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

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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 and intangible capital. Our approach relies on data on the cross-border operations of multinational enterprises (MNE). 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 that, across the countries in our sample, differences in aggregate firm know-how account for 40 percent of the cross-country differences in TFP, 22 percent of the differences in output per-worker, and are strongly correlated to observed differences in income per-capita.

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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. A well-known challenge of this decomposition is that available measures of factor stocks may not be directly comparable across countries.[1] In addition, 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.[2] Others highlight the role of codified technological know-how that is accumulated by individual firms and can be transferred across countries (e.g. blue-prints, patents, intangible capital, management practices).[3]

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.

Our approach separates these components by exploiting data on the cross-border operations of multinational enterprises (MNE). 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.

[1] See, for example, the surveys in Klenow and Rodriguez-Clare (1997), Caselli (2005), and Hsieh and Klenow (2010).

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

[3] See, 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).

We develop this logic in a multinational production model and measure aggregate firm know-how using firm-level revenue data. The advantage of this approach is that, for a wide cross-section of countries, firm-level revenue data are readily available, while firm-level productivity data at the firm-level are not. In the model, the revenue share of a MNE in a country depends only on the firm's idiosyncratic 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 (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 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 records 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 country in our sample relative to France.

We show that differences in aggregate firm know-how account for almost 40 percent of the cross-country variance in TFP, and almost 20 percent of the cross-country variance in output per-worker, for our sample of countries. For the average country, aggregate firm know-how is 0.12 log points lower than in France, more than 40 percent of the observed

[4] See, for example, Yeaple (2008).

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 Eastern Europe (Romania, Bulgaria) and in the Asian countries in our sample (Japan and Korea).

Finally, we provide a decomposition of the differences in output per-worker in the manufacturing and in the service sector separately. For the average country in our sample, the gap in aggregate firm know-how relative to France is larger in manufacturing than in services (-0.19 versus -0.14 log-points). In addition, 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 differences in country embedded factors are more important for services than for manufacturing sectors.

A common caveat in the literature using 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.[5] In the theoretical literature that builds on the Melitz (2003) model, firms select into foreign markets based on their productivity or quality (see Helpman et al., 2004). 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 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 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

[5] See the survey in Antràs and Yeaple (2014).

[6] This is the standard assumption in the multinational production literature, starting with Markusen (1984), and more recently Helpman et al. (2004), Guadalupe et al. (2012), Irarrazabal et al. (2013), and Ra-

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 explainig cross-country income differences.

Our project 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 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 develops a framework that formalizes the distinction between firm know-how and country-embedded factors. We show how firm-level data on the cross-border operations of MNEs can be used to decompose cross-country income differences into these two components.

mondo (2014).

[7]A 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).

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. 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

$$\mathcal{Y}_n = \left[\sum_i \int \left[Q\left(\omega\right) Y_{in}\left(\omega\right) \right]^{\frac{\rho-1}{\rho}} dG_{in}\left(\omega\right) \right]^{\frac{\rho}{\rho-1}}, \tag{1}$$

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

The production function for intermediate goods is

$$Y_{in}\left(\omega\right) = Z_n X\left(\omega\right) L_{in}\left(\omega\right), \tag{2}$$

where $L_{in}\left(\omega\right)$ 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, $X\left(\omega\right)$. 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, $X\left(\omega\right)$ is a productivity term that is idiosyncratic to producer ω. Like product quality, for now, we assume that the producers' idiosyncratic productivity is the same in all locations.

It is useful to define $A\left(\omega\right) \equiv Q\left(\omega\right) \times X\left(\omega\right)$. In what follows, we will refer to $A\left(\omega\right)$ 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:

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

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

$$Y_n \quad = \quad Z_n \Phi_n L_n,$$

where

$$\Phi_n \equiv \left[\sum_i \int A\left(\omega\right)^{\rho-1} dG_{in}\left(\omega\right)\right]^{\frac{1}{\rho-1}}, \tag{3}$$

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

$$y_n = z_n + \phi_n. \tag{4}$$

Equation (4) 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 start by showing how cross-country differences in z_n and ϕ_n can be computed using firm-level data on physical output per-worker. The log of output per-worker for firm ω is:

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

For MNEs that operate in two different countries, we can compute the difference between their output per -worker in Home country i and host country n :

$$y_{ii}(\omega) - y_{in}(\omega) = z_i - z_n. \tag{5}$$

Equation (5) 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, $x(\omega)$ cancels 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 (5) 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 cancel out from the above equation. For a MNE that operates in two countries we can further compute:

$$[y_{in}(\omega) - y_n] - [y_{ii}(\omega) - y_i] = \phi_i - \phi_n. \tag{6}$$

Equations (5) and (6) show how we can use data on firm-level and aggregate output per-worker 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 MNE decision to open affiliates in foreign countries is endogenous and the sample of firms that choose to become MNEs is selected.

As mentioned in the Introduction, 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 (e.g. Helpman et al., 2004), only the most productive—or best-quality— firms enter foreign markets. We emphasize that this type of selection does not present a problem for the procedure described by (5) and (6). 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, our procedure implies that we can obtain differences in z_n and ϕ_n across countries using data from just one firm-any firm-that simultaneously produces in two countries. Section 3.2 discusses other selection concerns after presenting the full quantitative model.

