Accounting for cross-country income differences: New evidence from multinational firms

Vanessa Alvarez  
UBC Sauder

Javier Cravino  
University of Michigan  
and NBER

Natalia Ramondo  
UCSD  
and NBER

June 2019

Abstract

We use data on the cross-border operations of multinational enterprises (MNE) to decompose cross-country differences in output-per worker into differences in ‘country-embedded factors’ vs. differences in ‘aggregate firm know-how’. By ‘country-embedded factors’ we refer to the components of productivity that are internationally immobile and impact all firms inside a country, such as institutions, natural amenities, and workers’ quality. In contrast, ‘firm know-how’ encompasses those components that generate differences across firms within a country, and which can be transferred internationally within firm boundaries, such as blue-prints and intangible capital. Our identification builds on the notion that MNEs can use their know-how around the world, but must use the factors that are embedded in the countries in which they produce. This implies that productivity differences between two affiliates of the same MNE that operate in different countries must be driven by country-embedded factors. We find that, across the countries in our sample, differences in aggregate firm know-how account for 40 percent of the cross-country differences in TFP, for 22 percent of the differences in output per-worker, and are strongly correlated to observed difference in income per-capita.

Keywords: Development Accounting, TFP, Multinational Firms

JEL Codes: O4, O1, F41, F23, F62

*Email: vanessa.alviarez@sauder.ubc.ca, jcravino@umich.edu, nramondo@ucsd.edu. We thank Ariel Burstein, Andrei Levchenko, Jonathan Vogel and seminar and workshop participants at the University of Michigan, UCLA and HKU for helpful suggestions.
1 Introduction

Differences in income per-capita across countries are enormous. Development accounting decomposes these differences into two determinants, factor stocks and total factor productivity (TFP), by comparing factor stocks across countries and computing TFP as a residual. A well-known challenge for this decomposition is that available measures of factor stocks may not be directly comparable across countries.\(^1\) In addition, the decomposition is silent about what determines TFP. Some theories emphasize the role of country-embedded factors, such as institutions, natural amenities, infrastructure, and workers’ quality. Others highlight the role of codified technological know-how that is accumulated by individual firms and can transferred across countries (e.g. blue-prints, intangible capital, management practices).

This paper introduces and implements a new framework to disentangle country-embedded factors from aggregate firm know-how using firm-level data on the cross-border operations of Multinational Enterprises (MNEs). By ‘country-embedded factors’ we refer to the components of productivity that are internationally immobile and impact all firms operating in a country. In contrast, ‘firm know-how’ refers to those components that generate productivity differences across firms inside a country, and which can be transferred internationally within firm boundaries. At the aggregate level, separating between these determinants is not straightforward, as different combinations of country-embedded factors and aggregate firm know-how can result in the same level of aggregate output per-worker.

Our framework builds on the notion that MNEs can use their idiosyncratic know-how around the world, but must use the factors that are embedded in the countries where they produce. This implies that productivity differences between two affiliates of the same MNE that operate in different countries must be driven by country-embedded factors. In contrast, differences between firm-level and aggregate productivity within a country depend only on the firm’s know-how relative to the aggregate firm know-how in the country, since all firms inside a country can use the same country-embedded factors.

We develop this logic in a standard model of horizontal multinational production to measure aggregate firm know-how using firm-level revenue data. The advantage of this approach is that, for a wide cross-section of countries, revenue data is much more readily available than productivity data at the firm-level. In the model, the revenue share of a MNE in a country depends only on its’ idiosyncratic know-how relative to the aggref-\(^1\)See for example the summaries in Klenow and Rodriguez-Clare (1997), Caselli (2005) and Hsieh and Klenow (2010) for a detailed description of these challenges.
gate firm know-how in the country. Since MNEs can use their know-how around the world, differences in revenue shares of the same MNE in two different countries pin-down the difference in aggregate firm know-how between those countries. Intuitively, MNEs should have larger revenue shares in countries where aggregate firm know-how is relatively scarce, since they face less competition in these countries.

Of course, MNEs may not be able to fully transfer their know-how across countries. In fact, a large literature has documented the importance of multinational production costs: MNEs tend to be larger in their home countries than abroad. Following this literature, we allow for imperfect technology transfers by assuming that MNEs can only use a (country-pair specific) fraction of their know-how when operating abroad. Under this assumption, the revenue share of an affiliate can be relatively low in a country both if aggregate firm know-how in that country is high, or if it faces large technology transfer costs. We show that if we observe MNEs from multiple source countries operating into multiple destinations, we can separately identify the technology transfer costs under assumptions that are common in the international trade and multinational production literature. These assumptions build on the notion that the technology transfer costs faced by say, French firms operating in Germany are informative about the technology transfer costs faced by German firms operating in France.

We implement our framework using data on MNEs sales from ORBIS, a worldwide dataset maintained by Bureau van Dijk. ORBIS documents detailed ownership information for a large set of firms operating in multiple countries. We use these data and the assumptions on the technology transfer costs to compute the aggregate firm know-how in each of country in our sample relative to France.

We show that differences in aggregate firm know-how account for 40 percent of the cross-country variance in TFP, and 22 percent of the cross-country variance in output per-worker in our sample of countries. In the average country, aggregate firm know-how is 0.12 log points lower than in France, about 40 percent of the observed 0.29 log-point difference in TFP. We find a strong correlation between our estimated differences in aggregate firm know-how and the observed cross-country differences in TFP and output per worker. Relative to income per-capita levels, aggregate firm know-how is particularly scarce in the Baltic countries (Estonia, Lithuania) and relatively high in the Balkans (Romania, Bulgaria) and in the Asian countries in our sample (Japan and Korea).

Cross-country differences in aggregate firm know-how can arise from cross-country differences in domestic firms, or from differences in the affiliates from foreign MNEs operating in the different countries. We disentangle between these two determinants by computing cross-country differences in the aggregate know-how embedded in domestic
firms, using a strategy that is analogous to the one described above. We show that most of the differences in aggregate firm know-how arise from differences in domestic firms. In fact, differences in the know-how embedded in the foreign affiliates of MNEs are not correlated with aggregate differences in TFP, and many developed and developing countries actually host better foreign affiliates than France.

Finally, we provide a decomposition of the differences in output per-worker in the manufacturing vs in the service sector. For the average country in our sample, the gap in aggregate firm know-how relative to France is smaller in manufacturing than in services (-0.12 vs. -0.17 log-points). In addition, differences in aggregate know-how account for only a quarter of the cross-country variance in output per worker in manufacturing, but for about a third of the cross-country variance in services. This implies that differences in country embedded factors are much more important for manufacturing than for service sectors.

