

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

Vanessa Alviarez
UBC Sauder

Javier Cravino
University of Michigan
and NBER

Natalia Ramondo
UCSD
and NBER

January 2020

Abstract

We develop a new accounting framework to decompose cross-country differences in output-per worker into differences in ‘country-embedded factors’ and 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 in 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 that can be transferred internationally, such as blue-prints, management practices and intangible capital. Our approach relies on data on the cross-border operations of multinational enterprises (MNEs). It builds on the notion that MNEs can use their know-how around the world, but they must use the factors from the countries where they produce. We find a strong positive correlation between our measure of aggregate firm know-how and external measures of TFP and output per worker across countries. In our sample, differences in aggregate firm know-how account for about 30 percent of the observed cross-country differences in TFP, and for 20 percent of the differences in output per-worker.

Keywords: Development Accounting, TFP, Multinational Firms

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

*Email: vanessa.alviarez@sauder.ubc.ca, jcravino@umich.edu, qramondo@ucsd.edu. We thank Ariel Burstein, David Lagakos, Andrei Levchenko, Todd Schoellman, Sebastian Sotelo, Jonathan Vogel, and seminar participants at various conferences and institutions for helpful suggestions.

1 Introduction

Differences in income per-capita across countries are enormous. Development accounting decomposes these differences into two components, factor stocks and total factor productivity (TFP), by measuring factor stocks across countries and computing TFP as a residual. The decomposition is silent about the determinants of TFP. Some theories emphasize the role of country-embedded factors, such as institutions, natural amenities, infrastructure, and workers' quality.¹ Others highlight the role of codified technological know-how that is accumulated by individual firms and can be transferred across countries (e.g. blueprints, patents, intangible capital, management practices).²

This paper introduces a new framework to disentangle country-embedded factors from aggregate firm know-how and their contributions to cross-country income differences. By 'country-embedded factors' we refer to the components of productivity that are internationally immobile and affect 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 that can be transferred internationally. 'Aggregate firm-know how' is the know-how embedded in all the firms in a country. Separating between these components 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.³

Our approach separates these components by exploiting data on the cross-border operations of multinational enterprises (MNEs). We build on the notion that MNEs can use their know-how in several distinct locations, but must use the factors that are specific to the countries where they produce. This implies that differences in performance between two affiliates of the same MNE that operate in two different countries must reflect differences in 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 operating in a country can use the same country-embedded factors.

We develop this logic in a multinational production model and measure aggregate firm know-how using firm-level revenue data. In the model, the revenue share of a MNE in a

¹See, for example, the surveys in [Acemoglu et al. \(2014\)](#) and [Caselli \(2016\)](#).

²See, for example, [Markusen \(1984\)](#); [Branstetter et al. \(2006\)](#); [Bloom and Reenen \(2007\)](#); [Antras et al. \(2008\)](#); [McGrattan and Prescott \(2009\)](#); [Bloom et al. \(2012\)](#); [Keller and Yeaple \(2013\)](#); [Bilir \(2014\)](#); and [Gumpert \(2018\)](#).

³[Burstein and Monge-Naranjo \(2009\)](#) is an early attempt to separate these two components using aggregate data. We explain how we relate to their work below.

country depends only on the MNEs' know-how relative to the aggregate 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.⁴ Following this literature, we allow for imperfect technology transfers by assuming that MNEs can only use a (firm-destination 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 in multiple destinations, we can separately identify the technology transfer costs under assumptions that are common in the international trade and multinational production literature (Eaton and Kortum, 2002; Waugh, 2010; Ramondo and Rodríguez-Clare, 2013; and Head and Mayer, 2014). These assumptions build on the notion that the technology transfer costs faced by, say, French firms operating in Germany are informative about the average technology transfer costs faced by German firms operating in France.

We implement our framework using data on MNE revenues from ORBIS, a worldwide dataset maintained by Bureau van Dijk. 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 build these links at the firm-sector level to ensure that the affiliates in our comparisons are producing similar goods and services across countries.

We use these data to estimate the key structural equation from our model, which states that the log of a firms' revenue share can be written as the sum of a firm-sector-specific

⁴See, for example, Yeaple (2008).

component, a destination-sector-specific component, and the technology transfer costs. We fit a two-way fixed-effect model and impose standard assumptions on the technology transfer costs to measure cross-country differences in aggregate firm know-how from the estimated destination fixed-effects.⁵ We find that for the average country, aggregate firm know-how is 0.14 log points lower than in France, more than 40 percent of the 0.30 log-point difference in TFP between France and the average country. However, the relative importance of aggregate firm know-how vs. country-embedded productivity differences varies considerably across country-pairs. For example, country-embedded factors are similar in Spain and Slovakia, but Spain has much higher aggregate firm know-how than Slovakia, which generates significant differences in TFP between these two countries. In contrast, aggregate firm know-how is similar in Spain and in Mexico, though TFP is much higher in Spain due to a large difference in country-embedded factors between these countries.

We show that there is a strong positive correlation between aggregate firm know-how and both TFP and output per worker. It is worth noting that while the development accounting literature documents a positive correlation between TFP and output per worker, it computes TFP as a residual using output per worker data. In contrast, we directly measure a component of TFP (aggregate firm know-how) using data on MNEs revenue shares, and show that this component is strongly correlated with external measures of both TFP and output per worker. In fact, differences in aggregate firm know-how account for over a quarter of the observed cross-country variance in TFP, and for one fifth of the cross-country variance in output per-worker. Differences in country-embedded factors account for the remaining 71 percent of the differences in TFP across countries, and 79 percent of the differences in income per capita.

We then evaluate why cross-country differences in aggregate firm know-how are so large. First, we show that aggregate firm know how is strongly correlated to TFP and output per worker across countries, but is orthogonal to production factors such as human capital or capital output ratios. Second, we show that these differences arise within sectors, and not are driven by cross-country differences in the sectorial composition of the economy. Third, we provide a decomposition of the differences in output per-worker in the manufacturing and in the service sector separately. Differences in aggregate firm know-how account for a quarter of the cross-country variance in output per worker in manufacturing, and for about a fifth of the cross-country variance in services. This implies that

⁵For our destination effects to be unbiased, the assignment of MNEs to countries must not be driven by the destination-specific component of the technology transfer costs. We evaluate how this assumption affects our results in Section 5.

differences in country embedded factors are relatively more important for services than for manufacturing sectors.

Finally, cross-country differences in aggregate firm know-how may arise from differences in the know-how of both foreign and domestic firms. We show that differences across domestic firms account for roughly 80 percent of the observed differences in firm-know how across countries. Differences across the affiliates of foreign multinationals account for the remaining 20 percent.

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 where 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 know-how as a non-rival factor that can be used (at a cost) simultaneously in many countries.⁶ This feature forms the basis of our methodology to measure aggregate firm know-how using firm-level data on MNE operations in multiple countries. In that sense, our approach is similar to that in [Hendricks and Schoellman \(2018\)](#), who exploit the idea that workers can take their human capital with them when moving to a foreign country. Using data on wage gains upon migration, they evaluate the role of human-capital in explaining cross-country income differences.

Our paper is also related to the large literature studying technology transfers through MNEs.⁷ [Cravino and Levchenko \(2017\)](#) and [Bilir and Morales \(Forthcoming\)](#) use parent-affiliate matched data to estimate how productivity and shocks are transmitted across parties of a MNE. In contrast, our focus is on measuring the contribution of aggregate firm know-how vs country-embedded factors in explaining cross-country income and TFP differences. As in those papers, the parent-affiliate matched data are key for our measurement strategy.

Finally, our measurement strategy uses tools from the international trade literature that

⁶This is the standard assumption in the multinational production literature, starting with [Markusen \(1984\)](#), and more recently [Helpman et al. \(2004\)](#), [Guadalupe et al. \(2012\)](#), [Irrazabal et al. \(2013\)](#), and [Ramondo \(2014\)](#).

⁷A non-exhaustive list of theoretical contributions includes [Markusen \(1984\)](#); [McGrattan and Prescott \(2009\)](#); [Keller and Yeaple \(2013\)](#); [Ramondo and Rodríguez-Clare \(2013\)](#); and [Fan \(2017\)](#).

estimates country-level productivity shifters using gravity models and aggregate revenue data (see Eaton and Kortum, 2002; Waugh, 2010; Ramondo and Rodríguez-Clare, 2013, and the long literature that followed). In economies with heterogeneous firms that select into becoming MNEs, having matched-firm level data is key to separate cross-country differences in aggregate firm know-how without taking a stand on the precise nature of selection—this is not the case when one uses aggregate MNE data.

The rest of the paper is organized as follows. Section 2 presents the accounting framework. Section 3 describes the data and our empirical strategy. Section 4 presents the quantitative results. Section 5 conducts robustness checks, and Section 6 concludes.

2 Accounting framework

This section first develops a stylized framework to formalize the distinction between firm know-how and country-embedded factors, and to illustrate how firm-level data on the cross-border operations of MNEs can be used to decompose cross-country income differences into these two components. It then presents a quantitative version of this framework that allows for multiple sectors and factors of production.

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 good producers that are owned by firms from different source countries. We refer to a firm that simultaneously operates in multiple countries as a MNE. Intermediate goods 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

$$\mathcal{Y}_n = \left[\sum_i \int_{\omega \in \Omega_{in}} [Q_{in}(\omega) Y_{in}(\omega)]^{\frac{\rho-1}{\rho}} d\omega \right]^{\frac{\rho}{\rho-1}}, \quad (1)$$

where $Y_{in}(\omega)$ is the output of firm ω from source country i that operates in country n , and ρ is the elasticity of substitution across intermediate goods. Ω_{in} denotes the set of firms

from country i that are active in country n . $Q_{in}(\omega)$ is a demand shifter for producer ω , which we interpret as product quality. Note that the idiosyncratic product quality $Q_{in}(\omega)$ can differ across production locations.

The production function for intermediate goods is

$$Y_{in}(\omega) = Z_n X_{in}(\omega) L_{in}(\omega), \quad (2)$$

where $L_{in}(\omega)$ is the amount of labor employed by firm ω in country n . The productivity of the firm depends on a country-specific component, Z_n , and a firm-specific component, $X_{in}(\omega)$. 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 and are not internationally mobile, such as infrastructure, workers’ quality, and natural amenities. In contrast, $X_{in}(\omega)$ is a productivity term that is idiosyncratic to firm ω . Like product quality, the idiosyncratic productivity $X_{in}^j(\omega)$ can differ across production locations.

It is useful to define $A_{in}(\omega) \equiv Q_{in}(\omega) \times X_{in}(\omega)$. In what follows, we will refer to $A_{in}(\omega)$ 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. We assume that firm know-how is transferred imperfectly across countries, so that the know-how of firm ω from country i that operates in country n is

$$A_{in}(\omega) = A_i(\omega) \times \exp(-\kappa_{in}(\omega)), \quad (3)$$

with $\kappa_{ii}(\omega) = 0$. Here, $A_i(\omega)$ is the know-how that firm ω has in its home country, and $\kappa_{in}(\omega)$ is a technology transfer cost that captures the degree to which firm know-how can be moved across countries. If $\kappa_{in}(\omega) = 0$, then a firm can use the same know-how in all the countries where it produces.