2.3 Decomposition based on firm-level revenue

This section shows how to compute the terms in (4) using firm-level data on MNE revenues. From the demand functions implied by (1), we can write the revenue of a firm from country i that operates in country n as:

$$R_{in}(\omega) = \left[\frac{A(\omega)}{\Phi_n}\right]^{\rho-1} R_n, \tag{7}$$

where $R_n \equiv \sum_i \int R_{in}(\omega) dG_{in}(\omega)$ denotes aggregate revenues in country n. Note that revenue per-worker is constant across firms in this economy, so that taking differences in revenue per-worker in a way analogous to (5) is uninformative about differences in country-embedded factors. Instead, we can compare the same firm across countries as in (6):

$$[r_{in}(\omega) - r_n] - [r_{ii}(\omega) - r_i] = [\rho - 1] [\phi_i - \phi_n]. \tag{8}$$

Equation (8) shows how to use firm-level revenue data to obtain $\phi_i - \phi_n$, for a given elasticity $\rho - 1$. MNEs should have larger (log) revenue shares in countries where aggregate firm know-how is relatively low, since they face less competition in these countries. After obtaining $\phi_i - \phi_n$, differences in country-embedded factors, $z_n - z_i$, can be computed as residuals from (4). On the one hand, the great advantage of using revenue rather than quantity data is that the former is readily available for many countries. On the other hand, it requires parameterizing the elasticity of substitution ρ. 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 ω from country i that operates in country n is

$$A_{in}(\omega) = A(\omega) \times exp(-\kappa_{in}(\omega)), \tag{9}$$

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 MNE can use the same know-how in all the locations where it operates.

Under this assumption, (8) becomes:

$$[r_{in}(\omega) - r_n] - [r_{ii}(\omega) - r_i] = [\rho - 1][\phi_i - \phi_n - \kappa_{in}(\omega)], \tag{10}$$

where ϕ_n is now given by:

$$\Phi_n \equiv \left[\sum_i \int A_{in}(\omega)^{\rho-1} dG_{in}(\omega)\right]^{\frac{1}{\rho-1}}. \tag{11}$$

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 (10) 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 technology transfer costs are large -high $\kappa_{in}(\omega)$.

However, 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 $\kappa_{in}(\omega)$ that are common in the trade and multinational production literature. In this case, we can write the analog to (8) for firms from country n that operate in country i:

$$[r_{ni}(\omega) - r_i] - [r_{nn}(\omega) - r_n] = [\rho - 1][\phi_n - \phi_i - \kappa_{ni}(\omega)]. \tag{12}$$

Under standard assumptions on how the average $\kappa_{in}(\omega)$ relates to the average $\kappa_{ni}(\omega)$, (10) and (12) pin-down $\phi_n - \phi_i$. Section 3.2.1 provides details on these assumptions and presents our estimation procedure.

2.5 Multiple factors of production

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,

$$Y_{in}(\omega) = Z_n X_{in}(\omega) \left[H_n L_{in}(\omega)\right]^{1-\alpha} K_{in}(\omega)^{\alpha}. \tag{13}$$

The variables $L_{in}(\omega)$ and $K_{in}(\omega)$ denote labor and the capital stock employed by firm ω in country n, and H_n is human capital per-worker in country n. We allow for the idiosyncratic productivity $X_{in}(\omega)$ to differ across production locations. In addition, we maintain the assumption that the production of the final good is given by (1), but allow for the idiosyncratic product quality $Q_{in}(\omega)$ to differ across destination countries. We define firm know-how as $A_{in}(\omega) \equiv Q_{in}(\omega) \times X_{in}(\omega)$, and assume that it satisfies (9).

The aggregate production function satisfies

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

Total factor productivity is given by

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

and output per worker can be written as

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

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

$$tfp_n \quad = \quad z_n + \phi_n, \tag{14}$$

and

$$y_n \quad = \quad \tilde{z}_n + \tilde{\phi}_n, \tag{15}$$

Equation (8) continues to hold in this more general setup, and can be used to compute $\phi_i - \phi_n$. 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 (15) and (14), respectively.

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 percent of an affiliate to identify an ownership link between the two firms.[8]

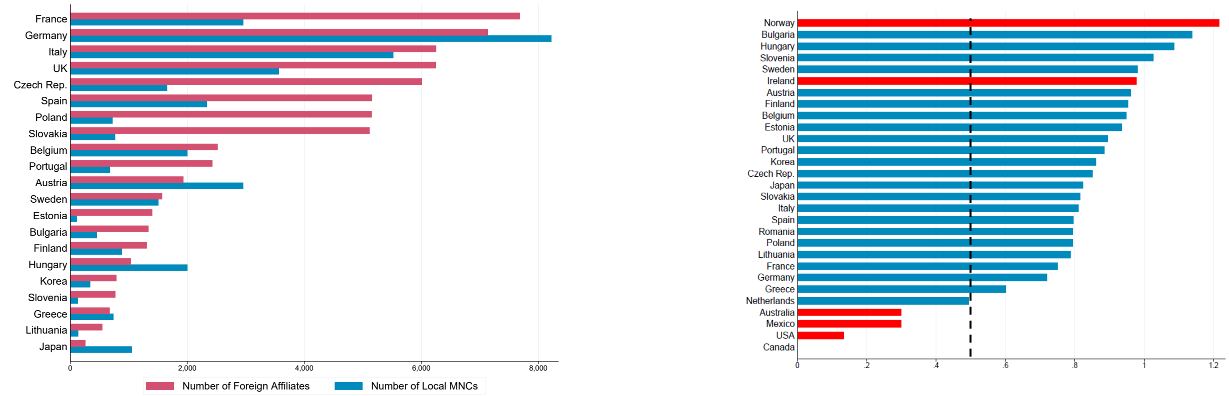
The main variable used in our analysis is the revenue (turnover) of each firm. While the ORBIS data cover the 2005-2013 period, we use data for the year 2011 for most of our analysis. The left panel of Figure 1 reports the number of MNEs from and in each country in our sample, while the right panel reports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

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

Figure 1: Data coverage

Number of domestic and foreign multinationals — Relative revenues



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.