A common caveat in the literature working with MNE data is that the decision to open affiliates in foreign markets is endogenous, and may be related to firm’s characteristics. In fact, a large empirical literature documents that MNEs are larger and more productive than domestic firms. In the theoretical literature that builds on the Melitz (2003) model, firms select into foreign markets based on their productivity or quality. We highlight that this type of selection does not present a problem for our estimation of aggregate firm know-how. Since we are always comparing the affiliates of the same MNE across countries, our estimation does not depend on the idiosyncratic know-how of the MNEs in our sample.

**Related literature:** Our paper is closely related to Burstein and Monge-Naranjo (2009), who separate country-embedded factors from firm know-how using aggregate data on FDI stocks in a setting where firm know-how is a rival factor. Their framework is based on the Lucas ‘span of control’ model and assumes that each firm or manager must choose one country in which to produce. Under these assumptions, firm know-how can be recovered from aggregate data using a non-arbitrage condition that equates after-tax managerial profits across countries. In contrast, our approach treats firm-embedded know as a non-rival factor that can be used simultaneously in many countries, and studies MNEs that manage affiliates in multiple countries. We build on this feature to estimate ag-

---

2See e.g. Javorcik (2004); Guadalupe et al. (2012); Fons-Rosen et al. (2013); and Alviarez (2018) among many others.

3See e.g. Helpman et al. (2004) and Arkolakis et al. (2018).

4This is the standard assumption in the multinational production literature, including McGrattan and Prescott (2009); Keller and Yeaple (2013) and Ramondo and Rodriguez-Clare (2013).
aggregate firm know-how using firm-level data on MNE sales across multiple countries. In that sense, our approach is similar to that in Hendricks and Schoellman (2018), who, exploiting the idea that workers take their human capital with them when they move across countries, use data on wage gains upon migration to separate human-capital from country-embedded factors that determine wages.

Our paper is also related to the large literature studying technology transfers through MNEs. Bilir and Morales (2016) and Cravino and Levchenko (2017) use parent-affiliate matched data to estimate how productivity and shocks are transmitted across parties of a MNE. In contrast, our focus is on splitting differences in aggregate firm know-how from differences in country-embedded factors across countries. The parent-affiliate matched data is what allows us to distinguish between these two components.

Finally, our paper is also related to the international trade literature that estimates country-level productivity shifters using gravity models (see Eaton and Kortum (2002), Waugh (2010), Ramondo and Rodríguez-Clare (2013), Arkolakis et al. (2018) and the long literature that followed). We show that in economies with heterogeneous firms and fixed costs, matched-firm level data is needed to separate cross-country differences in firm aggregate firm know-how, since aggregate data on MNE sales are contaminated by the selection concerns described above.

The rest of the paper is organized as follows. Section 2 develops our framework for disentangling aggregate firm know-how from country-embedded factors. Section 3 describes our data and empirical strategy. Section 4 presents our quantitative results, Section 5 conducts robustness checks, and Section 6 concludes.

2 Accounting framework

This section develops a framework that formalizes the distinction between firm know-how and country-embedded factors, and shows how firm-level data on the cross-border operations of MNEs can be used to decompose cross-country income differences into these two determinants.

2.1 A model economy

Preliminaries: We consider a world economy consisting of $N$ countries indexed by $i$ and $n$. Each country is populated by a continuum of differentiated intermediate goods.
producers that are owned by firms from different source countries. The output of the intermediate producers cannot be traded internationally. In each country, intermediates are aggregated into a final good by a competitive producer.

Technologies: The production function for the final good in each country \( n \) is given by

\[
Y_n = \left[ \sum_i \int [Q(\omega) Y_{in}(\omega)]^{1/\rho} dG_{in}(\omega) \right]^{\rho/(\rho - 1)},
\]  

where \( Y_{in}(\omega) \) is the output of intermediate producer \( \omega \) from source country \( i \) that operates in country \( n \), and \( \rho \) is the elasticity of substitution across intermediate goods. \( G_{in}(\omega) \) denotes the distribution of producers from country \( i \) that are active in country \( n \). \( Q(\omega) \) is a demand shifter for producer \( \omega \), which we interpret as product quality. For expositional purposes, for now we assume that the quality of product \( \omega \) is the same in all locations. We will relax this assumption below.

The production function for intermediate goods is

\[
Y_{in}(\omega) = Z_n X(\omega) L_{in}(\omega),
\]

where \( L_{in}(\omega) \) is the amount of labor employed by firm \( \omega \) in country \( n \). The productivity of the firm depends on a country specific component, \( Z_n \), and an idiosyncratic component, \( X(\omega) \). Following Burstein and Monge-Naranjo (2009) we refer to \( Z_n \) as “country-embedded productivity”, as it captures factors that are fixed in the country are not internationally mobile, such as infrastructure, workers’ quality, and natural amenities. In contrast, \( X(\omega) \) is a productivity term that is idiosyncratic to producer \( \omega \). Like product quality, for now we assume that the producers’ idiosyncratic productivity is the same in all locations.

It is useful to define \( A(\omega) \equiv Q(\omega) \times X(\omega) \). In what follows, we will refer to \( A(\omega) \) as “firm know-how”. It captures production, managerial, and marketing know-how that is specific to the firm. In contrast to country-embedded productivity, firm know-how can be transferred internationally within firm boundaries.

Aggregate output and TFP: The aggregate production function in country \( n \) is the maximum quantity of the final good that can be produced with the factors and technologies available in the country. It is defined by:

\[
Y(Z_n, \{G_{in}(\omega)\}_i, L_n) = \max Y_n,
\]
subject to (1), (2) and $L_n = \sum_i \int L_{in} (\omega) \, dG_{in} (\omega)$. It is easy to show that the aggregate production function can be written as:

$$Y_n = Z_n \Phi_n L_n,$$

where $\Phi_n \equiv \left[ \sum_i \int A (\omega) \rho^{-1} \, dG_{in} (\omega) \right]^{1/\rho-1}$ denotes aggregate firm know-how in country $n$, which is a sum of all firm know-how in country $n$.

In this simple economy, output per capita and TFP coincide, and are both given by $Y_n / L_n$. In what follows, we use lowercase to denote the log of a variable, and use $y_n \equiv \ln \left[ \frac{Y_n}{L_n} \right]$ to denote the log of output per-capita. We can thus write:

$$y_n = z_n + \phi_n. \quad (3)$$

Equation (3) states that cross-country differences in TFP arise from differences in country-embedded productivity, $z_n$, and differences aggregate firm know-how, $\phi_n$. Clearly, the same level of $y_n$ can arise form different combinations of $z_n$ and $\phi_n$, so that these two terms cannot be separated using aggregate data only. The next section shows how to use data on the cross-border operations of MNEs to compute $z_n$ and $\phi_n$.

