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 affect 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.

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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. 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 operating in a country. As noted by Burstein and Monge-Naranjo (2009), 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 and TFP.[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

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

[2] 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).

[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.

know-how using firm-level revenue data for firms that simultaneously operate in multiple countries. In the model, since country-embedded factors are the same for all the producers in a country, the revenue share of a MNE in a 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 those 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 the firm faces large technology transfer costs. We show that if we observe MNEs from multiple source countries operating in multiple destinations, we can separately identify cross-country differences in aggregate firm know-how under assumptions on the structure of the technology transfer costs that are common in the international trade and multinational production literature.[5]

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 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

[4] See, for example, Antras and Yeaple (2014).

[5] In particular, we can assume that technology transfer costs have an origin-specific but not a destination-specific component following Waugh (2010). Alternately, we can assume that these costs have a destination-specific but not an origin-specific component following Eaton and Kortum (2002).

that the log of a firms' revenue share in a sector can be written as the sum of a firm-sector-specific 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-sector fixed-effects.[6] We find that for the average country, aggregate firm know-how is 0.12 log points lower than in France, our reference country. This represents around 40 percent of the 0.30 log-point difference in TFP between France and the average country. The relative importance of the differences in aggregate firm know-how vs. country-embedded factors varies considerably across countries. For example, country-embedded factors are similar in Italy and Slovenia, but Italy has much higher aggregate firm know-how than Slovenia, which generates significant differences in TFP between these two countries. In contrast, aggregate firm know-how is similar for the Netherlands and Greece, though TFP is much higher in the Netherlands 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 almost a third of the observed cross-country variance in TFP, and for more than two-fifth of the cross-country variance in output per-worker.

We then evaluate the sources of cross-country differences in aggregate firm know-how. First, we show that while aggregate firm know-how is strongly correlated to TFP and output per worker across countries, it is uncorrelated to production factors such as human capital or capita-output ratios. Second, we show that these differences arise within sectors, and are not 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 manufacturing and in service (two-digit) sectors separately. Overall, differences in aggregate firm know-how account for more than a third of the cross-country variance in output per-worker in manufacturing, and for almost two-fifth of the cross-country vari-

[6] Destination-sector fixed effects are unbiased estimates of the destination-sector-specific components of the revenue shares if the assignment of MNEs to countries is not driven by a firm-destination-specific component of the technology transfer costs. We evaluate this assumption and how it affects our results in Section 5.

ance in services.

Finally, we show that cross-country differences in aggregate firm know-how arise both from cross-country differences in the aggregate know-how of domestic firms, and from differences in the aggregate know-how of the foreign affiliates operating in each country. We show that differences across domestic firms account for roughly 70 percent of the observed differences in firm-know how across countries, while differences across the foreign affiliates of MNEs account for the remaining 30 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 Foreign Direct Investment (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 simultaneously in many countries.[7] 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.[8] 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 paper is related to the international trade literature that estimates country-

[7]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 Ramondo (2014), among others.

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

level productivity shifters using gravity models and aggregate revenue data (see Head and Ries, 2001; Eaton and Kortum, 2002; Waugh, 2010; Ramondo and Rodriguez-Clare, 2013; and the long literature that followed). To identify differences in aggregate firm know-how in the presence of technology transfer costs, we make assumptions on the structure of the technology transfer costs that are common in this literature.

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 exercises and presents extensions to our framework, 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

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

where $Y_{in}(\omega)$ is the output of firm ω from source country i that operates in country n, and $\rho \geq 1$ 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

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

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 $X_{in}(\omega)$ 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

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

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 $\kappa_{in}(\omega) = 0$, 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

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

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

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

denotes aggregate firm know-how in country n, which is the sum of all firm know-how in country n.

In this simple economy, output per-worker 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-worker. We can thus write

$$y_n = z_n + \phi_n. \tag{5}$$

Equation (5) states that cross-country differences in output per-worker 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 ϕ_n from z_n.