Aggregate data: In addition to the firm-level data, the implementation of (10) 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 $[1 - \alpha]$, 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.

3.2 Empirical strategy

This section describes how we implement (10) to measure differences in aggregate firm know-how using the MNE data.

3.2.1 Disentangling aggregate firm know-how from technology transfer costs

We start by re-writing (10) in terms of log market shares:

$$s_{in}(\omega) - s_{ii}(\omega) = [\rho - 1][\phi_i - \phi_n] - [\rho - 1]\kappa_{in}(\omega), \tag{16}$$

where $s_{in}(\omega) \equiv r_{in}(\omega) - r_n$ is the log of the revenue share of firm ω from country i operating in country n. We can compute the left-hand side of (16) for each MNE from country i that has revenues in countries i and n. The technology transfer costs can be written without loss of generality as:

$$\kappa_{in}(\omega) = \delta_i^o + \delta_n^l + \delta_{in} + \delta_{in}(\omega). \tag{17}$$

The expression states that technology transfer costs can be decomposed into origin and location specific components, δ_i^o and δ_n^l, a bilateral symmetric component, δ_{in}, and an idiosyncratic component $\delta_{in}(\omega)$. Since (17) 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 ϕ_i and ϕ_n by using (16) and imposing restrictions on the terms in (17). This strategy follows a long tradition in international economics that separates country-specific technologies from trade and multinational production costs using gravity equations. As in this literature, we assume that the bilateral component of the transfer costs is a log-linear function of observable characteristics of each country pair, such as distance and sharing a language, $\delta_{in} = a_1 dist_{in} + a_2 lang_{in}$. Substituting into (16) and (17), we obtain the estimating equation:

$$s_{in}(\omega) - s_{ii}(\omega) = D_i^o + D_n^l + \beta_d dist_{in} + \beta_c lang_{in} + \epsilon_{in}(\omega). \tag{18}$$

The variables $D_i^o \equiv [\rho - 1]\left[\Delta\phi_i - \Delta\delta_i^o\right]$ and $D_n^l \equiv -[\rho - 1]\left[\Delta\phi_n + \Delta\delta_n^l\right]$ 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 with respect to a reference country (i.e. the country for which the dummies are omitted). In what follows, we use France as our reference country.

We obtain $[\rho - 1]\Delta\phi_i$ by imposing alternative identification restrictions on $\Delta\delta_i^o$ and $\Delta\delta_i^l$. First, we follow Eaton and Kortum (2002) and assume that costs have a destination-specific, but no source-specific, component, $\Delta\delta_n^o = 0$. Under this assumption, we can compute

$$D_n^o = [\rho - 1]\, \Delta\phi_n, \tag{19}$$

and obtain the firm-embedded know-how in 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, $\Delta\delta_n^l = 0$, following Waugh (2010). In that case we compute

$$-D_n^l = [\rho - 1]\, \Delta\phi_n. \tag{20}$$

Finally, a commonly used restriction in the literature is symmetry, $\Delta\delta_n^o = \Delta\delta_n^l$, following Head and Ries (2001). In this case, we compute

$$D_n^{sym} \equiv \frac{1}{2}\left[D_n^o - D_n^l\right] = [\rho - 1]\, \Delta\phi_n. \tag{21}$$

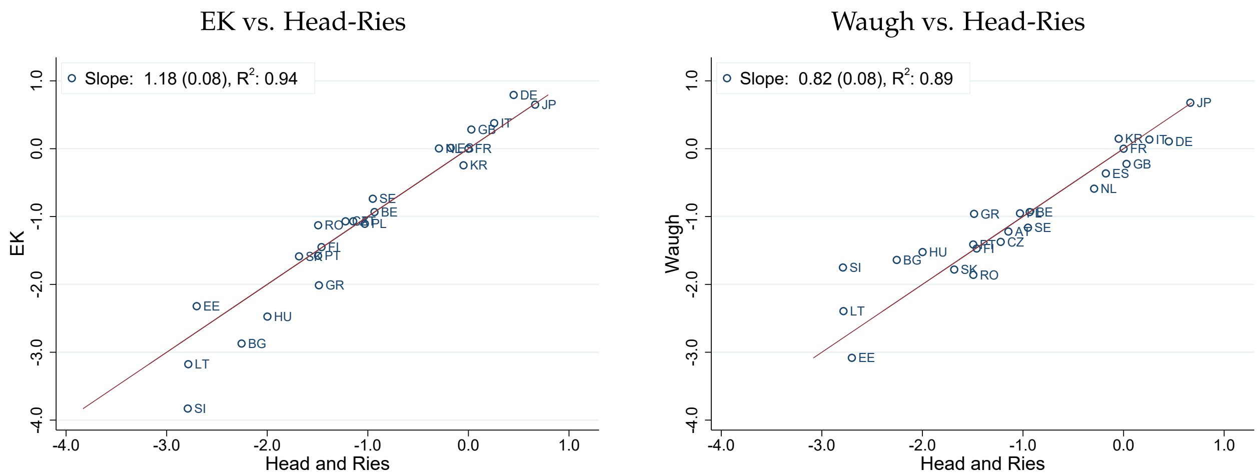
Figure 2 compares the estimates of $[\rho - 1]\, \phi_n$ that correspond to each of these alternative assumptions. We use data for the year 2011, with France as our reference country, so that the dummies should be interpreted as differences relative to France. The figure shows that the estimates using alternately (20), (19), and (21) are remarkably close to each other. A regression of D_n^o (D_n^l) on D_n^{sym} has an the R-squared of 0.94 (0.89) and a slope of 1.18 (0.82). This naturally implies that the estimates $[\rho - 1]\, \phi_n$ are not very sensitive to the choice of restrictions that underlie (19), (20), or (21). Appendix Figure A.1 shows very similar results if we separately estimate D_n^o and D_n^l for subsamples of manufacturing and service firms. In what follows, we compute $[\rho - 1]\, \Delta\phi_n$ using the restrictions imposed in (21) as our baseline results.