### 2.2 Decomposing cross-country differences in income per-capita

We start by showing how cross-country differences in $z_n$ and $\phi_n$ can be computed using firm-level data on physical output per-worker. The log of output per-worker of firm $\omega$ is:

$$y_{in} (\omega) = z_n + x (\omega).$$

For MNEs that operate in two different countries we can compute:

$$y_{ii} (\omega) - y_{in} (\omega) = z_i - z_n. \quad (4)$$

Equation (4) shows how to compute cross-country differences in country-embedded productivity using firm-level data on output-per worker. Note that by comparing affiliates of the same MNE across countries, $x (\omega)$ cancelled-out from the equation. Intuitively, since MNEs can use their know-how in every country, the difference in output per-worker between two affiliates of the same MNE must be driven by differences in country-specific factors, $z_i - z_n$.

An alternative to (4) is to compute the difference between firm-level and aggregate
output per-worker in a given country:

\[ y_{in}(\omega) - y_n = x(\omega) - \phi_n. \]

By comparing firms within a country, the country-specific factors \( z_n \) cancelled-out from the above equation. For a MNE that operates in two countries we can compute

\[ [y_{in}(\omega) - y_n] - [y_{ii}(\omega) - y_i] = \phi_i - \phi_n. \]  

Equations (4) and (5) show how data on firm-level and aggregate output per-worker can be used to compute differences in aggregate firm know-how and country-embedded productivity. There are, however, two challenges that need to be addressed before taking these equations to the data. First, firm-level data on physical output per-worker is hard to obtain for a large cross-section of countries. Second, MNEs may not be able to perfectly transfer their know-how across countries. The following two sections extend our framework to deal with these challenges. Before doing so, we briefly discuss how our procedure may be affected if the decision to open affiliates in foreign countries is endogenous and the sample of firms that choose to become MNEs is selected.

**A note on selection:** A large empirical literature documents that MNEs are larger and more productive than domestic firms. In the theoretical literature on multinational production that builds on the Melitz (2003) model, firms select into foreign markets based on their productivity or quality.\(^6\) We highlight that this type of selection does not present a problem for the procedure described in equations (4) and (5). As noted above, by looking at the same MNE in two different countries, the idiosyncratic know-how of the firm(s) used to compute the left-hand side of these equations cancels-out. In fact, the equations imply that we can obtain differences in \( z_n \) and \( \phi_n \) using data from just one firm -any firm- that simultaneously operates in two countries.\(^7\)

### 2.3 Decomposition based on firm-level revenue data

This section shows how to compute the terms in equations (3) using firm-level data on multinational firm’s revenues. From the demand functions implied by (1), we can write

---

\(^6\)See e.g. Helpman et al. (2004) and Arkolakis et al. (2018).

\(^7\)Section 3.2 discusses other selection concerns after presenting the full quantitative model.
the revenue of a firm from country $i$ that operates in country $n$ as:

$$R_{in}(\omega) = \left[ \frac{A(\omega)}{\Phi_n} \right]^{\rho-1} R_n,$$

(6)

where $R_n \equiv \sum_i \int R_{in}(\omega) dG_{in}(\omega)$ denotes aggregate revenues in country $n$. Note that revenue per-worker does not depend on firm know-how in this economy, so taking differences in revenue-per worker in a way analogous to (4) is uninformative. Instead, we can compare firms within and across countries like we did in equation (5) and compute

$$[r_{in}(\omega) - r_n] - [r_{ii}(\omega) - r_i] = [\rho - 1] [\phi_i - \phi_n].$$

(7)

Equation (7) shows how to use firm-level revenue data to obtain $\phi_n$, up to the elasticity $\rho - 1$. It states that MNEs should have larger (log) revenue shares in countries where aggregate firm know-how is relatively low, since they will face less competition in these countries. After obtaining $\phi_i - \phi_n$, differences in country-embedded factors $z_n - z_i$ can then be computed as residuals form equation (3). The eat advantage of using revenue rather than quantity data is that the former is more readily available for multiple countries. On the other hand, it requires parameterizing the elasticity of substitution $\rho$. Section 3.2.2 describes our strategy for identifying this parameter using our data.

2.4 Imperfect technology transfers

We now extend our framework to allow for imperfect technology transfers. In particular, we assume that firm know-how is transferred imperfectly across countries, so that the know-how of firm $\omega$ from country $i$ that operates in country $n$ is

$$A_{in}(\omega) = A(\omega) \times \exp(-\kappa_{in}(\omega)),$$

(8)

with $\kappa_{ii}(\omega) = 0$. Here, $\kappa_{in}(\omega)$ is a technology transfer cost that captures the degree to which firm know-how can be moved across locations. If $\kappa_{in}(\omega) = 0$, then a multinational firm can use the same know-how in all the locations that it operates.

Under this assumption, equation (7) becomes:

$$[r_{in}(\omega) - r_n] - [r_{ii}(\omega) - r_i] = [\rho - 1] [\phi_i - \phi_n - \kappa_{in}(\omega)].$$

(9)

In this more general case in which $\kappa_{in}(\omega) \neq 0$, differences in revenue shares between affiliates and parents are not enough to identify differences in aggregate firm know-how.
As (9) makes clear, this is because the revenue share of an affiliate can be relatively low in country \( n \) if either firm know-how is relatively large in country \( n \) - high \( \phi_n \) - , or if the technology transfer costs are large - high \( \kappa_{ni}(\omega) \) - .

If we observe bilateral MNE sales from multiple source countries and into multiple destinations, we can identify \( \phi_i - \phi_n \) by imposing assumptions on \( \kappa_{ni}(\omega) \) that are common in the multinational production literature. In this case, we can write the analog equation to (7) for the firms from country \( n \) that operate in country \( i \):

\[
[r_{ni}(\omega) - r_i] - [r_{nn}(\omega) - r_n] = [\rho - 1] [\phi_n - \phi_i - \kappa_{ni}(\omega)].
\] (10)

Under standard assumptions on how the average \( \kappa_{in}(\omega) \) relates to the average \( \kappa_{ni}(\omega) \), equations (9) and (10) pin-down the differences \( \phi_n - \phi_i \).\(^8\) Section 3.2.1 details these assumptions and our estimation procedure.

### 2.5 Multiple factors of production and quantitative framework

We now incorporate additional factors of production. For our quantitative application, we assume that intermediate goods are produced with a Cobb-Douglas technology that uses labor, human capital, and physical capital,

\[
Y_{in}(\omega) = Z_n X_{in}(\omega) [H_n L_{in}(\omega)]^{1-\alpha} K_{in}(\omega)^\alpha.
\] (11)

Here \( L_{in}(\omega) \) and \( K_{in}(\omega) \) denote labor and the capital stock employed by firm \( \omega \) in country \( n \), and \( H_n \) is human capital per-worker in country \( n \). Note that we allow the idiosyncratic productivity \( X_{in}(\omega) \) to differ across locations. In addition, we continue to assume that the production of the final good is given by (1), but allow the idiosyncratic product quality \( Q_{in}(\omega) \) to differ across locations. We define firm know-how as

\[ A_{in}(\omega) \equiv Q_{in}(\omega) \times X_{in}(\omega), \]

and assume that it satisfies equation (8).