2.2 Decomposing cross-country differences in output per-worker

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 equation (1), we can write the revenue of a firm from country i that operates in country n, relative to total revenues of all firms operating in n, as

$$S_{in}(\omega) \equiv \frac{P_{in}(\omega)\, Y_{in}(\omega)}{\sum_i \int_{\omega\in\Omega_{in}} P_{in}(\omega)\, Y_{in}(\omega)\, d\omega} = \left[\frac{A_{in}(\omega)}{\Phi_n}\right]^{\rho-1}. \tag{6}$$

A firm's share depends on its know-how, $A_{in}(\omega)$, relative to the know-how of all the other firms operating 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 those countries. Importantly, country-embedded productivity Z_n does not affect the revenue share $S_{in}(\omega)$, 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. Substituting equation (3) in (6), the revenue share in logs is

$$s_{in}(\omega) = [\rho - 1] \left[a_i(\omega) - \phi_n - \kappa_{in}(\omega)\right]. \tag{7}$$

Equation (7) 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 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. After obtaining cross-country differences in ϕ_n, differences in country-embedded factors, z_n, can be computed as residuals from equation (5). This two-way fixed-effect approach constitutes 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 equation (7) 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 competitive producer of final goods aggregates sectorial output according to

$$Y_n = \prod_j \left[Y_n^j\right]^{\theta_n^j}, \tag{8}$$

where Y_n^j denotes the final output from sector j and $\theta_n^j \in [0,1]$ and $\sum_j \theta_n^j = 1$. Sectorial output is produced by aggregating intermediate goods,

$$Y_n^j = \left[\sum_i \int_{\omega \in \Omega_{in}^j} \left[Q_{in}^j(\omega) Y_{in}^j(\omega)\right]^{\frac{\rho-1}{\rho}} d\omega\right]^{\frac{\rho}{\rho-1}}, \tag{9}$$

where $Y_{in}^j(\omega)$ is the output of intermediate-good producer 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,

$$Y_{in}^j(\omega) = Z_n^j X_{in}^j(\omega) \left[H_n L_{in}^j(\omega)\right]^{1-\alpha^j} K_{in}^j(\omega)^{\alpha^j}, \tag{10}$$

where $\alpha^j \in [0,1]$. 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 similarly to equation (3),

$$A_{in}^j(\omega) = A_i^j(\omega) \times exp\left(-\kappa_{in}^j(\omega)\right). \tag{11}$$

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 and country n.

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, $\alpha_n \equiv \sum_j \theta_n^j \alpha^j$ is the aggregate labor share, and $\bar{\theta}_n \equiv \prod_j \left[\theta_n^j \left[\frac{1-\alpha^j}{1-\alpha_n}\right]^{1-\alpha^j} \left[\frac{\alpha^j}{\alpha_n}\right]^{\alpha^j}\right]^{\theta_n^j}$ is a country-specific constant.

Total factor productivity is given by

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

and output per worker can be written as

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

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

$$tfp_n = z_n + \phi_n, \tag{12}$$

and

$$y_n = \tilde{z}_n + \tilde{\phi}_n. \tag{13}$$

We can compute the terms in equations (12) and (13) following steps analogous to those described in Section (2.2). In particular, the (log) revenue share of firm ω operating in country n and sector j is

$$s_{in}^j(\omega) = [\rho - 1]\left[a_i^j(\omega) - \phi_n^j - \kappa_{in}^j(\omega)\right], \tag{14}$$

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 be aggregated according to $\phi_n = \sum_j \theta_n^j \phi_n^j$, and scaled by the labor share $1 - \alpha_n$ to obtain $\tilde{\phi}_n$. Cross-country differences in z_n and $\tilde{z}_n$ can be computed as residuals from equations (12) and (13), respectively.

Finally, we will evaluate the contribution of aggregate firm know-how to the cross-country variance of TFP and output per-worker following the variance decomposition in Klenow and Rodriguez-Clare (1997):

$$1 = \frac{cov(tfp_n, z_n)}{var(tfp_n)} + \frac{cov(tfp_n, \phi_n)}{var(tfp_n)}, \tag{15}$$

and

$$1 = \frac{cov(y_n, \tilde{z}_n)}{var(y_n)} + \frac{cov(y_n, \tilde{\phi}_n)}{var(y_n)}. \tag{16}$$

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

3 Data and empirical strategy

This section describes the data used to implement our decomposition. We relegate the details of the construction of our dataset to Appendix A.