3.2.2 Estimating the elasticity of substitution

Equation (21) identifies differences in ϕ_n up to an elasticity ρ. This section shows how this elasticity can be estimated using our data. Combining (14) and (15) with (21), we can write

$$\Delta tfp_n = \frac{1}{\rho - 1} D_n^{sym} + \Delta z_n,$$

Figure 2: Estimating aggregate firm know-how: alternative assumptions on κ_{in}



Notes: Each circle represents a country. The axes 'EK', 'Waugh' and 'Head and Ries' respectively refer to the estimates of ΔD_n^o, $-\Delta D_n^l$, and $0.5 \times \left[\Delta D_n^o - \Delta D_n^l\right]$ from an OLS regression on (18).

and

$$\Delta y_n = \frac{1}{1-\alpha}\frac{1}{\rho-1} D_n^{sym} + \Delta \tilde{z}_n,$$

where D_n^{sym} is obtained from (21).

One could estimate $\frac{1}{\rho-1}$ from an OLS regression of Δtfp_n (or Δy_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 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:

$$\Delta tfp_n = b_0 + b_1 \hat{D}_n^{sym} + b_2 C_n + u_n, \tag{22}$$

and

$$\Delta y_n = b_0^y + b_1^y \hat{D}_n^{sym} + b_2^y C_n + u_n^y, \tag{23}$$

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 $\rho = \frac{1}{\hat{b}_1} + 1$ or $\rho = \frac{1}{\hat{b}_1^y}\frac{1}{1-\alpha} + 1$.

Table 1 reports these estimates. We present results both using data for the year 2011 (first panel), and also estimating D_n^{sym} 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 D_n^{sym} are 0.291 and 0.107, which imply values for ρ of 5.7 and 10.3 respectively.[9] 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 ρ's increase to 9.7 and 15.1 (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).

[9]To obtain these values, we compute $\rho = \frac{1}{\beta} + 1$ and $\rho = \frac{1}{\beta[1-\alpha]} + 1$, where β 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: ρ

	Year 2011						**Pooled**					
	Output per worker			**TFP**			**Output per worker**			**TFP**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
D_n^{sym}	0.291***	0.273***	0.155***	0.107***	0.113***	0.071**	0.310***	0.281***	0.161***	0.114***	0.123***	0.075**
	[0.066]	[0.061]	[0.062]	[0.027]	[0.028]	[0.029]	[0.068]	[0.058]	[0.052]	[0.027]	[0.028]	[0.027]
k_n/y_n		0.542*	0.152		-0.192*	-0.318***		0.552**	0.264*		-0.152	-0.251**
		[0.271]	[0.189]		[0.107]	[0.102]		[0.251]	[0.152]		[0.101]	[0.082]
h_n		0.880	-0.166		-0.304	-0.644*		0.781	0.004		-0.279	-0.556*
		[0.665]	[0.733]		[0.261]	[0.329]		[0.622]	[0.614]		[0.250]	[0.274]
Rule of law			0.369			0.095			0.168			0.022
			[0.315]			[0.140]			[0.261]			[0.132]
Corruption			0.201			0.097			0.338*			0.164*
			[0.230]			[0.097]			[0.185]			[0.087]
Obs.	23	23	23	23	23	23	184	184	184	184	184	184
R-squared	0.36	0.44	0.82	0.35	0.42	0.76	0.38	0.46	0.82	0.34	0.38	0.74
Implied ρ	**5.7**	**6.0**	**9.7**	**10.3**	**9.8**	**15.1**	**5.4**	**5.8**	**9.4**	**9.7**	**9.1**	**14.3**

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 uses the estimates obtained above to decompose differences in TFP and output per-worker across countries into country-embedded factors and aggregate firm know-how. 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, 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 (14). 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, more than 40 percent of the observed 0.29 log-point difference in TFP. 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 Great Britain and Korea, and is somewhat larger in Japan and Germany (0.07 and 0.05 log-difference relative to France). In contrast, firm know-how is quite low in the eastern European countries, such as Bulgaria, Hungary and Estonia.