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:

$$Y(Z_n, \{G_{in}(\omega)\}_i, L_n) = \max \mathcal{Y}_n,$$

subject to (1), (2) and $L_n = \sum_i \int_{\omega \in \Omega_{in}} L_{in}(\omega) d\omega$. It is easy to show that the aggregate production function can be written as:

$$Y_n = Z_n \Phi_n L_n,$$

where

$$\Phi_n \equiv \left[\sum_i \int_{\omega \in \Omega_{in}} A_{in}(\omega)^{\rho-1} d\omega \right]^{\frac{1}{\rho-1}}, \quad (4)$$

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 $y_n \equiv \ln[Y_n/L_n]$ to denote the log of output per-capita. We can thus write:

$$y_n = z_n + \phi_n. \quad (5)$$

Equation (5) states that cross-country differences in TFP arise from differences in country-embedded productivity, z_n , and differences in aggregate firm know-how, ϕ_n . Clearly, the same level of y_n can be achieved with different combinations of z_n and ϕ_n , so that these two terms cannot be separated using only aggregate data. Next, we show how to use data on the cross-border operations of MNEs to separate z_n from ϕ_n .

2.2 Decomposing cross-country differences in income per-capita

We now show how cross-country differences in z_n and ϕ_n can be computed using firm-level revenue data. From the demand functions implied by (1), we can write the revenue share of a firm from country i that operates in country n as:

$$S_{in}(\omega) \equiv \frac{P_{in}(\omega) Y_{in}(\omega)}{\sum_i \int_{\omega \in \Omega_{in}} P_{in}(\omega) Y_{in}(\omega) d\omega} = \left[\frac{A_{in}(\omega)}{\Phi_n} \right]^{\rho-1}.$$

A firm's share depends on its know-how, $A_{in}(\omega)$, relative to the know-how of all the other firms in the economy, Φ_n . Intuitively, MNEs should have larger revenue shares in countries where aggregate firm know-how is relatively low, since they face less competition in these countries. Importantly, country-embedded productivity Z_n does not affect

the revenue shares $S_{in}(\omega)$ since it proportionally affects all the firms producing in the same country.

We build on this intuition to identify cross-country differences in Φ_n . We can substitute for (3) and write the share in logs as:

$$s_{in}(\omega) = [\rho - 1] [a_i(\omega) - \phi_n - \kappa_{in}(\omega)]. \quad (6)$$

Equation (6) shows that if technology transfer costs do not vary across destinations, $\kappa_{in}(\omega) = \kappa_i(\omega)$, cross-country differences in revenue shares across affiliates of the same MNE pin-down differences in ϕ_n , up to an elasticity $\rho - 1$. In this case, one could regress firm-level revenue shares on firm- and destination-level dummies, and use the destination dummies to recover cross-country differences in ϕ_n . The firm-level dummies would capture the differences in $a_i(\omega) - \kappa_i(\omega)$ across firms, while the cross-country variation in shares within an MNE would identify the differences in ϕ_n .⁸ After obtaining cross-country differences in ϕ_n , differences in country-embedded factors, z_n , can be computed as residuals from (5). This will be the basis of our estimation strategy described in Section 3.2.

In the more general case where technology transfer costs vary across destinations, differences in revenue shares across affiliates of the same MNE are not enough to identify differences in aggregate firm know-how. As (6) 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 ϕ_n -, or if the costs to transfer technology into that country are large -high $\kappa_{in}(\omega)$ -. Section 3.2 shows how, if we observe bilateral MNE sales from multiple source countries and into multiple destinations, we can identify differences in ϕ_n by imposing assumptions on the structure of $\kappa_{in}(\omega)$ that are common in the trade and multinational production literature.

2.3 Quantitative model

We now extend our framework to incorporate additional sectors and factors of production. We assume that in each country there are J sectors indexed by j , and that a competi-

⁸If $\kappa_{in}(\omega)$ differed only between home and foreign markets, i.e. $\kappa_{ii}(\omega) = 0$ and $\kappa_{in}(\omega) = \kappa_i(\omega) > 0$, one could follow this procedure using only the sample of foreign affiliates.

tive producer of final goods aggregates sectorial output according to:

$$Y_n = \prod_j \left[Y_n^j \right]^{\theta_n^j}. \quad (7)$$

Here, Y_n^j denotes the final output from sector j . Sectorial output is produced by aggregating intermediate goods

$$Y_n^j = \left[\sum_i \int_{\omega \in \Omega_{in}^j} \left[Q_{in}^j(\omega) Y_{in}^j(\omega) \right]^{\frac{\rho-1}{\rho}} d\omega \right]^{\frac{\rho}{\rho-1}}, \quad (8)$$

where $Y_{in}^j(\omega)$ is the output of intermediate firm ω from country i in sector j . $Q_{in}^j(\omega)$ denotes the quality of firm ω .

Intermediate goods in each sector are produced with a Cobb-Douglas technology that uses labor, human capital, and physical capital,

$$Y_{in}^j(\omega) = Z_n^j X_{in}^j(\omega) \left[H_n L_{in}^j(\omega) \right]^{1-\alpha^j} K_{in}^j(\omega)^{\alpha^j}. \quad (9)$$

The variables $L_{in}^j(\omega)$ and $K_{in}^j(\omega)$ denote labor and capital employed by firm ω in country n and sector j , and H_n is human capital per-worker in country n . We allow for the idiosyncratic productivity $X_{in}^j(\omega)$ to differ across production locations. As in the previous section, we define firm know-how as $A_{in}^j(\omega) \equiv Q_{in}^j(\omega) \times X_{in}^j(\omega)$, and assume that it satisfies (3).

Aggregate output in each sector satisfies:

$$Y_n^j = Z_n^j \Phi_n^j \left[H_n L_n^j \right]^{1-\alpha^j} \left[K_n^j \right]^{\alpha^j},$$

where $\Phi_n^j \equiv \left[\sum_i \int_{\omega \in \Omega_{in}^j} A_{in}^j(\omega)^{\rho-1} d\omega \right]^{\frac{1}{\rho-1}}$ is the aggregate know-how in sector j .

The aggregate production function is given by

$$Y_n = Z_n \Phi_n \left[H_n L_n \right]^{1-\alpha_n} K_n^{\alpha_n}.$$

Here $\Phi_n \equiv \prod_j \left[\Phi_n^j \right]^{\theta_n^j}$ and $Z_n \equiv \bar{\theta}_n \prod_j \left[Z_n^j \right]^{\theta_n^j}$ are geometric averages of aggregate firm-know how and country embedded productivities across sectors, and $\alpha_n \equiv \sum_j \theta_n^j \alpha^j$ is the

aggregate labor share.

Total factor productivity is given by

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

and output per worker can be written as

$$\frac{Y_n}{L_n} = \tilde{Z}_n \tilde{\Phi}_n,$$

with $\tilde{\Phi}_n \equiv \Phi_n^{\frac{1}{1-\alpha}}$ and $\tilde{Z}_n \equiv Z_n^{\frac{1}{1-\alpha}} H_n \left[\frac{K_n}{Y_n} \right]^{\frac{\alpha}{1-\alpha}}$. Note that \tilde{Z}_n includes physical and human capital, in addition to the country-embedded productivity Z_n . We can thus write:

$$tfp_n = z_n + \phi_n, \quad (10)$$

and

$$y_n = \tilde{z}_n + \tilde{\phi}_n. \quad (11)$$

We can compute the terms in equations (11) and (10) following steps analogous to those described in Section (2.2). In particular, the (log) revenue share of firm ω operating in country n in sector j is

$$s_{in}^j(\omega) = [\rho - 1] \left[a_i^j(\omega) - \phi_n^j - \kappa_{in}^j(\omega) \right], \quad (12)$$

A firm's share in a sector depends on its know-how, $a_i^j(\omega)$, relative to the know-how of the other firms in the sector, ϕ_n^j . As explained in the previous section, we can use differences in sectorial revenue shares across affiliates of the same MNE that are located in different countries to pin-down differences in ϕ_n^j . These differences can then be aggregated according to $\phi_n = \sum_j \theta_n^j \phi_n^j$ to obtain differences in aggregate know-how, and then scaled by the labor share $1 - \alpha_n$ to obtain $\tilde{\phi}_n$. Finally, cross-country differences in z_n and \tilde{z}_n can then be computed as residuals from (10) and (11), respectively.

Finally, we are interested in evaluating the contribution of aggregate firm know-how to the cross-country variance of TFP and income per-worker. We will follow [Klenow and](#)

Rodriguez-Clare (1997) and measure these contributions as:

$$1 = \frac{\text{cov}(tfp_n, z_n)}{\text{var}(tfp_n)} + \frac{\text{cov}(tfp_n, \phi_n)}{\text{var}(tfp_n)}. \quad (13)$$

and

$$1 = \frac{\text{cov}(y_n, \tilde{z}_n)}{\text{var}(y_n)} + \frac{\text{cov}(y_n, \tilde{\phi}_n)}{\text{var}(y_n)}. \quad (14)$$

The next section explains how we implement this variance decomposition in our data.⁹

3 Data and empirical strategy

3.1 Data description

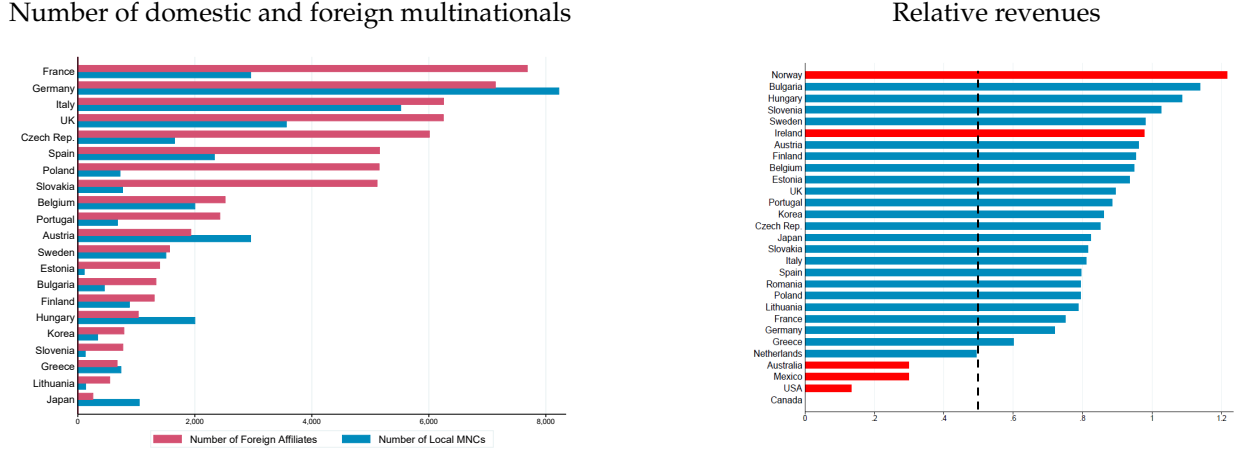
Firm level data: Our firm-level data come from ORBIS, a worldwide dataset maintained by Bureau van Dijk that includes comprehensive information on firm’s revenue and employment. ORBIS includes information on both listed and unlisted firms collected from various country-specific sources, such as national 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 percent of an affiliate to identify an ownership link between the two firms.¹⁰

The main variable used in our analysis is the revenue (turnover) of each firm. While the ORBIS data cover the 2005-2013 period, we use data for the year 2011 for most of our analysis. The left panel of Figure 1 reports the number of MNEs from and in each country in our sample, while the right panel reports the 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 include a large number of MNEs, and captures a large fraction of firm revenues in

⁹The decomposition in (13) follows from $\text{Var}(tfp_n) = \text{Cov}(tfp_n, tfp_n) = \text{Cov}(tfp_n, z_n) + \text{Cov}(tfp_n, \phi_n)$. Equation (14) is derived analogously.