3.1 Data description

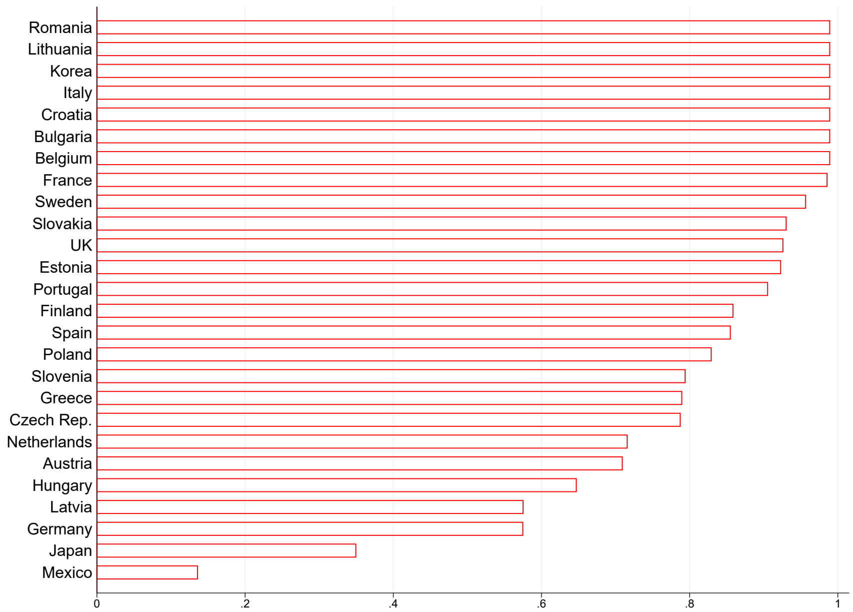
Firm level data: Our firm-level data come from ORBIS, a worldwide dataset maintained by Bureau van Dijk that includes comprehensive information on firm's revenue and employment. ORBIS includes information on both listed and unlisted firms collected from various country-specific sources, such as national 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 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 two firms.[10]

The main variable used in our analysis is the revenue (turnover) of each firm. We use

[9] The decomposition in (15) follows from $Var(tfp_n) = Cov(tfp_n, tfp_n) = Cov(tfp_n, z_n) + Cov(tfp_n, \phi_n)$. Equation (16) is derived analogously.

[10] 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: foreign-firm revenues.



Notes: Ratio of total foreign-affiliate revenues in ORBIS to total foreign-affiliate revenues reported by OECD/Eurostat, for each country in our sample.

data for the year 2016, which is the most recent year in ORBIS with good coverage. Figure 1 shows our sample of destination countries and reports, for each destination, the ratio of the foreign-firm revenues in ORBIS to the foreign-firms revenues reported by OECD/Eurostat. The figure shows that the ORBIS data include a large number of MNEs, and captures a large fraction of foreign-firm revenues in many countries. We focus on a subset of destinations for which aggregate foreign-firm revenues in ORBIS are at least 25 percent of the revenues reported by OECD/Eurostat. In contrast, every country in the world is a potential source country for the MNE's in ORBIS, so our sample of source countries is much larger than our sample of destination countries.[11]

Aggregate data: In addition to the firm-level data, the implementation of equation (7) requires data on aggregate sectoral revenues for each country. We use data on revenues across countries and sectors from EU KLEMS and the OECD. We obtain output per-worker, TFP, labor shares, and physical capital and human capital directly from the Penn World Tables (9.1). Finally, we measure output-per worker in international dollars at the

[11] Our sample of source countries, includes, among other countries, the United States, China and Canada. As destinations, these countries have very low or inexistent in ORBIS and thus are not in our sample of destination countries.

sector level using data on output per-worker from EU KLEMS and the PPP conversion factor from the Penn World Tables (9.1).