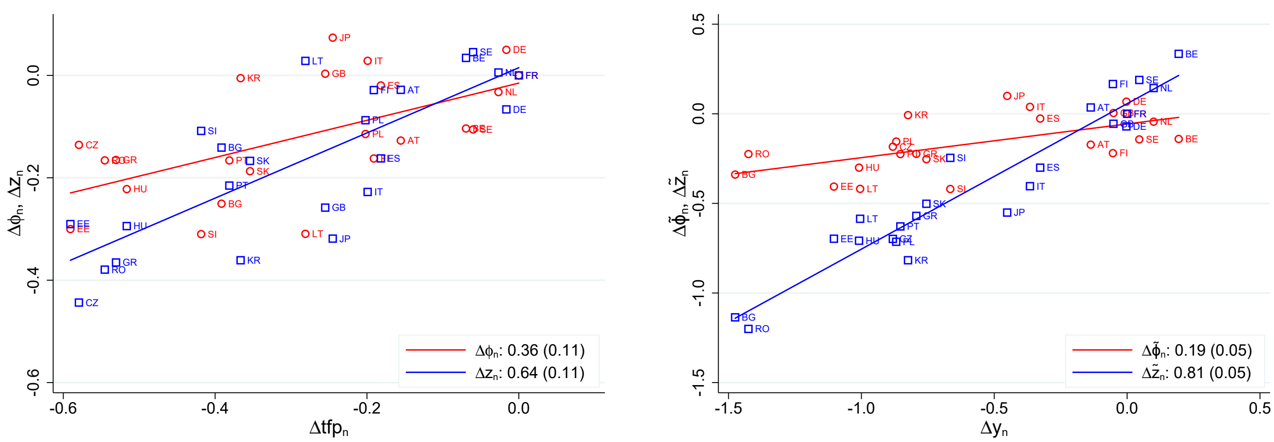
Figure 3b shows our decomposition in terms of output per-worker, following (15). For the average country, $\Delta\tilde{\phi}_n$ is 0.16 log points lower than in France, compared to a log-difference in output per-worker relative to France of -0.55, around 30 percent of the observed 0.55 log-point difference in output per-worker. 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.

Figure 3a and 3b reveal a strong positive relation between cross-country differences in aggregate firm know-how 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 (14) and (15), 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 Δtfp_n (resp. Δy_n), which are reported in the figures. Differences in aggregate firm know-how $\Delta\phi_n$ account for more than one third of the cross-country variance in TFP, while differences in $\tilde{\phi}_n$ account for almost one fifth of the cross-country variance in output per-worker.[10] Differ-

[10]Cross-country differences in $\Delta\phi_n$ (resp. $\Delta\tilde{\phi}_n$) account for more than 50 percent (28 percent) of cross-

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

(a) TFP (b) Output per-worker



Notes: Each circle (square) represents a country. Figure (3a) plots the decomposition in (14), 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 (15), 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.

ences in country-embedded factors account for the remaining two thirds of the differences TFP, and eighty 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.[11]

Sectoral results: We now conduct the decomposition in (15) for the Manufacturing and the Service sectors separately. We perform our sectoral decomposition in terms of output per-worker only using data on labor productivity from KLEMS, since we don't have any sectorial data on differences TFP levels.

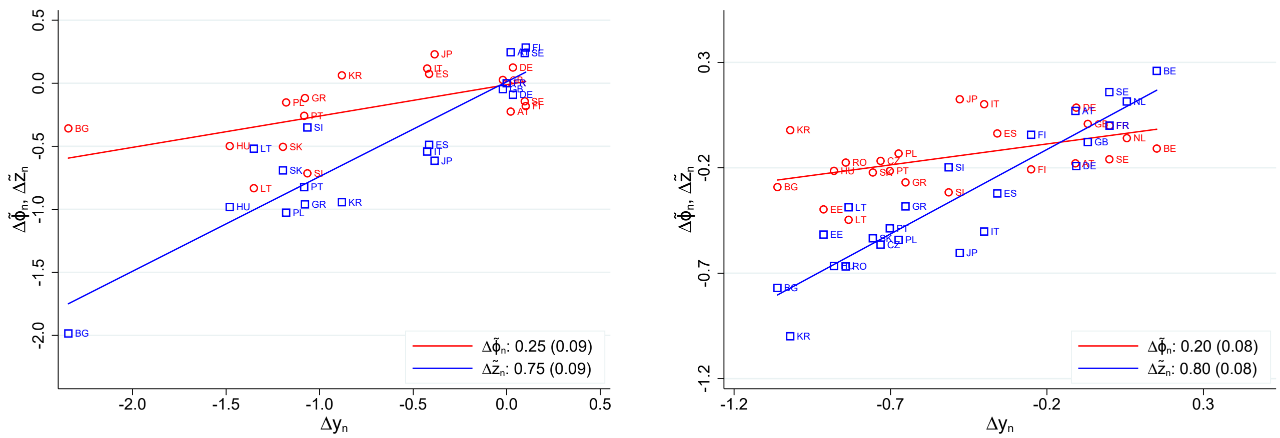
Figure 4 reports the results from the sectoral decompositions. For the average country, the gap in aggregate firm know-how relative to France is larger in manufacturing than in services sectors (-0.19 versus -0.14 log points). In addition, differences in aggregate firm know-how account for a quarter of the cross-country variance in output per worker in manufacturing, and about a fifith of the cross-country variance in services. This implies that differences in country-embedded factors are more important for services than for manufaturing sectors. Notice that the implied ρ from the Manufacturing and Services

country TFP differences (income per-capita) if $\rho = 7$, while these contributions decrease to 23 percent (12 percent) when $\rho = 15$.