¹⁰Other studies that have previously used the ORBIS data to study MNEs are Fons-Rosen et al. (2013), Cravino and Levchenko (2017), Alvarez et al. (2017) and Alfaro and Chen (2018).

Figure 1: Data coverage



Notes: In the left panel, ‘Number of foreign affiliates’ reports the number of foreign-owned affiliates in each country. ‘Number of local multinational’ reports the number of MNEs from each country. The right panel plots the ratio of total revenues in ORBIS to total revenues reported by KLEMS, for each country in our sample. Countries in bright red are not included in our final sample.

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 EU KLEMS. We also exclude Ireland and Norway from the sample, the former because of its 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 the right panel of Figure 1.

Aggregate data: In addition to the firm-level data, the implementation of (6) requires data on aggregate revenues for each country. 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 $[1 - \alpha_n]$, for a cross-section of countries. We construct these variables 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 both these variables for the aggregate economy and at a sectoral level. This disaggregation will allow us to also conduct our decompositions at the sectoral level.

Computing firm-level revenue shares: To implement the procedure in Section 2 we need to compute sectorial revenue shares at the firm level, $s_{in}^j(\omega)$. The original unit of ob-

servation in the raw ORBIS data is a tax identification number (tax-id). In many instances, different affiliates or plants that belong to the same corporate group are registered under different tax-ids in the same county. Our first step is to aggregate the employment and revenue data in ORBIS to make the unit of observation a corporate group-country-sector triplet. This means that a firm ω in the model corresponds to a corporate group in the data.

With this in mind, we add up revenues and employment across all the ORBIS firms that belong to the same corporate group and are in the same country and sector. For example, ORBIS shows multiple tax-identification numbers belonging to Renault in France in the Transportation and Equipment sector. We aggregate the revenues of these affiliates to obtain the Renault's total revenues in this sector in France. Our comparisons are at the firm-sector level. Continuing our example, that means we compare affiliates of Renault's in Transportation and Equipment sector and separately compare Renault's Retail affiliates across countries.

Our second step in computing revenue shares is to divide the revenues of each corporate group-country-sector by the aggregate revenues in each country-sector. Since ORBIS may not always cover the population of firms in each country-sector, we take this aggregate data from KLEMS.

3.2 Empirical strategy

This section describes how we measure cross-country differences in aggregate firm know-how ϕ_n using the ORBIS data. Our strategy builds on (12) and imposes structure on the technology transfer costs. This strategy follows a long tradition in International Economics that separates country-specific technologies from trade and multinational-production costs using gravity equations.¹¹

We assume that technology transfer costs are given by:

$$\kappa_{in}^j(\omega) = O_i^j + D_n^j + B_{in}^j + \varepsilon_{in}^j(\omega). \quad (15)$$

The assumption states that technology transfer costs can be decomposed into origin- and destination-specific components, O_i^j and D_n^j , a bilateral component, B_{in}^j , and a firm-destination specific component $\varepsilon_{in}^j(\omega)$. In addition, we assume that the bilateral com-

¹¹See eg. Eaton and Kortum (2002), Waugh (2010), Ramondo and Rodríguez-Clare (2013), and Head and Mayer (2014).

ponent of the transfer costs is symmetric and a log-linear function of observable characteristics of each country pair, such as distance and sharing a language, $B_{in}^j = a_d^j dist_{in} + a_l^j lang_{in}$.¹²

Substituting (15) into (12) we obtain the estimating equation:

$$s_{in}^j(\omega) = \delta_i^j(\omega) + \mathbb{A}_n^j + \mathbb{P}_n^j + \beta_d^j dist_{in} + \beta_l^j lang_{in} + \epsilon_{in}^j(\omega). \quad (16)$$

Here, \mathbb{A}_n^j is a set of dummies that take the value of 1 if the destination country is n and the firm is an affiliate, $i \neq n$, while \mathbb{P}_n^j is a set of dummies that take the value of 1 if the destination country is n and the firm is a parent, $i = n$. $\delta_i^j(\omega)$ are firm-level fixed-effects. The regression identifies the firm-effect $\delta_i^j(\omega)$ from the firms' average revenue share across destinations, controlling for destination characteristics and for the bilateral component of the technology transfer costs. Similarly, the destination effects \mathbb{A}_n^j (\mathbb{P}_n^j) are identified from the average revenue shares of the foreign affiliates (parents) that operate in each country, controlling for firm characteristics and the bilateral component of the technology transfer costs. The residual $\epsilon_{in}^j(\omega)$ is (the negative of) the firm-destination specific component of the technology transfer costs.

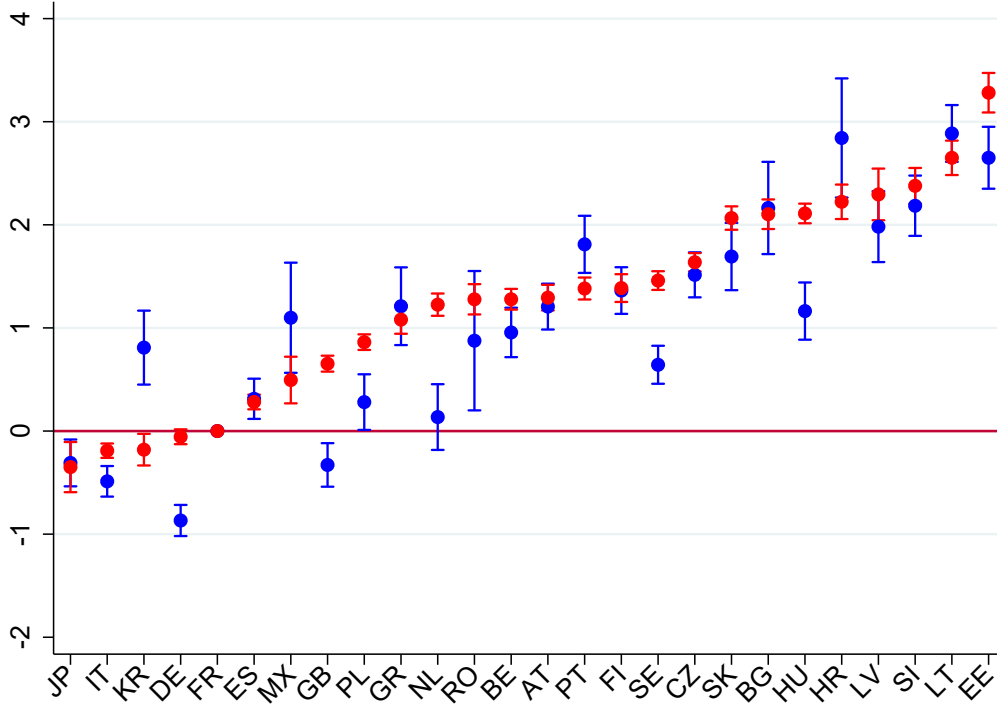
For the OLS estimates of the country effects to be unbiased, the assignment of MNEs to countries must be exogenous with respect to $\epsilon_{in}^j(\omega)$. This property is satisfied in most workhorse multinational-production models that build on Melitz (2003) (e.g. Helpman et al., 2004). In these models, selection is driven by firm and country characteristics, not by firm-destination specific costs. For the remainder of this section, we will assume that MNEs do not select into countries based on $\epsilon_{in}^j(\omega)$. Section 5 evaluates this assumption and shows that our main results are robust to reestimating our model using subsamples of our data where the assumption is most plausible.¹³

Estimated country effects: In what follows, we use the notation $\Delta x_n \equiv x_n - x_r$ to express the difference of a variable in country n with respect to France, which will be used as our reference country. The variables of interest are the destination-level dummies, which under our assumptions can be interpreted as $\Delta \mathbb{A}_n^j \equiv [1 - \rho] [\Delta \phi_n^j + \Delta D_n^j]$ and $\Delta \mathbb{P}_n^j \equiv [1 - \rho] [\Delta \phi_n^j - \Delta O_n^j]$. Using country-sector level expenditure shares and follow-

¹²Section 5 shows that we obtain very similar results under alternative assumptions for B_{in}^j .

¹³In particular, Section 5 shows that we obtain very similar estimates if we focus on a subset of large MNEs. These MNEs operate in most destinations and are less likely to select based on firm-destination specific costs.

Figure 2: Estimated country effects



Note: Red (blue) dots are OLS estimates of ΔA_n (ΔP_n) from (16). Bars reflect 5-percent confidence intervals, clustered at the country level.

ing the notation $\Delta x_n \equiv \sum \theta_n^j \Delta x_n^j$ to aggregate across sectors, we can compute aggregate country effects, $\Delta A_n \equiv [1 - \rho] [\Delta \phi_n + \Delta D_n]$ and $\Delta P_n \equiv [1 - \rho] [\Delta \phi_n - \Delta O_n]$.

Figure 2 reports our estimates of ΔA_n (red) and ΔP_n (blue). The country effects are precisely estimated and vary dramatically across countries. In particular, the country effects tend to be small in the richest countries in our sample, and large in the relatively poor Eastern European countries. Appendix Table A1 reports point estimates and standard errors for the sector-level estimates of the country effects, ΔA_n^j and ΔP_n^j . Note that to construct $\Delta P_n \equiv \sum_j \theta_n^j \Delta P_n^j$ we need data on at least one parent in each sector j . Since not every country in our sample has a parent firm operating in each sector, we can only compute ΔP_n for a subsample of countries. In addition, since there are more affiliate than parent firms, the affiliate dummies ΔA_n are more precisely estimated than the parent dummies ΔP_n . Appendix Table A1 reports the estimated coefficients on bilateral distance and common language, β_d^j and β_l^j , for each sector. Most of these estimates are significantly different from zero, ranging from -0.50 to -0.10 for distance, and from 0.15 to 0.60 for language.