The aggregate production function satisfies

\[
Y_n = Z_n \Phi_n [H_n L_n]^{1-\alpha} K_n^\alpha
\]

with \( \Phi_n \equiv \left[ \sum_i \int A_{in}(\omega)^{\rho-1} dG_{in}(\omega) \right]^{\frac{1}{\rho-1}} \). Total factor productivity is given by:

\[
TFP_n \equiv \frac{Y_n}{[H_n L_n]^{1-\alpha} K_n^\alpha} = Z_n \Phi_n.
\]

\(^8\)For example, one potential assumption is that on average these technology transfer costs are symmetric, \( \sum_\omega \kappa_{in}(\omega) = \sum_i \kappa_{ni}(\omega) \).
Output per worker can be written as:

\[ \frac{Y_n}{L_n} = \tilde{Z}_n \Phi_n, \]

where \( \Phi_n \equiv \Phi_n^{1-\alpha} \). Here, \( \tilde{Z}_n \equiv Z_n^{1-\alpha} H_n \left[ \frac{k_n}{Y_n} \right]^{\alpha-\alpha} \) measures all country-specific factors, including physical and human capital, in addition to the country-embedded productivity \( Z_n \). We can thus write:

\[ tfp_n = z_n + \phi_n, \quad (12) \]

and

\[ y_n = \tilde{z}_n + \tilde{\phi}_n, \quad (13) \]

Equation (7) continues to hold in this more general setup, and can be used to compute the differences \( \phi_i - \phi_n \). These differences can be scaled by the labor share \( 1 - \alpha \) to obtain \( \tilde{\phi}_i - \tilde{\phi}_n \). Cross-country differences in \( z_n \) and \( \tilde{z}_n \) can then be computed as residuals from equations (13) and (12).

3 Data and empirical strategy

3.1 Data description

Firm level data: Our firm level-data comes from ORBIS, a worldwide dataset maintained by Bureau van Dijk that includes comprehensive information on firm’s revenue and employment. ORBIS includes information on both listed and unlisted firms collected from various country-specific sources, such as national registries and annual reports. The main advantage of ORBIS is the scope and accuracy of its ownership information: it details the full lists of direct and indirect subsidiaries and shareholders of each company in the dataset, along with a company’s degree of independence, its global ultimate owner and other companies in the same corporate family. This information allows us to build links between affiliates of the same firm, including cases in which the affiliates and the parent are in different countries. We specify that a parent should own at least 50% of an affiliate to identify an ownership link between the two firms.\(^9\)

\(^9\)Other studies that have previously used the ORBIS data to study multinational firms are Fons-Rosen et al. (2013), Cravino and Levchenko (2017), Alviarez et al. (2017) and Alfaro and Chen (2018).
The main variable used in the analysis is the revenue (turnover) of each firm. While the ORBIS data covers the 2005-2013 period, we use data for the year 2011 for most of our analysis. Figure 1 reports the number of MNEs from and in each country in our sample, and also reports ratio of the sum of all firm-level revenues in ORBIS to aggregate revenues as reported by KLEMS. The figure shows that the ORBIS data includes a large number of MNEs, and captures a large fraction of firm revenues in many countries. In what follows, we focus on a subset of countries for which aggregate revenues in ORBIS are at least half of the revenues reported by KLEMS. We also exclude Ireland and Norway from the sample, the former because of it’s tax heaven status, and the later because our framework is not well suited to understand TFP in oil producing countries. Our final sample is comprised of the countries in blue in Figure 1.

**Aggregate data:** In addition to the firm-level data, to implement equation (9) we need data on aggregate revenues. We construct firm-level revenue shares using firm-level revenues from ORBIS, and aggregate revenues from EU KLEMS. We also use EU KLEMS to obtain output per worker and TFP, along with the labor share \(1 - \alpha\) for a cross-section of countries. We construct this data using the EU KLEMS and Productivity Levels databases maintained by the Groningen Growth and Development Centre. A great advantage of these datasets is that they provide these variables both for the aggregate economy and at a sectorial level. This will allow us to also conducting our decompositions at the sectoral
level.

3.2 Empirical strategy

This section describes how we can implement equation (9) to measure differences in aggregate firm know-how using our data.

3.2.1 Disentangling firm-embedded productivity from technology transfers costs

We start by re-writing equation (9) in terms of log market shares:

\[ s_{in}(\omega) - s_{ii}(\omega) = [\rho - 1] [\phi_i - \phi_n] - [\rho - 1] \kappa_{in}(\omega). \]  

(14)

Here \( s_{in}(\omega) \equiv r_{in}(\omega) - r_n \) is the log of the revenue share of firm \( \omega \) from country \( i \) operating in country \( n \). We can compute the left-hand side of equation (14) for each multinational firm from country \( i \) that has revenues in countries \( i \) and \( n \). The technology transfer costs can be written without loss of generality as:

\[ \kappa_{in}(\omega) = \delta^o_i + \delta^l_n + \delta_{in} + \delta_{in}(\omega). \]  

(15)

Equation (15) states that technology transfer costs can be decomposed into origin and location specific components, \( \delta^o_i \) and \( \delta^l_n \), a bilateral component, \( \delta_{in} \), and an idiosyncratic component \( \delta_{in}(\omega) \). Since (15) includes origin- and location-specific components, this implies that \( \sum_i \sum_\omega \delta_{in}(\omega) = \sum_i \sum_\omega \delta_{in}(\omega) = 0. \)

We identify \( \phi_i \) and \( \phi_n \) by using (14) and imposing restrictions on the terms in (15). This strategy follows a long tradition in international economics that separates country-specific technologies from trade and multinational production costs using gravity equations. Like this literature, we assume that the bilateral component of the transfer costs is a log-linear function of observable characteristics for each country-pair, such as distance between the countries and whether they share a common language, \( \delta_{in} = a_1 dist_{in} + a_2 com_{in} \).