[11]See Lagakos et al. (2018) and Hendricks and Schoellman (2018).

Figure 4: Development accounting: Manufacturing and Services

Manufacturing | Services



Notes: Each circle (square) represents a country. The figures plot the decomposition in (15) at the sectoral level. Δy_n^j is plotted in the x-axis and $\Delta\tilde{z}_n^j$ and $\Delta\tilde{\phi}_n^j$ are plotted in the y-axis for j =Manufacturing (left panel) and j =services (right panel) .

estimates are comparable to those presented on Table 1(see Table A1in the Appendix).

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. Alternately, 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 components. In particular, from the definition of Φ_n we can write:

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

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 Φ_{nn} denotes the aggregate know-how of the domestic firms. 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

$$\frac{\Phi_n}{\Phi_F} = \left[\frac{\Phi_{nn}^{\rho-1}}{\Phi_{FF}^{\rho-1}} \lambda + \frac{\sum_{i \neq n} \Phi_{in}^{\rho-1}}{\sum_{i \neq F} \Phi_{iF}^{\rho-1}} [1-\lambda] \right]^{\frac{1}{\rho-1}}, \tag{24}$$

where $\lambda \equiv R_{FF}/R_F = \Phi_{FF}^{\rho-1}/\Phi_F^{\rho-1}$ denotes the revenue share of French firms in France. To compute the terms in this equation, we follow the same steps used to derive (10) and obtain:

$$[r_{in}(\omega) - r_{nn}] - [r_{ii}(\omega) - r_{ii}] = [\rho - 1] [\phi_{ii} - \phi_{nn} - \kappa_{in}(\omega)]. \tag{25}$$

The difference between (10) and (25) is that (10) compares firm-level relative to aggregate revenues in a country n, $r_{in}(\omega) - r_n$, while (10) compares firm-level relative to total revenues by domestic firms in a country n, $r_{in}(\omega) - r_{nn}$. As (25) shows, the second comparison helps us pin down the cross-country differences in the aggregate know-how of domestic firms, $\phi_{ii} - \phi_{nn}$. We estimate these differences following the same procedure as the one described in Section 3. Then, we can compute $\Phi_{nn}^{\rho-1}/\Phi_{FF}^{\rho-1}$, and obtain $\sum_{i \neq n} \Phi_{in}^{\rho-1} / \sum_{i \neq F} \Phi_{iF}^{\rho-1}$ as a residual from (24).

Unlike (15), the expression in (10) is not log-linear. We evaluate the contribution of differences in the domestic firms know-how, Φ_{nn}/Φ_{FF}, to aggregate differences in know-how, Φ_n/Φ_F, in two alternative ways. First we compute

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

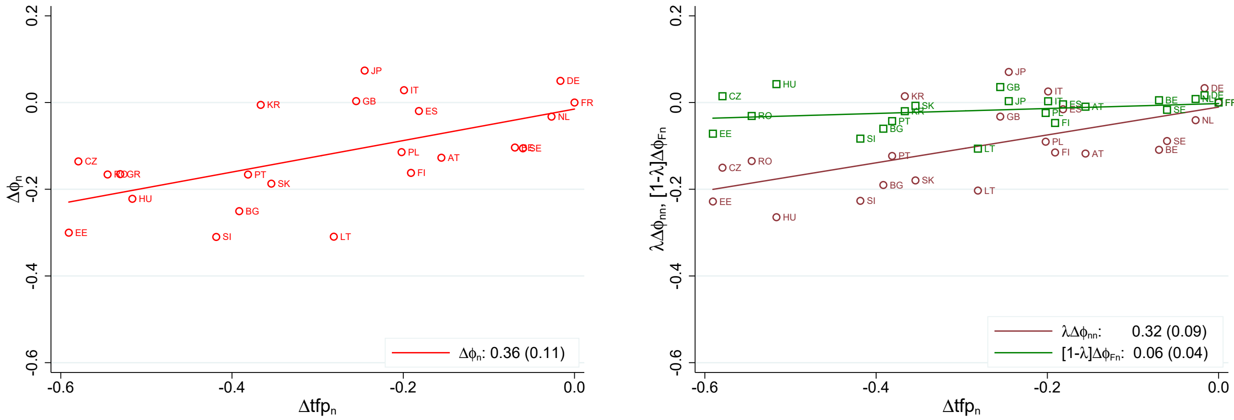
Alternately, we compute

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

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

$$ln\Upsilon_{nn}^1 \simeq ln\Upsilon_{nn}^2 \simeq \lambda \Delta \phi_{nn}.$$

Figure 5: 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 (26) (y-axis) and Δtfp (x-axis).

The difference in aggregate firm know-how is

$$\Delta\phi_n \simeq \lambda\Delta\phi_{nn} + [1-\lambda]\,\Delta\phi_{Fn}. \tag{26}$$

Figure 5 shows the two terms in (26). 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 (26) and depicted in green) are not correlated with aggregate differences in TFP, with many developed and developing countries actually having better foreign affiliates than France.