Computing firm-level revenue shares: To implement the procedure in Section 2 we need to compute sectoral revenue shares at the firm level, $s_{in}^{j}(\omega)$. The original unit of observation in the ORBIS data is a tax-identification number. In many instances, different affiliates or plants that belong to the same corporate group are registered under different tax-identification numbers in the same county. We pair a firm ω in the model with a corporate group in the data, and aggregate revenues and employment across all ORBIS firms that belong to the same corporate group and are in the same country and sector. Our unit of observation is then a corporate group-country-sector triplet.

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 those affiliates to obtain the Renault's total revenues in this sector in France. Our procedure compares affiliates of Renault's in the Transportation and Equipment sector located in different countries, and separately compares affiliates of Renault's in, e.g., the Retail sector 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 obtain this aggregate variable from EU KLEMS.

3.2 Empirical strategy

This section describes how we measure cross-country differences in aggregate firm know-how using the ORBIS data. Our strategy builds on equation (14) 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.

We assume that technology transfer costs are given by

$$\kappa_{in}^{j}(\omega) = O_i^j + D_n^j + B_{in}^j + \varepsilon_{in}^j(\omega). \tag{17}$$

The assumption states that technology transfer costs in each sector can be additively 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 component of the transfer costs is symmetric and a log-linear function of observable characteristics, such as bilateral distance and sharing a language, $B_{in}^j = a_d^j dist_{in} + a_l^j lang_{in}$.

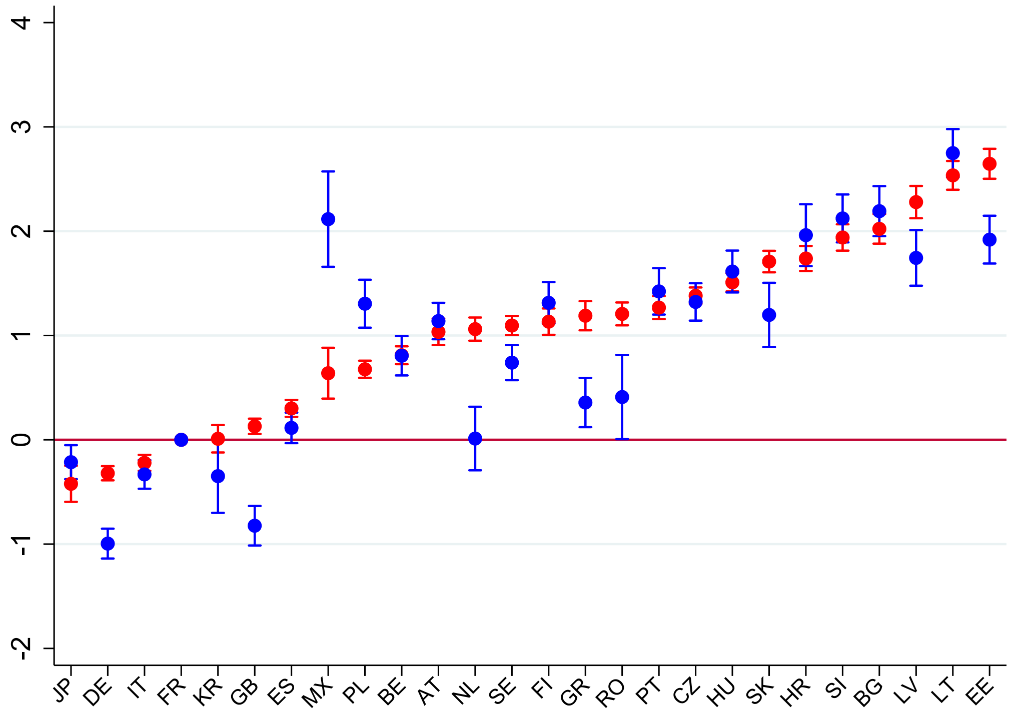
Substituting equation (17) into (14) we obtain the estimating equation:

$$s_{in}^{j}(\omega) = \delta_i^j(\omega) + \mathbb{A}_n^j + \mathbb{P}_n^j + \beta_d^j dist_{in} + \beta_l^j lang_{in} + \epsilon_{in}^j(\omega). \tag{18}$$