Substituting into equations (14) and (15) we obtain the estimating equation:

\[ s_{in}(\omega) - s_{ii}(\omega) = D^o_i + D^l_n + \beta_d dist_{in} + \beta_c com_{in} + \epsilon_{in}(\omega), \]  

(16)

where \( D^o_i \equiv [\rho - 1] [\Delta \phi_i - \Delta \phi^0] \) and \( D^l_n \equiv -[\rho - 1] [\Delta \phi_n + \Delta \phi^l] \) are country origin and location dummies, and the notation \( \Delta x_n \equiv x_n - x_b \) expresses the difference of a variable in country \( n \) vs. a reference country (i.e. the country for which the dummies are omitted). In what follows, we will use France as our reference country.
We then obtain \( [\rho - 1] \Delta \phi_i \) by imposing alternative identification restrictions on the transfer costs \( \Delta \delta^o_i \) and \( \Delta \delta^l_i \). First, we follow Eaton and Kortum (2002) and assume that costs have a destination-specific, but no source-specific component, \( \Delta \delta^o_n = 0 \). Under this assumption, we can compute

\[
D^o_n = [\rho - 1] \Delta \phi_n, \tag{17}
\]

and obtain the firm-embedded productivity of country \( n \) relative to France, scaled by the elasticity \( [\rho - 1] \). Alternatively, we can assume that costs have a source-specific, but no destination-specific component, \( \Delta \delta^l_n = 0 \), following Waugh (2010). In that case we compute

\[
-D^l_n = [\rho - 1] \Delta \phi_n. \tag{18}
\]

Finally, another restriction commonly used in the literature is that these costs are symmetric following Head and Ries (2001), so that \( \Delta \delta^o_n = \Delta \delta^l_n \). In this last case, we compute

\[
D^{sym}_n \equiv \frac{1}{2} \left[ D^o_n - D^l_n \right] = [\rho - 1] \Delta \phi_n. \tag{19}
\]

Figure 2 compares the estimates of \( [\rho - 1] \phi_n \) that correspond to each of these alternative assumptions. We use data for the 2011 year, with France as our reference country, so that the dummies should be interpreted as differences relative to France. The figure shows that the estimates from equations (18), (17), and (19) are remarkably close to each other. A regression of \( D^o_n \) (\( D^l_n \)) on \( D^{sym}_n \) has an the R-squared of 0.92 (0.87) and a slope of 1.12 (0.88). This implies that the estimates \( [\rho - 1] \phi_n \) are not very sensible to the choice of restrictions that underlie (17), (18), or (19). Appendix Figure A.1 shows very similar results if we separately estimate \( D^o_n \) and \( D^l_n \) for subsamples of manufacturing and service firms. In what follows, we will compute \( [\rho - 1] \Delta \phi_n \) using equation (19) for our baseline results.

### 3.2.2 Estimating the elasticity of substitution

Equation (19) identifies differences in \( \phi_n \) up to an elasticity \( \rho \). This section shows how this elasticity can be estimated using our data. Combining equations (12) and (13) with equation (19) we can write

\[
\Delta tf p_n = \frac{1}{\rho - 1} D^{sym}_n + \Delta z_n,
\]
Figure 2: Estimating firm-embedded productivity: alternative assumptions on $\kappa_{in}$

![Graphs showing EK vs. Head-Ries and Waugh vs. Head-Ries regressions](image)

Notes: Each circle represents a country. The axes ‘EK’, ‘Waugh’ and ‘Head and Ries’ respectively refer to the estimates of $\Delta D_{n}^{h} - \Delta D_{n}^{l}$ and $0.5 \times [\Delta D_{n}^{h} - \Delta D_{n}^{l}]$ from an OLS regression on equation (16).

\[
\Delta y_{n} = \frac{1}{1 - \alpha} \frac{1}{1 - \rho} D_{n}^{sym} + \Delta z_{n},
\]

where $D_{n}^{sym}$ is the estimate of $[\rho - 1] \Delta \phi_{n}$ obtained from (19).

One could estimate $\frac{1}{\rho-1}$ from an OLS regression of $\Delta t f p_{n}$ (or $\Delta y_{n}$) on $D_{n}^{sym}$, and compute $z_{n}$ and $\tilde{z}_{n}$ as the residuals from such regressions. Unfortunately, these estimates would not be consistent unless $D_{n}$ is orthogonal to $\Delta z_{n}$ and $\Delta \tilde{z}_{n}$. A concern would be that countries with policies that encourage accumulation of country-embedded factors captured in $\Delta \tilde{z}_{n}$ also improve aggregate firm know-how, $\Delta \phi_{n}$. One way to deal with this concern is to control for omitted factors embedded in $\Delta \tilde{z}_{n}$ that can simultaneously affect the accumulation of firm embedded productivity, such as the average human capital in the country or quality of institutions in country $n$. In particular we can estimate:

\[
\Delta t f p_{n} = b_0 + b_1 \hat{D}_{n}^{sym} + b_2 C_{n} + u_{n},
\]

and

\[
\Delta y_{n} = b_0^{y} + b_1^{y} \hat{D}_{n}^{sym} + b_2^{y} C_{n} + u_{n}^{y},
\]

where $C_{n}$ is a vector of controls that captures differences in human- and physical capital, and in institutions across countries. We can then obtain $\hat{\rho}$ from either $\rho = \frac{1}{b_1} + 1$ or $\rho = \frac{1}{b_1} \frac{1}{1 - \alpha} + 1$.

Table 1 reports these estimates. We present results both using data for the year 2011
(first panel), and also estimating $D_{n}^{sym}$ year-by-year in the ORBIS data for the 2005-2013 period and controlling for yearly-fixed effects (second panel). Columns (1) and (4) show the results of estimating equations (20) and (21) by OLS. The coefficients on $D_{n}^{sym}$ are 0.247 and 0.094, which imply values for $\rho$ of 7 and 11.6 respectively.\textsuperscript{10} We obtain very similar values if we control for the (log of the relative) capital-output ratio and the (log of the relative) years of schooling in the regression, as shown in Columns (2) and (5). If we also control for institutional variables, such as the quality of the rule of law and corruption, the coefficient on $D_{n}^{sym}$ decrease somewhat, which is consistent with and upward bias if these variable are omitted. In this case, the implied $\rho$’s increase to 11.6 and 17 (Columns 3 and 6). The second panel (labeled ‘pooled’) shows that we obtain very similar estimates if we pool our data across the 2005-2013 period and control for time effects. Give these estimates, we set a value of $\rho = 10$ for our baseline results. Note that this value is within the range of estimates used to match the average markups in the US (see i.e. Edmond et al. 2018).