5 Robustness

In this section, we present several robustness checks to our baseline estimates of aggregate firm know-how. Table 2 summarizes the results for our development accounting decomposition of TFP and output per worker. We also show the decomposition of output per worker for the manufacturing and the service sectors.

Table 2: Contribution of aggregate firm know-how. Robustness.

	TFP	**Output per worker**
Baseline	0.36 (0.11)	0.19 (0.05)
Selection		
>50p	0.37 (0.11)	0.19 (0.05)
<50p	0.42 (0.12)	0.22 (0.06)
>80p	0.40 (0.10)	0.20 (0.05)
<20p	0.37 (0.12)	0.20 (0.06)
>95p	0.35 (0.10)	0.18 (0.06)
<5p	0.52 (0.14)	0.29 (0.08)
Technology transfer costs		
Waugh dummies	0.30 (0.10)	0.15 (0.05)
EK dummies	0.43 (0.13)	0.23 (0.07)
No gravity	0.35 (0.10)	0.18 (0.05)
Narrow Industries		
2-digit SIC	0.38 (0.12)	0.21 (0.06)
4-digit SIC	0.38 (0.12)	0.22 (0.07)
Employment shares	0.47 (0.10)	0.22 (0.06)

Notes: Share of the cross-country variance of aggregate firm know-how (relative to France) in TFP and output per-worker cross-country variance. This corresponds to the slopes of a bivariate OLS regression of $\Delta\phi_n$ (resp. $\Delta\tilde{\phi}_n$) on Δtfp_n (resp. Δy_n). Standard errors are in parenthesis.

5.1 Selection

Our first robustness exercise addresses selection concerns.A potential concern with our estimation may be that the sample of MNEs that enters a given destination country is selected: We observe only affiliates of those MNEs that chose to enter a given market. Our framework, however, is based on comparing affiliates of the same multinational firm. In principle, 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 2 shows how our estimates of $\Delta\phi_n$ ($\Delta\tilde{\phi}_n$) change when we repeat our estimation with different subsamples of firms In particular, we rank parents by their revenue size in each source country, repeat our estimation in the following subsamples of firms: those above (below) the 50th size percentile; above (below) the 80th (20th) size percentile; and above (below) the 95th (5th) size percentile. The table shows that restricting the sample in these ways does not significatively alter our baseline estimates. Only when we restrict the sample to the top and bottom five percentile of parents point-estimates results start differing more substantially from the baseline (even though they are not significantly different from each other). Typically, if only affiliates of larger parents were considered, the resulting contribution of aggregate firm know-how to differences in TFP and output per-worker across countries would be smaller than if only affiliates of smaller parents were considered in the estimation.

5.2 Alternative assumptions on technology transfer costs

Next, we calculate the contribution of aggregate firm know-how to differences in cross-country TFP and income per-capita under alternative assumptions on the technology transfer costs. In particular, we consider the assumption in (19), following Waugh (2010), the assumption in (20), which follows Eaton and Kortum (2002), and a specification without any bilateral (observable) variable, such as distance. Results under alternative assumptions on κ_{in} are very similar to our baseline estimates, with the specification with only origin dummies (Waugh) acting as a lower bound and the one with only destination dummies (EK) acting as an upper bound. Including or not gravity variables barely changes our baseline development-accounting decomposition.

5.3 Estimation withinnarrow 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, and alternately, in the same 4-digit SIC sector. Table 2 shows that these alternative estimates lie very close to our baseline estimates.

5.4 Estimation using employment data

Equation (18) 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 (18) using data on log-employment shares as the dependent variable. The resulting estimates of $\Delta\phi_n$ are in Table 2where they are compared to our baseline estimates. The table shows that the contribution of aggregate firm know-how to to cross-country TFP difference are somewhat larger when computed with employment data. 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 residualcomputed as

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

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

(1).[12] 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 (10) 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 estimates 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 2.5. 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:

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

Here, $\Phi_{in} \equiv \left[\int A(\omega)^{\rho-1} dG_{in}(\omega)\right]^{\frac{1}{\rho-1}}$, where we omit country subscripts from $A(\omega)$ since we factored-out the technology transfer costs κ_{in} in (27). The share of country $i's$ firms in their home market is:

$$\frac{R_{ii}}{R_i} = \left[\frac{\Phi_{ii}}{\Phi_i}\right]^{\rho-1}. \tag{28}$$

Taking logs and subtracting (28) from (27)yields:

$$s_{in} - s_{ii} = [\rho - 1]\left[[\phi_i - \phi_n] - \kappa_{in} + [\phi_{in} - \phi_{ii}]\right], \tag{29}$$

where $\phi_{in} \equiv ln\left[\Phi_{in}\right]$ and $s_{in} \equiv ln\left[R_{in}/R_n\right]$. This equation differs from (16) since the left-hand side has differences in aggregate shares rather than firm-level shares. As we are no longer comparing the same MNE across-countries, the term $\phi_{in} - \phi_{ii}$ shows up in the right-hand side of (29), capturing that not every firm from country i operates in country

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

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 factoring out the technology transfer costs κ_{in}. Thus, selection into being a MNE will affect the estimates of $\phi_i - \phi_n$ if we were to base our procedure on aggregate data and (29). This result implies that it is not possible to recover cross-country differences in aggregate firm know-how using (29) and aggregate data without modeling selection explicitly.

6 Conclusion

This paper uses 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' and differences in 'aggregate firm know-how'. Across the countries in our sample, differences in aggregate firm know-how account for more than one third of the cross-country differences in TFP, for almost 20 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.

