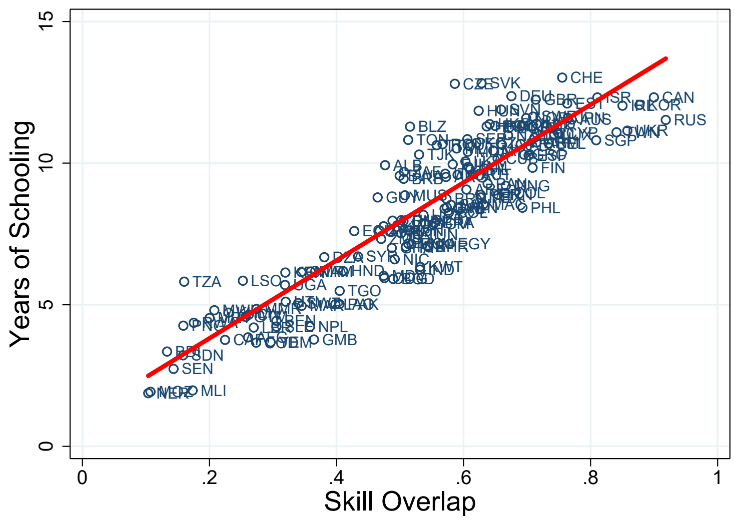
4.1 Figures

Figure 1: Educational attainment of the total population aged 15 and over



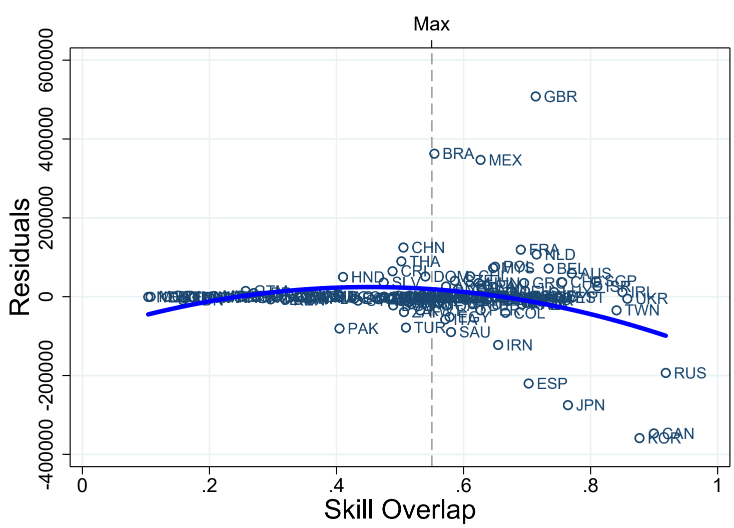
Notes: The figure denotes the highest education level attained for Niger, Russian Federation, and the U.S. in the year 2010.
Source: Barro and Lee (2013).

Figure 2: Scatter plot of years of schooling against skill overlap, country level, 2010



Notes: The skill overlap index is based on equation (1), and the U.S. is the reference country.
Source: Barro and Lee (2013).

Figure 3: 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 2. 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, 0.553, in column (1) of Table 2.

4.2 Tables

Table 1: Countries with the 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: Offshoring and Skill Overlap, country level, 2010
Dependent variable: Employment