\textsuperscript{10}To obtain these values, we compute $\rho = \frac{1}{\hat{\beta}} + 1$ and $\rho = \frac{1}{\hat{\beta}[1-\alpha]} + 1$, where $\hat{\beta}$ is the coefficient on $D_{n}$ on these regressions, and $1 - \alpha = 0.62$ is the labor share in France which we take from KLEMS.
Table 1: Estimating the elasticity of substitution: $\rho$

<table>
<thead>
<tr>
<th></th>
<th>Output per worker</th>
<th>TFP</th>
<th>Output per worker</th>
<th>TFP</th>
<th>Pooled</th>
<th>TFP</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Year 2011</td>
<td></td>
<td>Year 2011</td>
<td></td>
<td>Pooled</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
</tr>
<tr>
<td>$D_n$</td>
<td>0.247***</td>
<td>0.233***</td>
<td>0.140***</td>
<td>0.104***</td>
<td>0.062-</td>
<td>0.245***</td>
</tr>
<tr>
<td></td>
<td>[0.044]</td>
<td>[0.041]</td>
<td>[0.048]</td>
<td>[0.023]</td>
<td>[0.024]</td>
<td>[0.041]</td>
</tr>
<tr>
<td>$k_n/y_n$</td>
<td>0.332</td>
<td>0.042</td>
<td>-0.232-</td>
<td>-0.339***</td>
<td>0.372</td>
<td>0.183</td>
</tr>
<tr>
<td></td>
<td>[0.210]</td>
<td>[0.197]</td>
<td>[0.101]</td>
<td>[0.105]</td>
<td>[0.229]</td>
<td>[0.163]</td>
</tr>
<tr>
<td>$h_n$</td>
<td>0.611</td>
<td>-0.228</td>
<td>-0.338</td>
<td>-0.655-</td>
<td>0.596</td>
<td>0.047</td>
</tr>
<tr>
<td></td>
<td>[0.573]</td>
<td>[0.708]</td>
<td>[0.245]</td>
<td>[0.325]</td>
<td>[0.569]</td>
<td>[0.618]</td>
</tr>
<tr>
<td>Rule of law</td>
<td>0.514</td>
<td>0.144</td>
<td>0.128</td>
<td>-0.041</td>
<td>0.496</td>
<td>0.203</td>
</tr>
<tr>
<td>Corruption</td>
<td>0.173</td>
<td>0.136</td>
<td>0.428</td>
<td>0.280-</td>
<td>0.361</td>
<td>0.145</td>
</tr>
<tr>
<td></td>
<td>[0.496]</td>
<td>[0.203]</td>
<td>[0.438]</td>
<td>[0.209]</td>
<td>[0.361]</td>
<td>[0.145]</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Obs.</th>
<th></th>
<th>R-squared</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>23</td>
<td>23</td>
<td>0.45</td>
<td>0.48</td>
<td>0.78</td>
<td>0.36</td>
</tr>
<tr>
<td></td>
<td>23</td>
<td>23</td>
<td>0.36</td>
<td>0.44</td>
<td>0.75</td>
<td>0.44</td>
</tr>
<tr>
<td></td>
<td>158</td>
<td>158</td>
<td>0.44</td>
<td>0.50</td>
<td>0.77</td>
<td>0.38</td>
</tr>
<tr>
<td></td>
<td>158</td>
<td>158</td>
<td>0.38</td>
<td>0.43</td>
<td>0.74</td>
<td>0.74</td>
</tr>
<tr>
<td><strong>Implied $\rho</strong></td>
<td>7.0</td>
<td>7.4</td>
<td>11.6</td>
<td>11.6</td>
<td>10.6</td>
<td>17.0</td>
</tr>
<tr>
<td></td>
<td>7.1</td>
<td>7.5</td>
<td>11.8</td>
<td>10.5</td>
<td>9.9</td>
<td>15.6</td>
</tr>
</tbody>
</table>

Notes: ‘TFP’ reports the estimates from equation (20). ‘Output per worker’ reports the estimates from equation (21). ‘Year 2011’ report results using data from 2011, and ‘Pooled’ reports results using data from 2005-2012, and controlling from year fixed effects.
4 Quantitative results

This section uses the estimates obtained in Section 3 to decompose differences in TFP and output per-worker across countries according to equations (12) and (13). Figure 3 reports the results of these decompositions. The x-axis shows the log-difference in TFP and output per worker in each country relative to France, $\Delta t f p_n$ and $\Delta y_n$. In the y-axis, the red circles show the difference in aggregate firm know-how in each country relative to France, $\Delta \phi_n$ and $\Delta \phi^*_n$, and the blue squares show the differences in country-embedded productivities and country-embedded factors relative to France, $\Delta z_n$ and $\Delta \tilde{z}_n$. All the data correspond to the year 2011.

Figure 3a shows substantial differences in aggregate firm know-how across the countries in our sample. For the average country, aggregate firm know-how is 0.12 log points lower than in France, while TFP is 0.29 log points lower than in France. Thus, on average, differences in firm-know how account for about 40 percent of the TFP gap with France for our set of countries. Note, however, that there is wide variation across countries. Firm know-how in France is about the same as in the large developed nations in our sample, Italy, Netherlands and Korea, and is somewhat larger in Japan and Germany (0.07 log-difference relative to France). In contrast, firm-know how is quite low in the eastern European countries, such as Romania, Hungary and Estonia.

Figure 3b shows our decomposition in terms of output per-worker, following equation (13). For the average country, $\Delta \tilde{\phi}_n$ is -0.17, compared to a log-difference in output per worker relative to France of -0.55. Unsurprisingly, differences in country-embedded factors $\Delta \tilde{z}_n$ are larger than differences in county-embedded productivities, $\Delta z_n$, since former also captures differences in human capital and capital-output ratios across countries.

Figure 3a and 3b reveal a strong positive relation between cross-country differences in firm-embedded productivity and both TFP and output per worker. We can compute the share of the cross-country variance in both TFP and output per-worker that can be accounted for by the terms in equation (12) and (13), in the spirit of Klenow and Rodriguez-Clare (1997). This corresponds to the slopes of a bivariate OLS regression of $\Delta \phi_n$ (resp. $\Delta \tilde{\phi}_n$) on $\Delta t f p_n$ (resp. $\Delta y_n$), which are reported in the figures. Differences in aggregate firm know-how $\Delta \phi_n$ account for 40 percent of the cross-country variance of in TFP, while difference $\tilde{\phi}_n$ account for 22 percent of the cross-country variance in output per-worker.

**Sectorial results:** We now conduct the decomposition in equation (13) separately for the Manufacturing and the Service sectors. We perform our sectorial decomposition in terms of output per-worker only using data on labor productivity from KLEMS, since we don’t
Notes: Each circle represents a country. Figure (3a), plots the decomposition in equation (12), where $\Delta tfp_n$ is plotted in the x-axis and $\Delta z_n$ and $\Delta \phi_n$ are plotted in the y-axis. Figure (3b), plots the decomposition in equation (13), where $\Delta y_n$ is plotted in the x-axis and $\Delta \tilde{z}_n$ and $\Delta \tilde{\phi}_n$ are plotted in the y-axis.

have any sectorial data on differences TFP levels.

Figure 4 reports the results from the sectorial decompositions. For the average country, the gap in aggregate firm know-how relative to France is smaller in manufacturing than in services (-0.12 vs. -0.15). In addition, differences know-how account for only a quarter of the cross-country variance in output per worker in manufacturing, but for about a third of the cross-country variance in services. This implies that differences in country embedded factors are much more important for manufacturing than for service sectors.