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, $i = n$, in sector j. $\delta_i^j(\omega)$ are sector-firm-level fixed effects. The regression identifies the firm effect, $\delta_i^j(\omega)$, from the within-firm average revenue share across destinations, in each sector j, controlling for destination characteristics and the bilateral component of the technology transfer costs. Similarly, the destination effects $\mathbb{A}_n^j$ are identified from the average revenue shares of the foreign affiliates that operate in each country, in sector j, controlling for within-firm characteristics and the bilateral component of the technology transfer costs. In turn, the destination effects $\mathbb{P}_n^j$ are identified from the average revenue shares of parents that operate in each country, controlling for the average revenue share of affiliates of the same corporation across countries and the bilateral component of the technology transfer costs, in sector j. The residual $\epsilon_{in}^j(\omega)$ is (the negative of) the sector-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, for instance, in the workhorse model of multinational production in Helpman et al., 2004. In that model, selection is driven by firm and by destination-country characteristics, not by firm-destination characteristics. For the reminder of this section, we assume that MNEs do not select into countries based on sector-firm-country characteristics, $\varepsilon_{in}^j(\omega)$. In Section 5, we evaluate this assumption and show that our main results are robust to reesti-

Figure 2: Estimated country effects.



Note: Red (blue) dots are OLS estimates of $\Delta\mathbb{A}_n$ ($\Delta\mathbb{P}_n$) from equation (18). Bars reflect 95-percent confidence intervals, clustered at the country level.

mating equation (18) using subsamples of our data where the assumption is most plausible.

Estimates of 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, our reference country. Our variables of interest are the sector-destination level dummies, which under our assumptions, can be interpreted as $\Delta\mathbb{A}_n^j \equiv [1-\rho]\left[\Delta\phi_n^j + \Delta D_n^j\right]$ and $\Delta\mathbb{P}_n^j \equiv [1-\rho]\left[\Delta\phi_n^j - \Delta O_n^j\right]$. Using country-sector level expenditure shares and defining $\Delta x_n \equiv \sum \theta_n^j \Delta x_n^j$ as the aggregate across sectors, we can compute aggregate country effects,

$$\Delta\mathbb{A}_n \equiv [1-\rho]\left[\Delta\phi_n + \Delta D_n\right], \tag{19}$$

and

$$\Delta\mathbb{P}_n \equiv [1-\rho]\left[\Delta\phi_n - \Delta O_n\right]. \tag{20}$$

Figure 2 reports our estimates of $\Delta\mathbb{A}_n$ (red) and $\Delta\mathbb{P}_n$ (blue).[12] 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 poorer Eastern European countries. The confidence intervals for the two dummies overlap for the majority of countries in our sample. However, given that there are many more affiliate firms than parent firms in our data, the affiliate dummies $\Delta\mathbb{A}_n$ are more precisely estimated than parent dummies $\Delta\mathbb{P}_n$.[13]

Disentangling aggregate firm know-how from technology transfer costs: 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 two alternative assumptions next.

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

$$\Delta\mathbb{A}_n = [1-\rho]\,\Delta\phi_n \tag{21}$$

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 (21) will understate the contribution of aggregate firm know-how to the cross-country variance of TFP,

$$cov\left(\Delta tfp_n, \frac{\Delta\mathbb{A}_n}{1-\rho}\right) = cov\left(\Delta tfp_n, \Delta\phi_n + \Delta D_n\right) \leq cov\left(\Delta tfp_n, \Delta\phi_n\right). \tag{22}$$

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,

$$\Delta\mathbb{P}_n = [1-\rho]\,\Delta\phi_n \tag{23}$$

[12] Appendix Figures A2 and A3 report our estimates of of $\Delta\mathbb{A}_n$ (red) and $\Delta\mathbb{P}_n$ (blue) for each subsector.