Disentangling aggregate firm know-how from technology transfer costs: Finally, we obtain differences in aggregate firm know-how $\Delta\phi_n$ using our estimated country effects $\Delta\mathbb{A}_n$ and $\Delta\mathbb{P}_n$, and imposing alternative identification assumptions on either ΔO_n or ΔD_n . We describe these assumptions in steps. First, following [Waugh \(2010\)](#), we can assume that costs have an origin-specific, but not destination-specific component, $\Delta D_n = 0$. In that case, the affiliate dummies

$$\Delta\mathbb{A}_n = [1 - \rho] \Delta\phi_n, \quad (17)$$

can be interpreted as the firm-embedded know-how in country n relative to France, scaled by the elasticity $[1 - \rho]$. What happens if this identification assumption is not satisfied, $\Delta D_n \neq 0$? If ΔD_n is high for low TFP countries (i.e. it is harder to transfer technology into less developed countries), then $cov(\Delta tfp_n, \Delta D_n) \leq 0$. This implies that estimates of $\Delta\phi_n$ that are based on (17) will understate the contribution of aggregate firm know-how to the cross-country variance of TFP:¹⁴

$$cov\left(\Delta tfp_n, \frac{\Delta\mathbb{A}_n}{1 - \rho}\right) = cov(\Delta tfp_n, \Delta\phi_n + \Delta D_n) \leq cov(\Delta tfp_n, \Delta\phi_n). \quad (18)$$

Alternately, we can follow [Eaton and Kortum \(2002\)](#) and assume that costs have a destination-specific, but no origin-specific, component, $\Delta O_n = 0$. Under this assumption,

$$\Delta\mathbb{P}_n = [1 - \rho] \Delta\phi_n \quad (19)$$

can be interpreted as the firm-embedded know-how in country n relative to France, scaled by $[1 - \rho]$. If the assumption is not satisfied and the origin-specific component of the transfer cost is higher for low TFP countries, $cov(\Delta tfp_n, \Delta O_n) \leq 0$, estimates based on (19) will overstate the contribution of aggregate firm know-how to the cross-country variance of TFP:

$$cov\left(\Delta tfp_n, \frac{\Delta\mathbb{P}_n}{1 - \rho}\right) = cov(\Delta tfp_n, \Delta\phi_n - \Delta O_n) \geq cov(\Delta tfp_n, \Delta\phi_n). \quad (20)$$

The discussion above highlights that, if technology transfer costs into/out of low-TFP countries are large, then our two alternative identification assumptions on the technology transfer cost provide a lower and an upper bound for the contribution of aggregate firm

¹⁴As noted in Section 2, we will measure decompose the variance of Δtfp_n according to (13), and measure the contribution of aggregate firm know-how by: $cov(\Delta tfp_n, \Delta\phi_n) / var(\Delta tfp_n)$.

know-how to the cross-country variance of TFP:

$$\frac{\text{cov}\left(\Delta t f p_n, \frac{\Delta A_n}{1-\rho}\right)}{\text{var}\left(\Delta t f p_n\right)} \leq \frac{\text{cov}\left(\Delta t f p_n, \Delta \phi_n\right)}{\text{var}\left(\Delta t f p_n\right)} \leq \frac{\text{cov}\left(\Delta t f p_n, \frac{\Delta P_n}{1-\rho}\right)}{\text{var}\left(\Delta t f p_n\right)}. \quad (21)$$

In what follows, we report our baseline results for $\Delta \phi_n$ using the restrictions imposed in (17).¹⁵ Section 5 reports results based on (17), and shows that the bounds in (21) are relatively tight.

3.2.1 Estimating the elasticity of substitution

Finally, we need a value for the elasticity ρ to recover ϕ_n from (17). This section shows how this elasticity can be estimated using our data. Combining (10) and (11) with (17), we can write

$$\Delta t f p_n = \frac{1}{1-\rho} \Delta A_n + \Delta z_n,$$

and

$$\Delta y_n = \frac{1}{1-\rho} \frac{\Delta A_n}{1-\alpha_n} + \Delta \tilde{z}_n,$$

where ΔA_n is obtained from (17).

One could estimate $\frac{1}{1-\rho}$ from an OLS regression of $\Delta t f p_n$ (or Δy_n) on ΔA_n , and compute z_n and \tilde{z}_n as the residuals from such regressions. Unfortunately, these estimates would not be consistent unless ΔA_n is orthogonal to Δz_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 included in $\Delta \tilde{z}_n$ that can simultaneously affect the accumulation of firm embedded productivity, such as the average human capital or the quality of institutions in country n . In particular, we can estimate:

$$\Delta t f p_n = b_0 + b_1 \Delta A_n + b_2 C_n + u_n, \quad (22)$$

¹⁵This is a natural choice for our baseline specification since, as highlighted above, the dummies ΔA_n are more precisely estimated than the dummies ΔP_n .

and

$$\Delta y_n = b_0^y + b_1^y \frac{\Delta A_n}{1 - \alpha_n} + b_2^y C_n + u_n^y, \quad (23)$$

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 $\rho = 1 - \frac{1}{\hat{\beta}_1}$ or $\rho = 1 - \frac{1}{\hat{\beta}_1^y}$.

Table 1 reports these estimates. We present results both using data for the year 2011 (first panel), and also estimating ΔA_n pooling years for the period 2005-2013 and controlling for year-fixed effects (second panel). Columns (1) and (4) show the results of estimating (22) and (23) without any additional control. The coefficients on ΔA_n are -0.153 and -0.096, which imply values for ρ of 7.5 and 11.3 respectively.¹⁶ 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 ΔA_n decrease somewhat, which is consistent with and upward bias if these variable are omitted. In this case, the implied ρ 's increase to 11 and 16.6 (Columns 3 and 6). We obtain comparable estimates if we pool our data across the 2005-2013 period and control for year-fixed effects. Given these estimates, we set a value of $\rho = 10$ for our baseline results. This value is within the range of estimates used to match the average markups in the United States (see i.e. Edmond et al. 2018).

¹⁶To obtain these values, we compute $\rho = 1 - \frac{1}{\hat{\beta}}$ and $\rho = 1 - \frac{1}{\hat{\beta}[1-\alpha]}$, where β is the coefficient on ΔA_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: ρ

	Year 2011						2005-2011					
	Output per worker			TFP			Output per worker			TFP		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ΔA_n	-0.153*** [0.0328]	-0.146*** [0.0393]	-0.095*** [0.0314]	-0.096*** [0.029]	-0.096*** [0.030]	-0.064** [0.026]	-0.157*** [0.033]	-0.141*** [0.037]	-0.099*** [0.030]	-0.099*** [0.031]	-0.101*** [0.031]	-0.075*** [0.025]
k_n/y_n		0.581** [0.233]	-0.032 [0.182]		-0.145 [0.106]	-0.409*** [0.086]		0.671*** [0.229]	0.067 [0.151]		-0.100 [0.091]	-0.374*** [0.075]
h_n		1.406** [0.523]	-0.316 [0.674]		0.165 [0.295]	-0.549** [0.248]		1.178** [0.472]	-0.203 [0.646]		0.042 [0.259]	-0.562** [0.220]
Rule of law			0.606*** [0.095]			0.242*** [0.039]			0.582*** [0.089]			0.250*** [0.036]
Obs.	26	26	26	26	26	26	205	205	205	205	205	205
R-squared	0.29	0.44	0.80	0.25	0.31	0.74	0.29	0.46	0.78	0.26	0.28	0.71
Implied ρ	7.52	7.83	11.53	11.39	11.37	16.58	7.36	8.08	11.10	11.09	10.88	14.41

Notes: 'TFP' reports the estimates from (22). 'Output per worker' reports the estimates from (23). 'Year 2011' report results using data from 2011, and 'Pooled' reports results using data from 2005-2012, and controlling for year fixed effects.

4 Quantitative results

This section combines the estimates from (17) with our elasticity estimates to decompose differences in TFP and output per-worker across countries into country-embedded factors and aggregate firm know-how. Figure 3 plots the result of this decomposition. The x-axis shows the log-difference in TFP and output per worker in each country relative to France, Δtfp_n and Δy_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 $\Delta\tilde{\phi}_n$, while the blue squares show the differences in country-embedded productivities and country-embedded factors relative to France, Δz_n and $\Delta\tilde{z}_n$. All the data correspond to the year 2011.

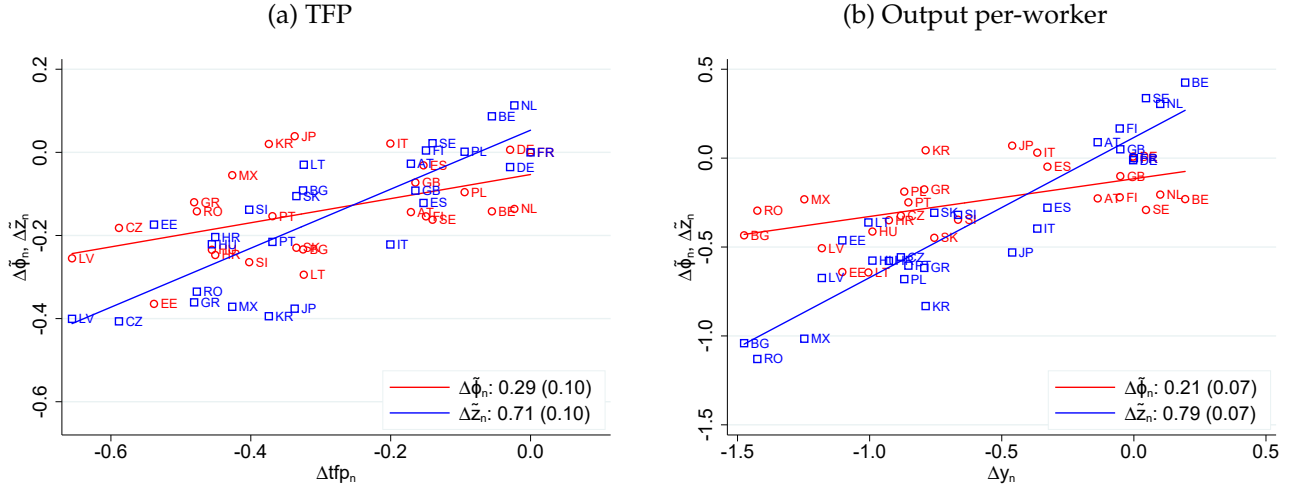
Figure 3a shows our decomposition in terms of TFP, following (10). For the average country, aggregate firm know-how is 0.14 log points lower than in France, more than 40 percent of the 0.30 log-point difference in TFP between France and the average country. There is, however, a wide variation across countries. Firm know-how in France is about the same as in some of the large developed nations in our sample, such as Germany and Korea, and is somewhat smaller than in Japan (0.05 log-difference relative to France). In contrast, firm know-how is quite low in the Eastern European countries, such as Lithuania, Slovenia and Estonia.

The relative importance of aggregate firm know-how vs. country-embedded productivity differences also varies considerably across country-pairs. For example, Spain and Slovakia (both EU members) have similar levels of country-embedded productivity. However, Spain has much higher aggregate firm know-how, which generates significant differences in TFP between these two countries. In contrast, aggregate firm know-how is similar for Spain and Mexico, though TFP is much higher in Spain due to a large difference in country-embedded productivity.

Figure 3b shows our decomposition in terms of output per-worker, following (11). For the average country, $\Delta\tilde{\phi}_n$ is 0.25 log points lower than in France, compared to a log-difference in output per-worker relative to France of -0.62, more than 30 percent of the observed log-point difference in output per-worker. The implied log-difference in country-embedded factors for the average country relative to France, $\Delta\tilde{z}_n$, is -0.37 .

Figures 3a and 3b reveal a strong positive relation between cross-country differences in aggregate firm know-how and both TFP and output per worker. It is worth noting that the development accounting literature documents a positive correlation between TFP and output per worker, but it computes TFP as a residual using output per worker data. In

Figure 3: Development accounting: Aggregate firm know-how and country-embedded factors.