4.1 Understanding differences in aggregate firm know-how

Cross-country differences in aggregate firm know-how $\Delta \phi_n$ may arise from two reasons. First, the know-how of a country’s domestic firms may be large. Alternatively, a country may be good at attracting foreign MNEs that have high know-how. This section decomposes differences in aggregate firm know-how into these two determinants. In particular, from the definition of $\Phi_n$ we can write:

$$\Phi_n \equiv \left[ \sum_i \int A_{in} (\omega) \rho^{-1} dG_{in} (\omega) \right]^{\frac{1}{\rho-1}} = \left[ \Phi_{in}^{\rho-1} + \sum_{i \neq n} \Phi_{in}^{\rho-1} \right]^{\frac{1}{\rho-1}},$$

where $\Phi_{in} \equiv \left[ \int A_{in} (\omega) \rho^{-1} dG_{in} (\omega) \right]^{\frac{1}{\rho-1}}$ is the aggregate know-how of the firms from country $i$ that operate in country $n$, and $\Phi_{nn}$ denotes the aggregate know-how of the
Figure 4: Development accounting: Manufacturing vs. Services

Manufacturing

Services

Notes: Each circle represents a country. The figures plot the decomposition in equation (13) at a sector level. \( \Delta y_n \) is plotted in the x-axis and \( \Delta \tilde{z}_n \) and \( \Delta \tilde{\phi}_n \) are plotted in the y-axis for sectors \( j = \) Manufacturing (first panel) and \( j = \) services (second panel).

domestic firms. We are interested in decomposing cross-country differences in \( \Phi_n \). We note that we can write aggregate know-how relative to France as

\[
\frac{\Phi_n}{\Phi_F} = \left[ \Phi_F^{-1} \lambda + \frac{\Phi_F^{-1}}{\Phi_{IF}} \sum_{i \neq n} [\Phi_F^{-1} \Phi_{IN}^{-1} [1 - \lambda]] \right]^{1/\rho-1},
\]

where \( \lambda \equiv \frac{\Phi_{FF}}{\Phi_F} = \frac{\Phi_F^{-1}}{\Phi_{FF}} \) denotes the revenue share of French firms in France. To compute the terms in this equation, we follow the same steps used to derive equation (9) and obtain:

\[
[r_{in}(\omega) - r_{nn}] - [r_{ii}(\omega) - r_{ii}] = [\rho - 1] [\phi_{ii} - \phi_{nn} - \kappa_{in}(\omega)].
\]

The difference between equations (9) and (23) is that (9) compares firm-level vs. aggregate revenues a country \( n \), \( r_{in}(\omega) - r_n \), while (9) compares firm-level vs. total revenues by domestic firms a country \( n \), \( r_{in}(\omega) - r_n \). As equation (23) shows, the latter help us pin down the cross-country differences in the aggregate know-how of domestic firms, \( \phi_{ii} - \phi_{nn} \). We estimate this differences following the same procedure that we described in Section 3. Then, we can compute \( \frac{\Phi_F^{-1}}{\Phi_{FF}} \), and obtain \( \frac{\sum_{i \neq n} \Phi_{IN}^{-1}}{\sum_{i \neq F} \Phi_{IF}} \) as a residual from equation (22).

Unlike equation (13), equation (9) is not log-linear. We evaluate the contribution of
Figure 5: Differences in aggregate know-how of domestic vs. foreign MNEs

Notes: The first panel shows $\Delta \phi_n$ (y-axis), and $\Delta tfp$ (x-axis), already depicted in Figure 3. The second panel plots the two terms in equation (24) (y-axis) and $\Delta tfp$ (x-axis).

The differences in the domestic firms know-how, $\Phi_{nn}$, to aggregate differences in know-how, $\Phi_{n}$, in two alternative wages. First we compute

$$Y_{1nn}^1 \equiv \left[ \frac{\Phi_{nn}^{\rho-1}}{\Phi_{FF}^{\rho-1}} \lambda + [1 - \lambda] \right]^{\frac{1}{1-\rho}},$$

where alternatively, we also compute

$$Y_{2nn}^2 = \frac{\Phi_n}{\Phi_F} \left[ \lambda + [1 - \lambda] \frac{\sum_{i \neq n} \Phi_{in}^{\rho-1}}{\sum_{i \neq F} \Phi_{iF}^{\rho-1}} \right]^{\frac{1}{1-\rho}}.$$

Note that to a first order approximation around a symmetric equilibrium, these two coincide and are given by:

$$ln Y_{1nn}^1 \simeq ln Y_{2nn}^2 \simeq \lambda_{FF} \Delta \phi_{nn},$$

and the difference in aggregate firm know-how is

$$\Delta \phi_n \simeq \lambda \Delta \phi_{nn} + [1 - \lambda] \Delta \phi_{Fnn}.$$

Figure 5 shows the terms in equation (24). Differences in aggregate know-how of domestic firms account for the majority of the differences in aggregate firm know-how. In fact, differences in the know-how embedded in the foreign affiliates of MNEs (computed as a residual using (24) and depicted in green) are not correlated with aggregate differences in TFP, and many developed and developing countries actually have better foreign affiliates than France.
5 Robustness and alternative measurement strategies

5.1 Estimation with employment data

Equation (16) shows how data on revenue-shares can be used to compute differences in aggregate firm know-how. Note that, since in this model revenue shares and employment shares coincide, we could have used data on employment shares to compute these differences. We show that our results are not sensitive to this choice. In particular, we re-estimate equation (16) using data on log-employment shares as the dependent variable. The resulting estimates of $\Delta \phi_n$ are plotted in Figure 6a and are compared to our baseline estimates. The figure shows that these two estimates are quite close to each other, though the differences relative to France tend to be somewhat larger when computed with the employment. We use the revenue data as our baseline, since it is available for a much larger set of firms in ORBIS.

5.2 Estimation within narrow industries

An important assumption behind our estimates is that parents and affiliates use the same production functions. One may be concerned that this assumption is violated if parent and affiliates operate in different industries. In this section, we restrict our sample of MNEs to parents and affiliates that operate in the same 2-digit SIC sector. Figure 6b shows that our these alternative estimates lie very close to our original estimates.