	All				Majority-owned			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Skill Overlap	9.854***	9.238**	11.355***	11.143***	11.348***	10.373***	13.107***	12.907***
	(3.750)	(3.675)	(4.090)	(3.984)	(3.955)	(3.811)	(4.341)	(4.056)
(Skill Overlap)^2	-8.914***	-8.625***	-9.857***	-9.843***	-9.710***	-9.259***	-10.811***	-10.880***
	(2.684)	(2.645)	(2.909)	(2.851)	(2.821)	(2.761)	(3.052)	(2.921)
GDP	1.035***	1.022***			1.006***	0.984***		
	(0.039)	(0.042)			(0.040)	(0.043)		
PCGDP			0.911***	0.855***			0.862***	0.766***
			(0.187)	(0.183)			(0.198)	(0.191)
Population			1.034***	1.017***			1.004***	0.978***
			(0.039)	(0.043)			(0.040)	(0.043)
Distance	-0.422***	-0.337**	-0.447***	-0.359**	-0.483***	-0.342**	-0.511***	-0.370**
	(0.135)	(0.153)	(0.145)	(0.163)	(0.148)	(0.157)	(0.158)	(0.168)
Contiguity	0.605**	0.835**	0.570**	0.819**	0.509**	0.884***	0.469*	0.866**
	(0.241)	(0.331)	(0.240)	(0.337)	(0.252)	(0.336)	(0.250)	(0.343)
Language	0.587***	0.579***	0.546***	0.523***	0.598***	0.589***	0.550***	0.518***
	(0.143)	(0.148)	(0.160)	(0.165)	(0.159)	(0.164)	(0.176)	(0.183)
Colony	1.022***	1.061***	0.928***	0.945***	1.095***	1.156***	0.984***	1.002***
	(0.185)	(0.187)	(0.198)	(0.202)	(0.193)	(0.195)	(0.217)	(0.213)
DoingBusiness	0.029***	0.020*	0.033***	0.025*	0.027***	0.013	0.033***	0.019
	(0.008)	(0.012)	(0.011)	(0.014)	(0.008)	(0.012)	(0.012)	(0.015)
Rule of Law		0.157		0.178		0.261**		0.290**
		(0.124)		(0.126)		(0.121)		(0.125)
Observations	130	130	130	130	130	130	130	130
R-squared	0.942	0.944	0.943	0.943	0.923	0.928	0.924	0.927

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

	All				Majority-owned			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Skill Overlap	14.244***	12.819***	15.689***	14.692***	11.363***	8.441*	12.520***	10.327**
	(3.740)	(3.852)	(3.323)	(3.455)	(4.318)	(4.612)	(4.445)	(4.463)
(Skill Overlap)^2	-11.478***	-10.628***	-12.378***	-11.804***	-9.396***	-7.672**	-10.118***	-8.861***
	(2.575)	(2.650)	(2.306)	(2.399)	(3.003)	(3.244)	(3.031)	(3.141)
GDP	0.938***	0.923***			0.975***	0.942***		
	(0.042)	(0.037)			(0.057)	(0.049)		
PCGDP			0.827***	0.772***			0.887***	0.797***
			(0.097)	(0.097)			(0.136)	(0.160)
Population			0.934***	0.917***			0.972***	0.936***
			(0.042)	(0.036)			(0.055)	(0.048)
Distance	-0.335***	-0.246**	-0.356***	-0.269***	-0.438***	-0.249*	-0.455***	-0.275**
	(0.098)	(0.096)	(0.090)	(0.089)	(0.124)	(0.144)	(0.119)	(0.126)
Contiguity	0.652***	0.882***	0.622**	0.856***	0.443**	0.934***	0.420*	0.901***
	(0.251)	(0.272)	(0.248)	(0.268)	(0.225)	(0.202)	(0.230)	(0.177)
Language	0.481***	0.485***	0.443***	0.433***	0.599***	0.595***	0.568***	0.543***
	(0.128)	(0.128)	(0.121)	(0.117)	(0.176)	(0.165)	(0.151)	(0.139)
Colony	0.830***	0.874***	0.737***	0.754***	0.943***	1.050***	0.871**	0.934**
	(0.221)	(0.228)	(0.214)	(0.215)	(0.330)	(0.326)	(0.382)	(0.370)
DoingBusiness	0.025***	0.016***	0.029***	0.021***	0.022***	0.004	0.025***	0.009
	(0.004)	(0.006)	(0.006)	(0.007)	(0.007)	(0.013)	(0.007)	(0.011)
Rule of Law		0.160		0.171		0.340**		0.345**
		(0.113)		(0.113)		(0.162)		(0.162)
Fixed effects:								
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	728	728	728	728	728	728	728	728
R-squared	0.666	0.666	0.667	0.667	0.639	0.640	0.639	0.640