Notes: Each circle (square) represents a country. Figure (3a) plots the decomposition in (10), where Δtfp_n is plotted in the x-axis and Δz_n and $\Delta \phi_n$ are plotted in the y-axis. Figure (3b) plots the decomposition in (11), where Δy_n is plotted in the x-axis and $\Delta \tilde{z}_n$ and $\Delta \tilde{\phi}_n$ are plotted in the y-axis. The legends report the slopes of a bivariate OLS regression of $\Delta \phi_n$ (resp. $\Delta \tilde{\phi}_n$) on Δtfp_n (resp. Δy_n).

contrast, our measure aggregate of firm know-how uses data on MNEs revenue shares, and it is strongly correlated with 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 (13) and (14) in the spirit of [Klenow and Rodriguez-Clare \(1997\)](#). The contribution of aggregate firm know-how corresponds to the slope of a bivariate OLS regression of $\Delta \phi_n$ (resp. $\Delta \tilde{\phi}_n$) on Δtfp_n (resp. Δy_n), which is reported in the figure. Differences in $\Delta \phi_n$ account for over a quarter of the cross-country variance in TFP, while differences in $\tilde{\phi}_n$ account for one fifth of the cross-country variance in output per worker. Differences in country-embedded factors account for the remaining 71 percent of the differences in TFP across countries, and 79 percent of the differences in income per capita. To put these numbers in perspective, recent studies estimate that human capital alone account for about 60 percent of the observed differences in income per-capita.¹⁷ Unsurprisingly, differences in country-embedded factors $\Delta \tilde{z}_n$ are larger than differences in county-embedded productivities, Δz_n , since the former also includes differences in human capital and capital-output ratios across countries.

¹⁷See [Hendricks and Schoellman \(2018\)](#) and [Lagakos et al. \(2018\)](#).

Table 2: Correlations with factors

dep var.	Δtfp_n	$\Delta\phi_n$	Δz_n	Δy_n	$\Delta\tilde{\phi}_n$	$\Delta\tilde{z}_n$
$\Delta [k_n - y_n]$	-0.160 [0.122]	-0.017 [0.069]	-0.143 [0.104]	0.675** [0.317]	0.072 [0.134]	0.604** [0.239]
Δh_n	0.093 [0.299]	-0.083 [0.186]	0.176 [0.290]	1.416** [0.668]	0.006 [0.315]	1.408** [0.525]
Obs.	26	26	26	26	26	26
R-squared	0.05	0.01	0.07	0.18	0.01	0.21

Notes: $\Delta [k_n - y_n]$ denotes the capital-output ratio, in logs, relative to France. Δh_n denotes human capital, relative to France. Data from Penn World Tables (9.0).

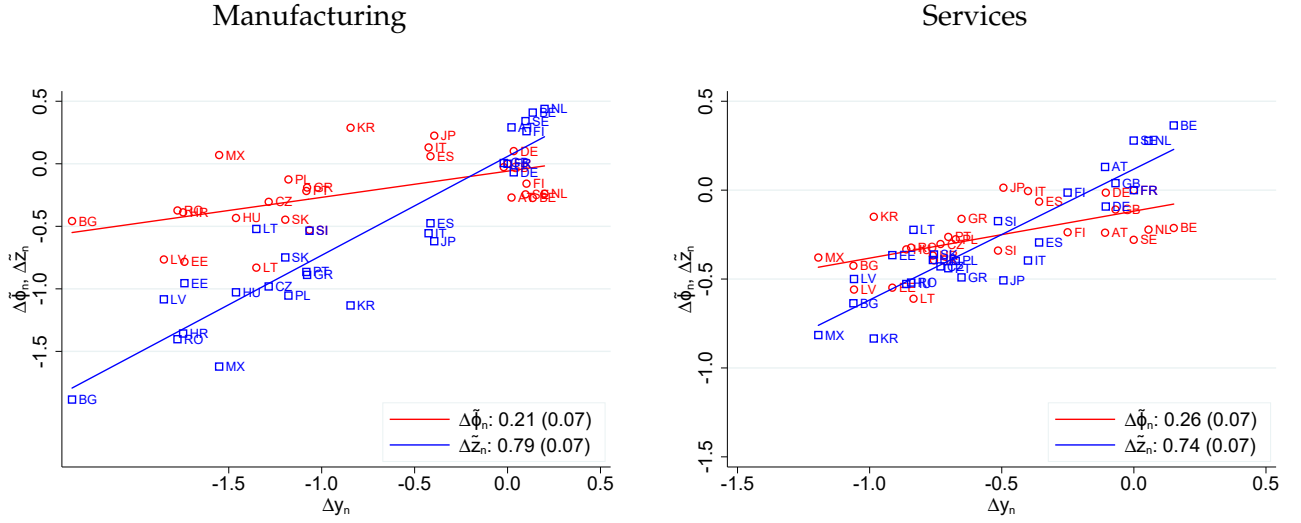
Correlation with observables: Table 2 evaluates how our measures of aggregate firm know-how and country-embedded factors correlate with measures of human and physical capital. The table shows that differences in TFP are uncorrelated with these factors in the countries in our sample, and that the same is true for the components of TFP, ϕ_n and z_n . In contrast, output per worker y_n is higher in countries with high capital-output ratios and with high levels of human capital. Measures of physical and human capital are in turn positively correlated with our measure of country-embedded factors, \tilde{z}_n , and are uncorrelated to our measure of aggregate firm know-how, $\Delta\tilde{\phi}_n$. These results are reassuring given that, as explained in Section 2.3, difference in factors across countries should be captured by \tilde{z}_n rather than by $\tilde{\phi}_n$.

4.1 Sector-level results

We now decompose differences in output per-worker within Manufacturing and Services. We do so by aggregating our sectorial estimates of the country effects into these two broad sectorial categories. We perform this sectoral decomposition in terms of output per-worker only since data on sectoral TFP levels are not available for most countries in our sample.

Figure 4 reports the results. For the average country, the gap in aggregate firm know-how relative to France is only slightly lower in Manufacturing than in Service sectors (-0.24 versus -0.26 log points). However, for the average country, this gap represents more than a quarter of the observed log-point difference in output per-worker relative to France in Manufacturing, but almost 50 percent in Services. In turn, country-embedded factors accounts for 75 and 50 percent of the observed log-point differences in output per

Figure 4: Development accounting: Manufacturing and Services

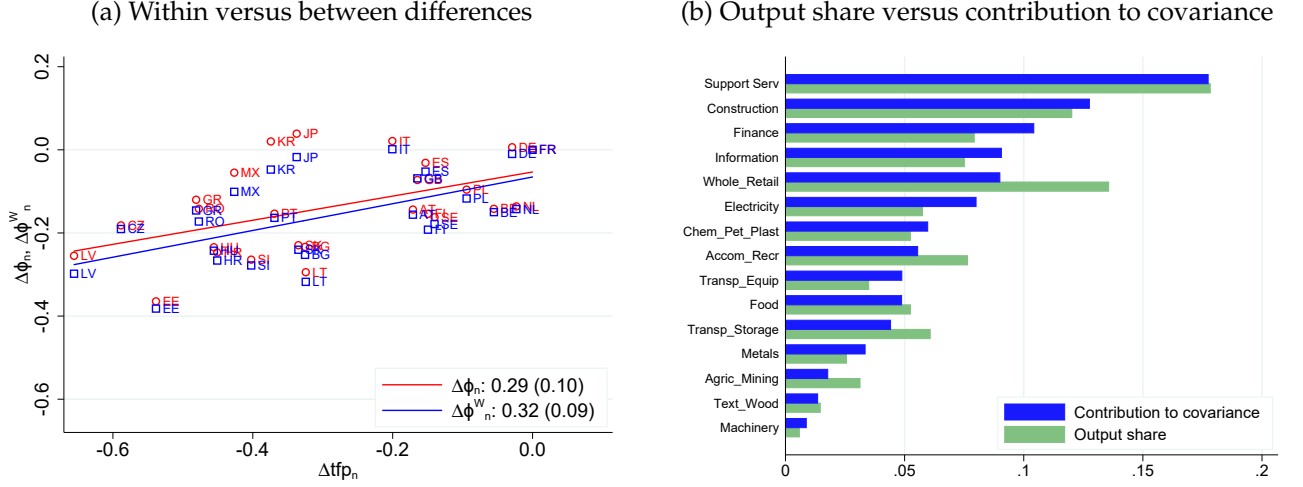


Notes: Each circle (square) represents a country. The figures plot the decomposition in (11) at the sectoral level. Δy_n^j is plotted in the x-axis and Δz_n^j and $\Delta \tilde{\phi}_n^j$ are plotted in the y-axis for $j = \text{Manufacturing}$ (left panel) and $j = \text{services}$ (right panel).

worker, in Manufacturing and Services. In addition, differences in aggregate firm know-how account for less of the cross-country variance in output per worker in Manufacturing than in Services (0.21 versus 0.26). This implies that differences in country-embedded factors are more important for manufacturing than for service sectors.

Differences within and between sectors: We now evaluate if the estimated differences in aggregate firm know-how arise from differences within sectors or from differences in sectorial shares across countries. We do so by computing a measure of aggregate firm know-how that aggregates sectorial differences using the output shares from France $\Delta \phi_n^w \equiv \sum_j \theta_{FR}^j \Delta \phi_n^j$. We compare this measure with our baseline measure $\Delta \phi_n \equiv \sum_j \theta_n^j \Delta \phi_n^j$ that uses country-specific sectorial shares. Figure (5a) plots these two measures along with each country's TFP. The figure shows that the two measures are very close to each other, indicating that cross-country differences in aggregate firm know-how are not driven by cross-country differences in sectorial output shares. Differences within sectors in aggregate firm know-how explain one third of cross-country differences in TFP. Differences in the participation of each sector in the economy of each country in our sample accounts for a negligible part of TFP differences across countries.

Figure 5: Differences in aggregate firm know-how across sectors



Notes: Each circle (square) represents a country. Figure (5a) plots the decomposition in (10), where Δtfp_n is plotted in the x-axis and $\Delta \phi_n^w \equiv \sum_j \theta_{FR}^j \Delta \phi_n^j$ and $\Delta \phi_n \equiv \sum_j \theta_n^j \Delta \phi_n^j$ are plotted in the y-axis. The legend reports the slopes of a bivariate OLS regression of $\Delta \phi_n$ (resp. $\Delta \phi_n^w$) on Δtfp_n . Figure (5b) plots the output share of sector j in France, θ_{FR}^j , and the contribution of sector j to the covariance between Δtfp_n and $\Delta \phi_n^w$, $\theta_{FR}^j \frac{cov(\Delta tfp_n, \Delta \phi_n^j)}{cov(\Delta tfp_n, \Delta \phi_n^w)}$.

Contributions to covariance: Finally, we explore the contribution of each sector to the cross-country covariance between $\Delta \phi_n^w$ and Δtfp_n . Note that $cov(\Delta tfp_n, \Delta \phi_n^w) = \sum_j \theta_{FR}^j cov(\Delta tfp_n, \Delta \phi_n^j)$ so that the contribution of sector j in $cov(\Delta tfp_n, \Delta \phi_n^w)$ is $\theta_{FR}^j \frac{cov(\Delta tfp_n, \Delta \phi_n^j)}{cov(\Delta tfp_n, \Delta \phi_n^w)}$. Figure (5b) plots this contribution and sectoral output shares for France, θ_{FR}^j . In general, sectoral contributions are similar to output shares, with service sectors accounting for around two thirds of the cross-country difference in TFP coming from aggregate firm know-how.