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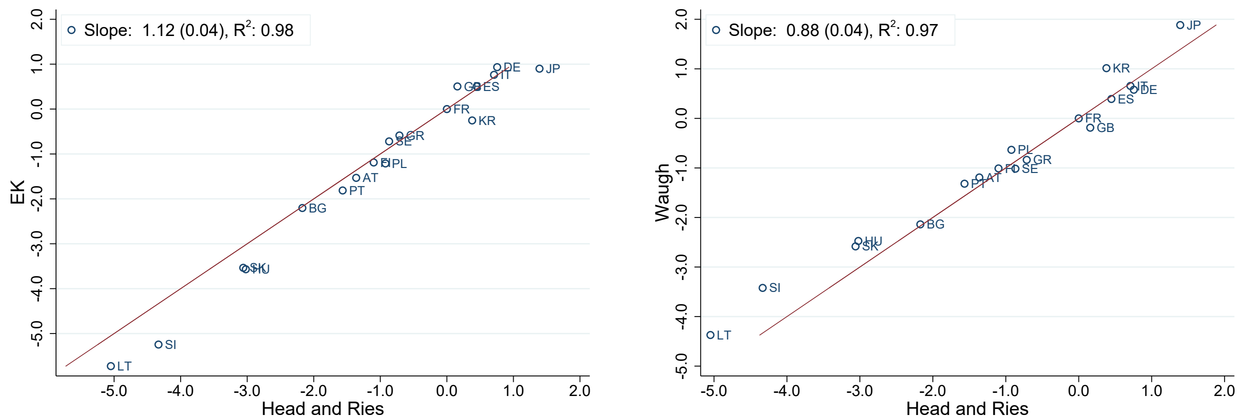
Figure A.1: Estimating aggregate firm know-how by sector

Manufacturing



Services

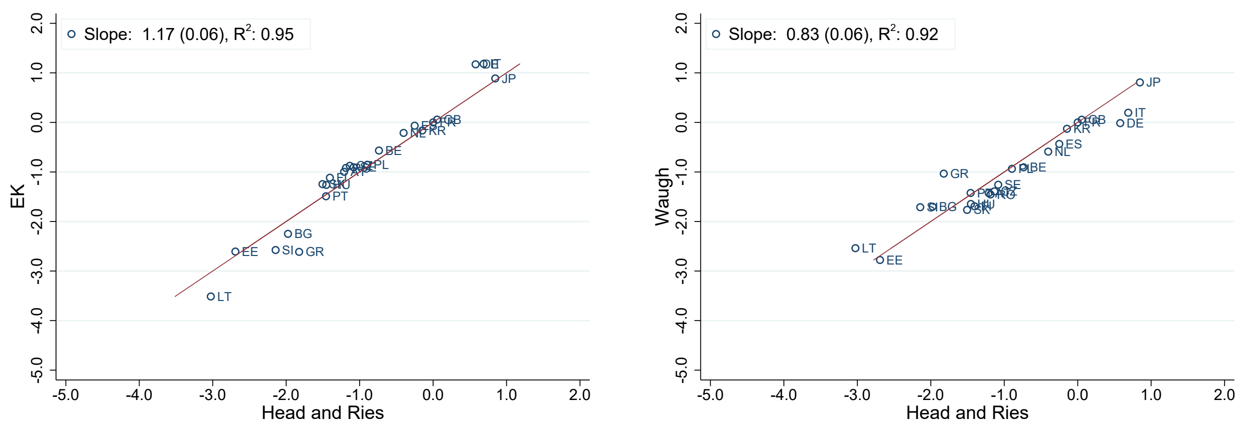


Table A1: Estimating the elasticity of substitution: ρ

	Year 2011						Pooled					
	Manufacturing			**Services**			**Manufacturing**			**Services**		
D_n	0.219***	0.188***	0.126***	0.182***	0.172***	0.095	0.230***	0.205***	0.143***	0.194***	0.178***	0.098**
	[0.050]	[0.050]	[0.042]	[0.053]	[0.054]	[0.057]	[0.042]	[0.042]	[0.035]	[0.050]	[0.047]	[0.043]
k_n/y_n		1.282**	0.484		0.368*	0.107		1.167***	0.563**		0.331*	0.155
		[0.510]	[0.295]		[0.194]	[0.176]		[0.374]	[0.254]		[0.178]	[0.116]
h_n	1.451**	2.951***	0.744	0.000	0.336	-0.344	1.329**	2.507***	0.819	0.169	0.299	-0.202
	[0.666]	[0.847]	[0.642]	[0.457]	[0.557]	[0.684]	[0.516]	[0.641]	[0.605]	[0.407]	[0.522]	[0.555]
Rule of law			0.949**			0.145			0.534			0.014
			[0.379]			[0.367]			[0.384]			[0.269]
Corruption			-0.071			0.250			0.225			0.331
			[0.248]			[0.281]			[0.220]			[0.220]
Observations	18	18	18	23	23	23	140	140	140	183	183	183
R-squared	0.39	0.59	0.91	0.24	0.30	0.72	0.38	0.54	0.89	0.28	0.33	0.70
Implied ρ	**7.8**	**8.9**	**12.8**	**8.3**	**8.7**	**15.0**	**7.5**	**8.2**	**11.4**	**7.8**	**7.9**	**14.6**

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.