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. 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, and the binary variables, such as contiguity, language and colony. Standard errors in parentheses are clustered at the industry level. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Offshoring and skill overlap, country-industry level, 2010
Dependent variable: Employment

	Manufacturing				Other Industries			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Skill Overlap	14.702*	15.928**	15.383**	16.292***	14.717***	12.210***	16.741***	15.280***
	(7.928)	(7.358)	(6.619)	(6.287)	(3.878)	(4.394)	(3.669)	(4.142)
(Skill Overlap)^2	-12.148**	-12.918**	-12.578***	-13.148***	-11.601***	-10.154***	-12.855***	-12.080***
	(5.630)	(5.248)	(4.797)	(4.561)	(2.632)	(2.935)	(2.498)	(2.798)
GDP	0.868***	0.879***			0.974***	0.946***		
	(0.066)	(0.055)			(0.056)	(0.051)		
PCGDP			0.818***	0.850***			0.818***	0.702***
			(0.169)	(0.141)			(0.115)	(0.130)
Population			0.867***	0.878***			0.969***	0.935***
			(0.068)	(0.056)			(0.055)	(0.050)
Distance	-0.246	-0.313	-0.258	-0.318	-0.378***	-0.209***	-0.404***	-0.242***
	(0.255)	(0.261)	(0.230)	(0.244)	(0.082)	(0.070)	(0.081)	(0.063)
Contiguity	1.078***	0.909**	1.061***	0.904***	0.450	0.892**	0.412	0.855**
	(0.336)	(0.363)	(0.301)	(0.349)	(0.340)	(0.410)	(0.344)	(0.407)
Language	-0.011	-0.017	-0.029	-0.027	0.736***	0.740***	0.683***	0.658***
	(0.090)	(0.082)	(0.090)	(0.088)	(0.126)	(0.119)	(0.101)	(0.089)
Colony	0.435	0.411	0.394	0.387	0.990***	1.089***	0.859***	0.895***
	(0.403)	(0.388)	(0.312)	(0.304)	(0.205)	(0.203)	(0.230)	(0.220)
DoingBusiness	0.017**	0.023**	0.019	0.024*	0.028***	0.012	0.034***	0.020***
	(0.008)	(0.010)	(0.012)	(0.013)	(0.003)	(0.008)	(0.005)	(0.008)
Rule of Law		-0.113		-0.111		0.313**		0.330**
		(0.136)		(0.132)		(0.155)		(0.153)
Fixed effects:								
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	364	364	364	364	364	364	364	364
R-squared	0.658	0.660	0.658	0.660	0.707	0.705	0.709	0.708

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, and the binary variables, such as contiguity, language, and colony. Standard errors in parentheses are clustered at the industry level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 5: 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	15.106**	10.947*	16.156**	11.505*	20.125**	13.898*
	(7.003)	(6.633)	(7.115)	(6.701)	(8.029)	(7.194)
(Skill Overlap)^2	-9.063*	-6.696	-9.979**	-7.193	-12.472**	-8.708*
	(4.737)	(4.467)	(4.828)	(4.525)	(5.402)	(4.816)
GDP$_{source}$	1.179***	1.156***	1.204***	1.182***	1.193***	1.173***
	(0.075)	(0.071)	(0.075)	(0.072)	(0.072)	(0.068)
GDP$_{host}$	0.987***	0.930***	0.990***	0.934***	1.009***	0.944***
	(0.092)	(0.081)	(0.092)	(0.081)	(0.086)	(0.073)
Distance	-0.520***	-0.421***	-0.483***	-0.394***	-0.537***	-0.422***
	(0.091)	(0.088)	(0.095)	(0.092)	(0.095)	(0.087)
Contiguity	0.196	0.352	0.396*	0.477*	0.026	0.209
	(0.226)	(0.231)	(0.237)	(0.251)	(0.235)	(0.225)
Language	0.473**	0.276	0.361*	0.208	0.358*	0.177
	(0.199)	(0.199)	(0.216)	(0.211)	(0.203)	(0.202)
Colony	0.500**	0.393*	0.534**	0.412*	0.413*	0.299
	(0.230)	(0.219)	(0.226)	(0.220)	(0.226)	(0.213)
Rule of Law		0.655***		0.664***		0.717***
		(0.103)		(0.103)		(0.116)
Observations	2,179	2,179	2,219	2,219	1,777	1,777
R-squared	0.543	0.593	0.548	0.594	0.605	0.656