4.2 Understanding differences in aggregate firm know-how

Cross-country differences in aggregate firm know-how $\Delta \phi_n$ may arise from differences in the know-how of both foreign and domestic firms. This section decomposes differences in aggregate firm know-how into these two components. To do so, note that from the definition of Φ_n^j we can write

$$[\Phi_n^j]^{\rho-1} = [\Phi_{nn}^j]^{\rho-1} + [\Phi_{Fn}^j]^{\rho-1}, \quad (24)$$

where $[\Phi_{nn}^j]^{\rho-1} \equiv \int_{\Omega_{nn}^j} A_{nn}^j(\omega)^{\rho-1} d\omega$ denotes the aggregate know-how of the domestic firms, and $[\Phi_{Fn}^j]^{\rho-1} \equiv \sum_{i \neq n} \int_{\Omega_{in}^j} A_{in}^j(\omega)^{\rho-1} d\omega$ is the aggregate know-how of foreign MNEs in country n . Since we are interested in decomposing cross-country differences in Φ_n , we first note that we can write aggregate firm know-how relative to France as

$$\Delta\phi_n = \sum_j \theta_n^j S_{rr}^j \Delta\phi_{nn}^j + \sum_j \theta_n^j [1 - S_{rr}^j] \Delta\phi_{Fn}^j = \Delta\phi_{nn} + \Delta\phi_{Fn}, \quad (25)$$

where

$$S_{nn}^j \equiv \int_{\Omega_{nn}^j} S_{nn}^j(\omega) d\omega = \left(\frac{\Phi_{nn}^j}{\Phi_n^j} \right)^{\rho-1} \quad (26)$$

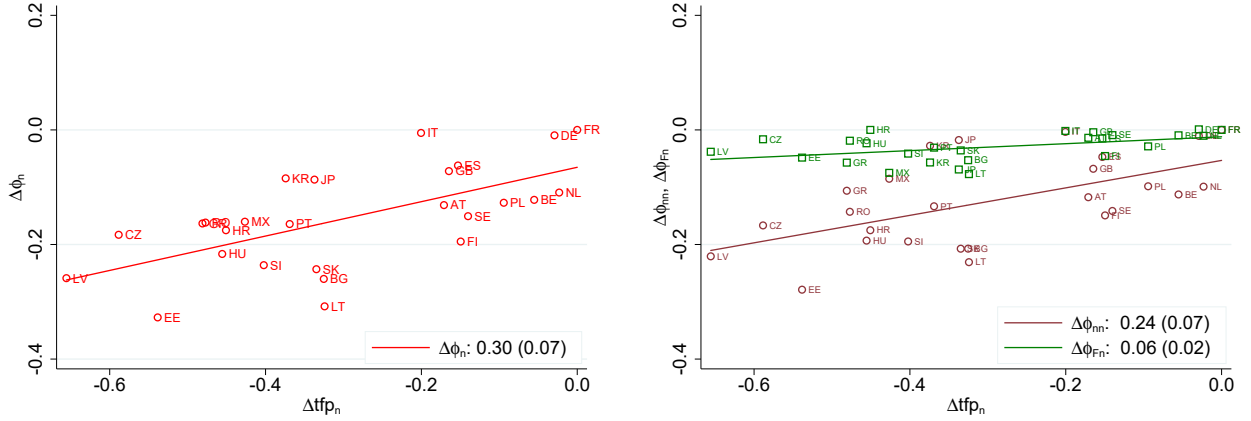
denotes the revenue share of from n in country n , in sector j . We use the domestic share S_{nn}^j from the data and (26) to compute the terms in (25).

Figure 6 shows the two terms in (24). The average country has a -0.11 log-point difference relative to France regarding domestic-firm know-how, while the gap for foreign firms is only -0.03. Differences in aggregate know-how of domestic firms account for 80 percent of the cross-country differences in aggregate firm know-how (0.24 vs 0.3). Differences in the know-how embedded in the foreign affiliates of MNEs (computed as a residual using (24) and depicted in green) are less correlated with aggregate differences in TFP, with several developing countries having better foreign MNE affiliates than developed countries. Notably, Japan has better aggregate and domestic firm know-how than most developed countries, but it hosts worse foreign MNE affiliates than most developed and developing countries in our sample. Conversely, countries such as Czech Republic, Romania, and Croatia have lower domestic-firm know-how than most of the more developed countries in our sample. However, they host foreign MNE affiliates as productive as the ones located in those richer countries.

5 Robustness

This section presents several robustness results for our baseline estimates of aggregate firm know-how.

Figure 6: Aggregate firm know-how: Domestic and foreign firms



Notes: Each circle (square) represents a country. The left panel shows $\Delta\phi_n$ (y-axis), and Δtfp (x-axis), already depicted in Figure 3. The right panel plots the two terms in (25) (y-axis) and Δtfp (x-axis).

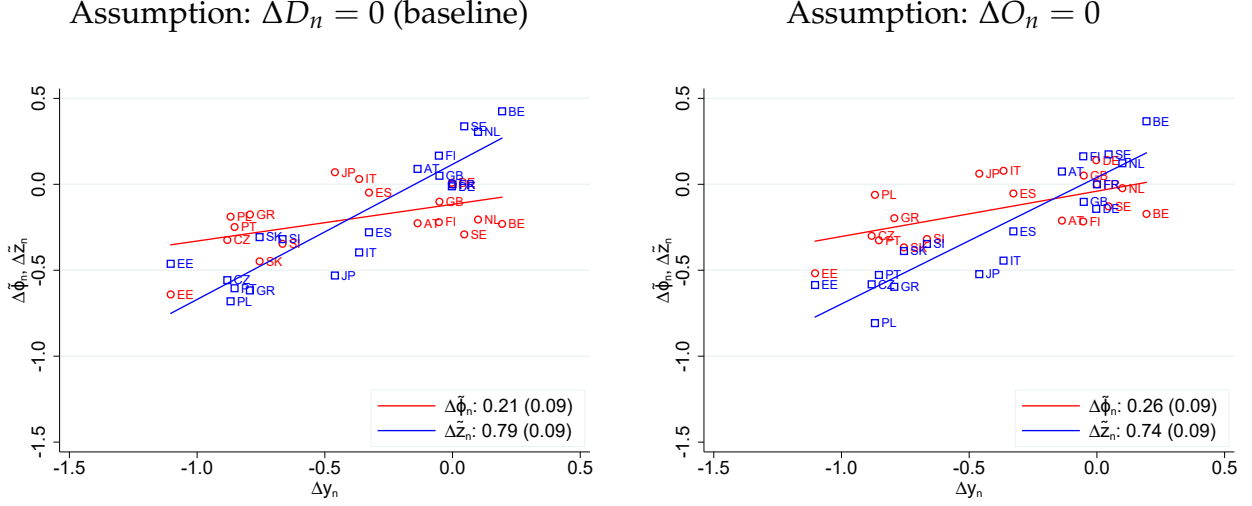
5.1 Alternative assumptions on the technology transfer costs

Our baseline estimates for $\Delta\phi_n$ were obtained from (17), which was derived under the assumption that technology transfer costs could have an origin-specific, but not a destination-specific component, $\Delta D_n = 0$. As explained in Section 3.2, if this assumption does not hold, and it is harder to transfer technology to less developed countries ($cov(D_n, tfp_n) < 0$), our baseline estimates understate the contribution of aggregate firm know-how to the cross-country variance of TFP.

Alternatively, we can estimate $\Delta\phi_n$ using (19), which allows for a destination-specific component in the technology transfer, but it rules out the possibility of an origin-specific component, $\Delta O_n = 0$. As noted in Section 3.2, if $cov(O_n, tfp_n) < 0$, these estimates will overstate the contribution of aggregate firm know-how to the cross-country variance of TFP.

Figure 7 presents the estimates based on (19) and compares them to our baseline results. The figure shows that the two alternative assumptions yield very similar estimates for the cross-country differences in aggregate firm know-how $\Delta\phi_n$. For the average country, $\Delta\phi_n$ ranges between -0.14 and -0.12. In addition, the contribution of aggregate firm know-how to cross-country differences in output per worker (TFP) is between 0.29 to 0.40 (0.21 to 0.26). These narrow bands indicate that our main conclusions are robust to the alternative the assumptions on the technology transfer costs.

Figure 7: Alternative assumptions on the technology transfer costs



Notes: Each circle (square) represents a country. The upper panel plots the decomposition in (11), where Δy_n is plotted in the x-axis and $\Delta\tilde{z}_n$ and $\Delta\phi_n$ are plotted in the y-axis. The lower panel plots the decomposition in (10), where Δtfp_n is plotted in the x-axis and Δz_n and $\Delta\phi_n$ are plotted in the y-axis. The legends report the slopes of a bivariate OLS regression of $\Delta\phi_n$ (resp. $\Delta\tilde{z}_n$) on Δtfp_n (resp. Δy_n). Standard errors are in parenthesis.

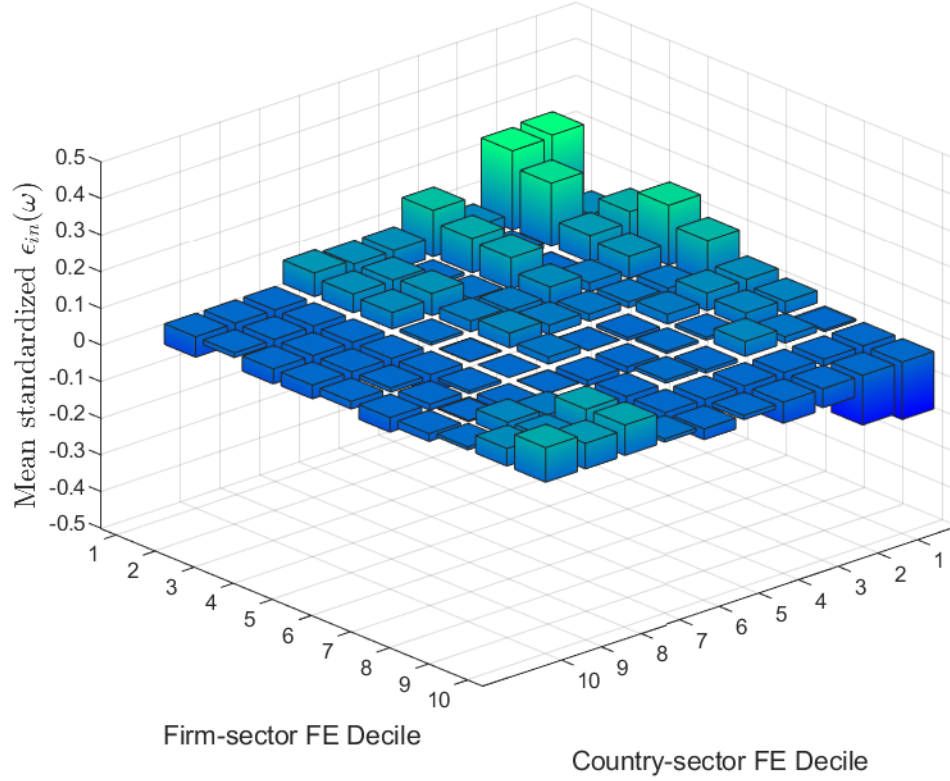
5.2 Selection based on firm-destination specific technology transfer costs

Section 3.2 noted that our OLS estimates of the country effects are biased if firm-destination specific transfer costs drive the assignment of MNEs to countries (i.e. if selection is based on match-specific effects). If unproductive firms enter unattractive locations only when their firm-destination specific component of the transfer cost $\varepsilon_{in}^j(\omega)$ is low, then the average of $\varepsilon_{in}^j(\omega)$ across the firms that choose to enter each destination will vary across n and thus be captured by the country effects \mathcal{A}_n^j .