5.3 Measurement issues in the aggregate data

We now show how our estimates are affected if statistical agencies mismeasure aggregate output per worker and TFP. In particular, assume that statistical agencies cannot perfectly measure $\Delta TFP$. Instead, they measure a Solow residual, which is computed as

$$\Delta \tilde{p}_n = \Delta r_n - \Delta p_n - \Delta l_n$$

$$= \Delta t f p_n + \Delta p_n - \Delta P_n.$$  

Here, $p_n$ is a price deflator used by the statistical agency that expresses prices in country $n$ relative to prices in country 0, and $P_n$ is the ideal price index associated with (1).\footnote{This follows from the definitions of aggregate revenues and the ideal price index, $R_n = \sum_i \int P_i(\omega)Y_i(\omega)dG_i(\omega) = P_n Y_n$.}
Figure 6: Robustness

(a) Estimation with employment data

(b) Industry-level matching

Notes: Each circle represents a country. The figures plot the decomposition in equation (12) at a sector level. \( \Delta y_{jn} \) is plotted in the x-axis and \( \Delta \hat{z}_{jn} \) and \( \Delta \hat{\phi}_{jn} \) are plotted in the y-axis for sectors \( j = \)Manufacturing (first panel) and \( j = \)services (second panel).

In this case, differences in measured TFP are given by:

\[
\Delta \tilde{f}P_n = \Delta z_n + \Delta \phi_n + \epsilon_n,
\]

where \( \epsilon_n \equiv \Delta p_n - \Delta P_n \) is the bias that arises if the statistical agency mismeasures the ideal price index. Note, however, that it is still possible to use equation (9) to obtain \( \Delta \phi_n \) from the sales data.

5.4 Estimation with aggregate data

A large literature in international trade uses gravity models to estimate country-level productivity shifters from aggregate trade or multinational production data. This section describes how our procedure relates to this literature and underscores the importance of the firm-level data for measuring aggregate firm know-how.

We can close the model in Section 2.5 by assuming that firms are heterogeneous and there are fixed costs of producing abroad. We also assume for simplicity that the technology transfer costs are common across firms, \( \kappa_{in}(\omega) = \kappa_{in} \). Letting \( R_{in} \) denote total sales by country \( i \)'s firms that operate in country \( n \) we can write:

\[
\frac{R_{in}}{R_n} = \left[ \frac{\Phi_{in} \exp \left( -\kappa_{in} \right)}{\Phi_n} \right]^{\rho - 1}.
\]
Here we defined $\Phi_{in} \equiv \left[ \int A(\omega)^{\rho-1} dG_{in}(\omega) \right]^{1/\rho-1}$, and omit country subscripts from $A(\omega)$ since we factored-out the technology transfer costs $\kappa_{in}$ in from equation (25). The share of country $i$’s firms in their home market is:

$$\frac{R_{ii}}{R_i} = \left[ \frac{\Phi_{ii}}{\Phi_i} \right]^{\rho-1}. \quad (26)$$

Taking logs and subtracting yields:

$$s_{in} - s_{ii} = \left[ \rho - 1 \right] \left[ \phi_i - \phi_n \right] - \kappa_{in} + \left[ \phi_{in} - \phi_{ii} \right], \quad (27)$$

where $\phi_{in} \equiv \ln \Phi_{in}$ and $s_{in} \equiv \ln \left[ \frac{R_{in}}{R_n} \right]$. Note that his equation differs from equation (14) since left hand side has differences in aggregate shares instead of firm-level shares. As we are no longer comparing the same MNE across-countries, the term $\phi_{in} - \phi_{ii}$ shows up in the equation, capturing that not every firms from country $i$ operating in country $n$. That is, the aggregate know-how of the MNEs from country $i$ that operate in country $n$ may differ from that of the firms that operate in country $i$, even after taking out the technology transfer costs $\kappa_{in}$. Thus, selection into being a multinational firm will affect the estimates of $\phi_i - \phi_n$ based on equation (27).

### 6 Conclusion

This paper used data on the cross-border operations of multinational enterprises (MNE) to decompose cross-country differences in output-per worker into differences in ‘country-embedded factors’ vs. differences in ‘aggregate firm know-how’. Across the countries in our sample, differences in aggregate firm know-how account for 40 percent of the cross-country differences in TFP, for 22 percent of the differences in output per-worker, and are strongly correlated to observed difference in income per-capita. Differences in aggregate firm know-how are mainly driven by differences in the productivity of domestic firms, while differences in the productivity of foreign MNE affiliates are uncorrelated to income per-capita.
References


Figure A.1: Estimating firm-embedded productivity by sector

**Manufacturing**

- Slope: 1.04 (0.12), $R^2$: 0.90

**Services**

- Slope: 0.91 (0.06), $R^2$: 0.90
Table A1: Estimating the elasticity of substitution: $\rho$

<table>
<thead>
<tr>
<th></th>
<th>Year 2011 Manufacturing</th>
<th>Year 2011 Services</th>
<th>Pooled Manufacturing</th>
<th>Pooled Services</th>
</tr>
</thead>
<tbody>
<tr>
<td>$D_n$</td>
<td>0.400***</td>
<td>0.339**</td>
<td>0.190***</td>
<td>0.388***</td>
</tr>
<tr>
<td></td>
<td>[0.0976]</td>
<td>[0.117]</td>
<td>[0.0503]</td>
<td>[0.0329]</td>
</tr>
<tr>
<td>$\ln \left( k_n / y_n \right)$</td>
<td>1.114**</td>
<td>0.336</td>
<td>0.874***</td>
<td>0.281***</td>
</tr>
<tr>
<td></td>
<td>[0.417]</td>
<td>[0.233]</td>
<td>[0.189]</td>
<td>[0.0851]</td>
</tr>
<tr>
<td>$h_n$</td>
<td>0.908</td>
<td>-0.227</td>
<td>0.677</td>
<td>0.0192</td>
</tr>
<tr>
<td></td>
<td>[0.990]</td>
<td>[1.329]</td>
<td>[0.574]</td>
<td>[0.340]</td>
</tr>
<tr>
<td>Rule of law</td>
<td>0.662</td>
<td>0.556</td>
<td>0.235</td>
<td>0.312*</td>
</tr>
<tr>
<td></td>
<td>[0.883]</td>
<td>[0.574]</td>
<td>[0.222]</td>
<td>[0.161]</td>
</tr>
<tr>
<td>Corruption</td>
<td>0.383</td>
<td>-0.000122</td>
<td>0.730***</td>
<td>0.163</td>
</tr>
<tr>
<td></td>
<td>[0.643]</td>
<td>[0.495]</td>
<td>[0.153]</td>
<td>[0.124]</td>
</tr>
<tr>
<td>Observations</td>
<td>19</td>
<td>19</td>
<td>24</td>
<td>156</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.38</td>
<td>0.52</td>
<td>0.43</td>
<td>0.38</td>
</tr>
<tr>
<td>Implied $\rho$</td>
<td>5.5</td>
<td>5.1</td>
<td>6.3</td>
<td>10.4</td>
</tr>
</tbody>
</table>

Notes: *p < 0.1, **p < 0.05, ***p < 0.01.