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 column (1) is extrapolated from M&A transactions from Thomson and Reuters. In column (2), affiliate revenue is imputed from FDI stocks from UNCTAD. Column (3) presents raw affiliate revenue from UNCTAD. All variables are in logarithms, except affiliate sales, the skill overlap indices, 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 6: Robustness Check: Offshoring and skill overlap, panel analysis
Dependent variable: Value Added

	(1)	(2)	(3)	(4)	(5)	(6)
Skill Overlap	2.419***	2.417***	2.362***	2.358***	2.380***	2.378***
	(0.759)	(0.758)	(0.765)	(0.758)	(0.797)	(0.796)
(Skill Overlap)^2	-1.474**	-1.471**	-1.444**	-1.440**	-1.460**	-1.457**
	(0.705)	(0.698)	(0.719)	(0.705)	(0.721)	(0.712)
GDP_{source}	0.855***	0.855***	0.854***	0.854***	0.854***	0.854***
	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)
GDP_{host}	0.842***	0.842***	0.845***	0.845***	0.845***	0.845***
	(0.041)	(0.041)	(0.042)	(0.042)	(0.041)	(0.040)
PCGDP_{source}	0.333***	0.332***	0.329***	0.328***	0.335***	0.334***
	(0.074)	(0.074)	(0.075)	(0.074)	(0.074)	(0.074)
PCGDP_{host}	0.175**	0.186	0.167**	0.175	0.172**	0.182
	(0.077)	(0.189)	(0.075)	(0.179)	(0.077)	(0.189)
Distance	-0.530***	-0.531***	-0.532***	-0.532***	-0.532***	-0.533***
	(0.053)	(0.054)	(0.053)	(0.055)	(0.053)	(0.054)
Contiguity	0.361**	0.360**	0.364**	0.363**	0.363**	0.362**
	(0.167)	(0.165)	(0.166)	(0.165)	(0.166)	(0.163)
Language	0.175**	0.177***	0.175**	0.176***	0.175**	0.177***
	(0.073)	(0.064)	(0.069)	(0.061)	(0.072)	(0.064)
Colony	0.278**	0.275*	0.252**	0.250*	0.253**	0.250*
	(0.129)	(0.145)	(0.123)	(0.142)	(0.126)	(0.142)
Rule of Law		-0.012		-0.008		-0.011
		(0.214)		(0.207)		(0.214)
Fixed effects:						
Industry	No	No	Yes	Yes	Yes	Yes
Year	Yes	Yes	No	No	Yes	Yes
Observations	98,436	98,436	98,436	98,436	98,436	98,436
R-squared	0.239	0.239	0.571	0.571	0.572	0.572

Notes: The dependent variable, value-added, is constructed using the World Input-Ouput Database (WIOD). It is defined as the value-added content embodied in the final goods that each country produces in each industry. We use years 1995, 2000, 2005, and 2010 to construct panel dataset. All variables are in logarithms, except value-added, the skill overlap indices, and the binary variables, such as contiguity, language, colony, and the rule of law. Standard errors in parentheses are two-way clustered at source country and host country as in Cameron, Gelbach and Miller (2012). *** p<0.01, ** p<0.05, * p<0.1.