To assess the severity of this potential bias, we follow the literature on two-way matching (see [Abowd et al., 1999](#)) and analyze the residuals of estimating (16) by OLS. If the assignment of MNEs to countries is driven by firm-destination specific transfer costs, then we should expect these costs to be lower on average for low-productivity firms in unattractive markets.¹⁸ If this is the case, then our specification should underestimate revenue shares, as it does not take into account that the $\varepsilon_{in}^j(\omega)$'s can systematically vary with firm productivity among the firms that choose to enter any given market. We evaluate this implication in Figure 8, which plots the mean standardized residuals, $\hat{\varepsilon}_{in}^j(\omega) = \frac{s_{in}^j(\omega) - \bar{s}_{in}^j(\omega)}{\sigma_s}$,

¹⁸As noted above, this is because these firms would need low $\varepsilon_{in}^j(\omega)$ to enter unattractive markets. In contrast, highly productive firms are more likely to enter these markets irrespective of their $\varepsilon_{in}^j(\omega)$.

Figure 8: OLS residuals, by market-sector and firm-sector deciles



against deciles of estimates of the firm-sector fixed effects and deciles of estimates of the country-sector fixed effects. Indeed, we tend to see positive residuals for the less productive firms (decile 1 of the firm-sector fixed effect) in less profitable markets (decile 1 of the country-sector fixed effect). In contrast, the we overestimate the revenue shares of the most productive firms (decile 10 of the firm-sector fixed effect) in these markets. Note that the residuals are very close to zero in the remaining bins of the figure, indicating that technology transfer costs do not vary systematically across firms and locations in those bins.

With this in mind, we proceed to re-estimate (16) using alternative subsamples, which we restrict to exclude the firms at the extreme of the know-how distribution. In particular, we rank firms according to their estimated fixed-effects in each sector. We then restrict the sample to the subset of firms that lie within the 2nd to 9th , 3rd to 8th, 4th to 7th deciles, and 5th and 6th deciles of the fixed effects distribution.

Table 3 shows the contribution of $\Delta\phi_n$ ($\Delta\tilde{\phi}_n$) to the cross-country variance in $tfp_n(y_n)$ in each of these restricted samples. The table shows that the contribution of firm know-how

Table 3: Contribution of aggregate firm know-how. Robustness.

	$\frac{cov(\Delta tfp_n, \Delta \phi_n)}{var(\Delta tfp_n)}$	$\frac{cov(\Delta y_n, \Delta \phi_n)}{var(\Delta y_n)}$
Baseline	0.28 (0.10)	0.20 (0.07)
2nd to 9th Decile	0.34 (0.11)	0.24 (0.07)
3rd to 8th Decile	0.37 (0.11)	0.26 (0.08)
4th to 7th Decile	0.41 (0.12)	0.30 (0.08)
5th to 6th Decile	0.46 (0.13)	0.33 (0.09)

Notes: Slopes of a bivariate OLS regression of $\Delta \phi_n$ (resp. $\Delta \tilde{\phi}_n$) on Δtfp_n (resp. Δy_n). Deciles refer to firm-country fixed effect deciles from estimating 16 by OLS. Standard errors are in parenthesis.

to the cross-country variance is somewhat larger in the alternative samples, although it lies within the confidence intervals estimated in our baseline. If anything, focusing on the at middle of the distribution increases the importance of aggregate firm know-how in accounting for TFP (output per worker) differences across countries.

Estimation using narrow samples of firms: Our framework identifies cross-country differences in aggregate firm know-how from cross-country differences in shares within across affiliates of the same MNE. If the linearity assumption holds, then a single MNE observation, either from a large or small MNE, would suffice to pin down the aggregate firm know-how of a country (relative to France). Table 4 shows how the contribution of $\Delta \phi_n$ ($\Delta \tilde{\phi}_n$) to the cross-country variance in tfp_n (y_n), when we repeat our estimation with different subsamples of firms. In particular, we rank affiliates by their revenue size in each destination country, and repeat our estimation for the firms above and below the 50th size percentile. The table shows that we find a positive correlation between aggregate firm know-how and TFP and output per worker in the two samples. The resulting contribution of aggregate firm know-how to differences in TFP and output per-worker across countries would be smaller than if only small affiliates were considered in the estimation.¹⁹

¹⁹Results are similar if instead of ranking affiliates by their revenue size, we rank parents by their domestic sales.

5.3 Estimation using narrow industries

An important assumption behind our estimates is that parents and affiliates use the same production functions within two-digit industry classification. One may be concerned that this assumption is violated if parent and affiliates operate in different 4-digit industries. To address this concern, we apply our procedure in 16 including 4-digit, instead of 2-digit, industry fixed effect, interacted with firm and country fixed effects. We also experiment with a 6-digit industry disaggregation. Table 4 shows that these alternative estimates are very close to our baseline estimates.

5.4 Estimation using employment data

Equation (16) shows how data on revenue shares can be used to compute differences in aggregate firm know-how. Since in this model revenue shares and employment shares coincide, we could have used data on employment shares to compute these differences. In particular, we re-estimate (16) using data on log-employment shares as the dependent variable. The resulting estimates of $\Delta\phi_n$ are in Table 4 where they are compared to our baseline estimates. The contribution of aggregate firm know-how to cross-country TFP differences when we use employment data is very similar to our baseline estimates. We use the revenue data as our baseline since they are available for a much larger set of firms in ORBIS.

5.5 Other measurement issues

Measurement issues in the aggregate data: We now show how our estimates are affected if statistical agencies mis-measure aggregate output per worker and TFP. In particular, we assume that statistical agencies cannot perfectly measure TFP . Instead, they measure a Solow residual computed as

$$\begin{aligned}\widetilde{\Delta t f p}_n &\equiv \Delta r_n - \Delta p_n - \Delta l_n \\ &= \Delta t f p_n + \Delta p_n - \Delta \mathcal{P}_n.\end{aligned}$$

The variable p_n is a price deflator used by the statistical agency that expresses prices in country n relative to prices in country 0, and \mathcal{P}_n is the ideal price index associated with

Table 4: Contribution of aggregate firm know-how. Robustness.

	$\frac{\text{cov}(\Delta tfp_n, \Delta \phi_n)}{\text{var}(\Delta tfp_n)}$	$\frac{\text{cov}(\Delta y_n, \Delta \bar{\phi}_n)}{\text{var}(\Delta y_n)}$
Baseline	0.28 (0.10)	0.20 (0.07)
Dropping firms		
below 50p size	0.23 (0.09)	0.17 (0.06)
above 50p size	0.45 (0.13)	0.35 (0.09)
Narrow Industries:		
4-digit SIC	0.28 (0.10)	0.21 (0.07)
6-digit SIC	0.33 (0.11)	0.23 (0.07)
Employment shares	0.26 (0.10)	0.17 (0.07)

Notes: Slopes of a bivariate OLS regression of $\Delta \phi_n$ (resp. $\Delta \bar{\phi}_n$) on Δtfp_n (resp. Δy_n). Standard errors are in parenthesis.

(1).²⁰ In this case, differences in measured TFP are given by:

$$\Delta \widetilde{tfp}_n = \Delta z_n + \Delta \phi_n + \varepsilon_n,$$

where $\varepsilon_n \equiv \Delta p_n - \Delta \mathcal{P}_n$ is the bias that arises if the statistical agency mis-measures the ideal price index. Note, however, that it is still possible to use (6) to obtain an estimate of $\Delta \phi_n$ from the revenue data.

Estimation using 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.

With this in mind, we incorporate heterogeneous firms and fixed costs of producing abroad into the model in Section 2.3. 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

²⁰This follows from the definitions of aggregate revenues and the ideal price index, $R_n = \sum_i \int P_{in}(\omega) Y_{in}(\omega) dG_{in}(\omega) = \mathcal{P}_n Y_n$.

by country i 's firms that operate in country n we can write:

$$\frac{R_{in}}{R_n} = \left[\frac{\Phi_{in} \exp(-\kappa_{in})}{\Phi_n} \right]^{\rho-1}. \quad (27)$$

Here, $\Phi_{in} \equiv \left[\int_{\omega \in \Omega_{in}} A^j(\omega)^{\rho-1} d\omega \right]^{\frac{1}{\rho-1}}$, where we omit country subscripts from $A(\omega)$ since we factored-out the technology transfer costs κ_{in} in (27). Taking logs we obtain:

$$s_{in} = [\rho - 1] [\phi_{in} - \phi_n - \kappa_{in}]. \quad (28)$$

This equation differs from (6) since it expresses aggregate shares rather than firm-level shares. Note that ϕ_{in} varies across n 's if not all the multinationals from country i operate in the same destinations (the set $\omega \in \Omega_{in}$ differs across n 's). 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 factoring out the technology transfer costs κ_{in} . Thus, selection into being a MNE will affect the estimates of ϕ_n if we were to base our procedure on aggregate data and (28). This result implies that it is not possible to recover cross-country differences in aggregate firm know-how using (28) and aggregate data without modeling selection explicitly.

6 Conclusion

This paper proposes and implements a framework for decomposing cross-country differences in output-per worker into differences in country-embedded factors and differences in aggregate firm know-how. Our key insight is that, if MNEs can use their know-how around the world but must use the factors from the countries where they produce, then differences in performance of across affiliates of the same MNE that operate in different countries can be used to measure cross-country differences aggregate firm know-how. We implement this idea in a multinational production model and measure aggregate firm know-how using firm-level revenue data. We estimate that differences in aggregate firm know how are large, but are far from fully accounting for the observed differences in TFP across countries. Across the countries in our sample, differences in aggregate firm know-how account for about 30 percent of the cross-country differences in TFP, 20 percent of the differences in output per-worker, and are strongly correlated to observed differences in income per-capita. Differences in aggregate firm know-how are mainly driven by dif-

ferences in the productivity of domestic firms, while differences in the productivity of foreign MNE affiliates not strongly correlated to income per-capita.

References

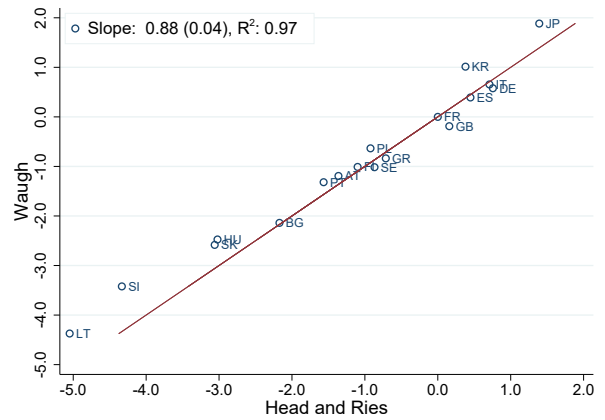
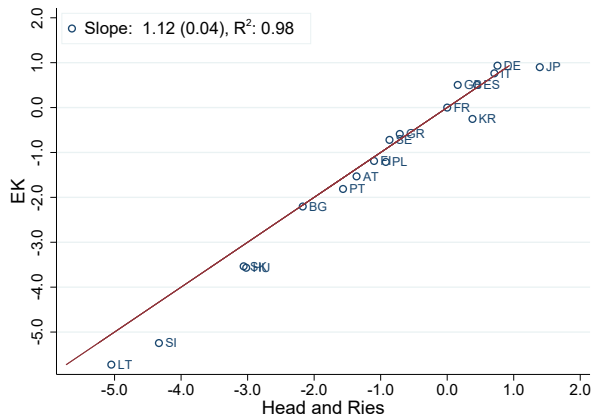
- Abowd, John M, Francis Kramarz, and David N Margolis**, “High Wage Workers and High Wage Firms,” *Econometrica*, March 1999, 67 (2), 251–333.
- Acemoglu, Daron, Francisco A. Gallego, and James A. Robinson**, “Institutions, Human Capital, and Development,” *Annual Review of Economics*, 2014, 6 (1), 875–912.
- Alfaro, Laura and Maggie Xiaoyang Chen**, “Selection and Market Reallocation: Productivity Gains from Multinational Production,” *American Economic Journal: Economic Policy*, May 2018, 10 (2), 1–38.
- Alvarez, Vanessa, Javier Cravino, and Andrei A. Levchenko**, “The Growth of Multinational Firms in the Great Recession,” *Journal of Monetary Economics*, 2017, 85 (C), 50–64.
- Antras, Pol, Luis Garicano, and Esteban Rossi-Hansberg**, “Organizing Offshoring: Middle Managers and Communication Costs,” in Elhanan Helpman, Dalia Marin, and Thierry Verdier, eds., *The Organization of Firms in a Global Economy*, Harvard University Press, 2008.
- Bilir, Kamran L.**, “Patent Laws, Product Lifecycle Lengths, and Multinational Activity,” *American Economic Review*, 2014, 104 (7), 1979–2013.
- Bilir, L. Kamran and Eduardo Morales**, “Innovation in the Global Firm,” *Journal of Political Economy*, Forthcoming.
- Bloom, Nicholas and John Van Reenen**, “Measuring and explaining management practices across firms and countries,” *Quarterly Journal of Economics*, 2007, 122 (4), 1351–1408.
- , **Raffaella Sadun, and John Van Reenen**, “Americans Do IT Better: US Multinationals and the Productivity Miracle,” *American Economic Review*, 2012, 102 (1), 167–201.
- Branstetter, Lee G., Raymond Fisman, and C. Fritz Foley**, “Do stronger intellectual property rights increase international technology transfer? Empirical evidence from US firm-level panel data,” *Quarterly Journal of Economics*, February 2006, 121 (1), 321–349.

- Burstein, Ariel T. and Alexander Monge-Naranjo**, “Foreign Know-How, Firm Control, and the Income of Developing Countries,” *Quarterly Journal of Economics*, February 2009, 124 (1), 149–195.
- Caselli, Francesco**, *Technology Differences over Space and Time*, Princeton University Press, 2016.
- Cravino, Javier and Andrei A. Levchenko**, “Multinational Firms and International Business Cycle Transmission,” *The Quarterly Journal of Economics*, 2017, 132 (2), 921–962.
- Eaton, Jonathan and Samuel Kortum**, “Technology, Geography, and Trade,” *Econometrica*, September 2002, 70 (5), 1741–1779.
- Edmond, Chris, Virgiliu Midrigan, and Daniel Yi Xu**, “How Costly Are Markups?,” Mar 2018. NBER Working Paper No. 24800.
- Fan, Jingtin**, “Talent, Geography, and Offshore R&D,” *Mimeo, Penn State University*, 2017.
- Fons-Rosen, Christian, Sebnem Kalemli-Ozcan, Bent E. Sørensen, Carolina Villegas-Sanchez, and Vadym Volosovych**, “Quantifying Productivity Gains from Foreign Investment,” Mar 2013. NBER Working Paper No. 18920.
- Guadalupe, Maria, Olga Kuzmina, and Catherine Thomas**, “Innovation and Foreign Ownership,” *American Economic Review*, December 2012, 102 (7), 3594–3627.
- Gumpert, Anna**, “The Organization of Knowledge in Multinational Firms,” *Journal of the European Economic Association*, 2018, 16 (6), 1929–1976.
- Head, Keith and Thierry Mayer**, “Gravity Equations: Workhorse, Toolkit, and Cookbook,” in Elhanan Helpman Gopinath, Gita and Kenneth Rogoff, eds., *Handbook of International Economics*, Elsevier, 2014.
- Helpman, Elhanan, Marc J. Melitz, and Stephen R. Yeaple**, “Export versus FDI with Heterogeneous Firms,” *American Economic Review*, March 2004, 94 (1), 300–316.
- Hendricks, Lutz and Todd Schoellman**, “Human Capital and Development Accounting: New Evidence from Wage Gains at Migration,” *The Quarterly Journal of Economics*, 2018, 133 (2), 665–700.
- Irrazabal, Alfonso, Andreas Moxnes, and Luca David Oromolla**, “The Margins of Multinational Production and the Role of Intrafirm Trade,” *Journal of Political Economy*, February 2013, 121 (1), 74–126.

- Keller, Wolfgang and Stephen Ross Yeaple**, “The Gravity of Knowledge,” *American Economic Review*, June 2013, 103 (4), 1414–44.
- Klenow, Peter and Andres Rodriguez-Clare**, “The Neoclassical Revival in Growth Economics: Has It Gone Too Far?,” in “NBER Macroeconomics Annual 1997, Volume 12” NBER Chapters, National Bureau of Economic Research, Inc, 03-2018 1997, pp. 73–114.
- Lagakos, David, Benjamin Moll, Tommaso Porzio, Nancy Qian, , and Todd Schoellman**, “Life Cycle Wage Growth across Countries,” *Journal of Political Economy*, 2018, 126 (2), 797–849.
- Markusen, James R.**, “Multinationals, multi-plant economies, and the gains from trade,” *Journal of International Economics*, May 1984, 16 (3-4), 205–226.
- McGrattan, Ellen R. and Edward C. Prescott**, “Openness, technology capital, and development,” *Journal of Economic Theory*, November 2009, 144 (6), 2454–2476.
- Melitz, Marc J.**, “The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity,” *Econometrica*, November 2003, 71 (6), 1695–1725.
- Ramondo, Natalia**, “A quantitative approach to multinational production,” *Journal of International Economics*, May 2014, 93 (1), 108 – 122.
- **and Andrés Rodríguez-Clare**, “Trade, Multinational Production, and the Gains from Openness,” *Journal of Political Economy*, 2013, 121 (2), 273 – 322.
- Waugh, Michael E.**, “International Trade and Income Differences,” *American Economic Review*, December 2010, 100 (5), 2093–2124.
- Yeaple, Stephen Ross**, “Firm Heterogeneity, Intra-Firm Trade, and the Role of Central Locations,” in Elhanan Helpman, Dalia Marin, and Thierry Verdier, eds., *The Organization of Firms in a Global Economy*, Harvard University Press, 2008.

Figure A.1: Estimating aggregate firm know-how by sector

Manufacturing



Services

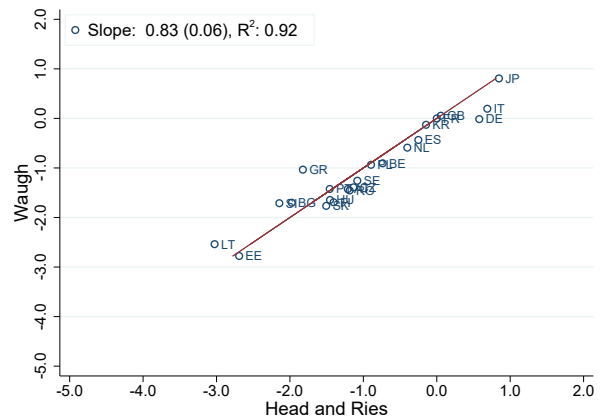
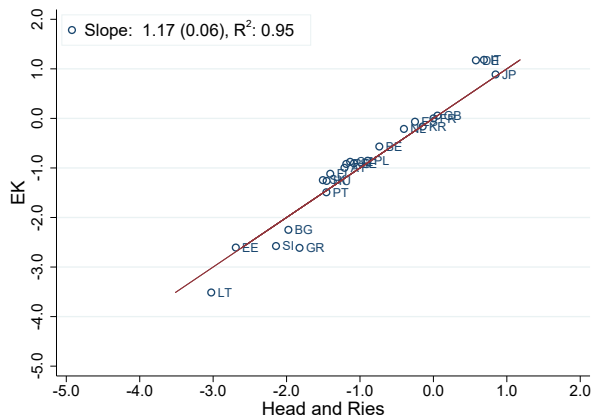


Table A1: Estimates of gravity coefficients

	Distance		Common Language	
	Coeff	S.E	Coeff	S.E
Agriculture and Mining	-0.151	0.218	-0.125	0.341
Electricity	-0.399	0.309	0.399	0.586
Construction	-0.264	0.166	0.574	0.181
Food and Beverage	-0.15	0.085	0.345	0.139
Textiles, Apparel and Wood	-0.001	0.106	0.126	0.117
Chemicals, Petroleum and Plastic	-0.218	0.095	0.24	0.14
Basic Metals	-0.14	0.083	0.271	0.119
Electrical Equipment and Machinery	-0.176	0.058	0.194	0.182
Transport Equipment and Other Manufacturing	-0.09	0.115	0.367	0.221
Wholesale Trade and Retail Trade	-0.211	0.071	0.156	0.096
Transportation and Storage	-0.357	0.082	0.033	0.19
Information	-0.485	0.128	0.367	0.164
Financial and Insurance Services	-0.284	0.078	0.245	0.202
Support Services	-0.112	0.057	0.407	0.12
Accommodation and Recreation	-0.347	0.123	-0.242	0.279

Notes: This table reports OLS coefficients on distance, β_d^j , and common language, β_l^j , from estimating 16.

Table A2: Estimating the elasticity of substitution: ρ

	Year 2011						Pooled					
	Manufacturing			Services			Manufacturing			Services		
ΔA_n	-0.147***	-0.152***	-0.111***	-0.155***	-0.142***	-0.089***	-0.166***	-0.161***	-0.128***	-0.153***	-0.137***	-0.088***
	[0.036]	[0.042]	[0.030]	[0.029]	[0.0322]	[0.027]	[0.0366]	[0.0410]	[0.0296]	[0.027]	[0.029]	[0.024]
k_n/y_n		0.966**	-0.081		0.296*	-0.116		1.064***	0.0262		0.326**	-0.076
		[0.417]	[0.285]		[0.173]	[0.124]		[0.365]	[0.250]		[0.154]	[0.111]
h_n		1.942**	-0.863		0.817*	-0.397		1.473*	-0.765		0.741*	-0.240
		[0.861]	[0.941]		[0.432]	[0.514]		[0.759]	[0.942]		[0.395]	[0.455]
Rule of law			0.969***			0.449***			0.944***			0.427***
			[0.116]			[0.077]			[0.119]			[0.070]
Observations	26	26	26	26	26	26	205	205	205	205	205	205
R-squared	0.28	0.43	0.85	0.37	0.44	0.75	0.27	0.44	0.82	0.37	0.45	0.72
Implied ρ	7.80	7.59	10.02	7.45	8.03	12.26	7.02	7.22	8.80	7.52	8.31	12.34

Notes: This table reports estimates from (23), for manufacturing and services respectively. 'Year 2011' report results using data from 2011, and 'Pooled' reports results using data from 2005-2012, and controlling for year fixed effects.