[13] Appendix Table A1 reports the OLS coefficients on bilateral distance and common language, β_d^j and β_l^j, for each sector. Our OLS estimates of the country-sector dummies $\Delta\mathbb{A}_n^j$ explain 0.27 of the total variance of $s_{in}^j(\omega)$ in equation (18), while the firm-sector dummies $\delta_i^j(\omega)$ account for 0.45. The R-squared of the regression is 0.72.

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 equation (23) will overstate the contribution of aggregate firm know-how to the cross-country variance of TFP,

$$cov\left(\Delta tfp_n, \frac{\Delta \mathbb{P}_n}{1-\rho}\right) = cov\left(\Delta tfp_n, \Delta\phi_n - \Delta O_n\right) \geq cov\left(\Delta tfp_n, \Delta\phi_n\right). \tag{24}$$

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

$$\frac{cov\left(\Delta tfp_n, \frac{\Delta \mathbb{A}_n}{1-\rho}\right)}{var\left(\Delta tfp_n\right)} \leq \frac{cov\left(\Delta tfp_n, \Delta\phi_n\right)}{var\left(\Delta tfp_n\right)} \leq \frac{cov\left(\Delta tfp_n, \frac{\Delta \mathbb{P}_n}{1-\rho}\right)}{var\left(\Delta tfp_n\right)}. \tag{25}$$

In what follows, we report our baseline results for $\Delta\phi_n$ using the restrictions imposed in equation (21). This is a natural choice for our baseline specification since the dummies $\Delta\mathbb{A}_n$ are more precisely estimated than the dummies $\Delta\mathbb{P}_n$, and these restrictions give us a conservative estimate of the contribution of differences in aggregate firm know-how to cross-country TFP and output per-worker differences. Section 5 reports results based on equation (21), and shows that the bounds in equation (25) are relatively tight.

3.2.1 Estimating the elasticity of substitution

The final step of our procedure is to estimate a value for the elasticity ρ to recover ϕ_n from equation (21). This section shows how this elasticity can be estimated using our data. Substituting $\Delta\mathbb{A}_n^j = [1-\rho]\,\phi_n^j$ into equation (13) we can write

$$\Delta y_n^j = \frac{1}{1-\rho}\frac{\Delta\mathbb{A}_n^j}{1-\alpha^j} + \Delta\tilde{z}_n^j.$$

One could estimate $\frac{1}{1-\rho}$ from an OLS regression of Δy_n^j on $\Delta\mathbb{A}_n^j$, and compute $\tilde{z}_n^j$ as the residuals from such regressions. Unfortunately, these estimates would not be consistent unless $\Delta\mathbb{A}_n^j$ is orthogonal to $\Delta\tilde{z}_n^j$. A concern would be that countries with policies that encourage accumulation of country-embedded factors captured in $\Delta \tilde{z}_n^j$ also improve aggregate firm know-how, $\Delta \phi_n^j$. One way to deal with this concern is to control for omitted factors included in $\Delta \tilde{z}_n^j$ 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

$$\Delta y_n^j = b_0^j + b_1 \frac{\Delta \mathbb{A}_n^j}{1-\alpha^j} + b_2 C_n + u_n^j, \tag{26}$$

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 $\rho = 1 - 1/b_1$.[14]

Table 1 reports these estimates. Columns (1),(4) and (7) respectively show the results for the pooled sample of sectors, the Manufacturing sectors, and the Services sectors. The coefficients on b_1 are precisely estimated around -0.12 in the three samples, which implies values for ρ around 9.4 . In addition, 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), (5), (7). If we also control for institutional variables, such as the quality of the rule of law and corruption, the coefficient on b_1 is somewhat lower, which is consistent with an upward bias if these variables were omitted. In this case, the implied ρ's increases ranging from 10.4 to 12.8.

Appendix Table A2 shows the results of estimating a separate b_1^j for each sub-sector in Manufacturing and Services, which would be consistent with a sector-specific value for ρ^j. . Estimates range from $\rho = 6$ for Textiles, Apparel and Wood to $\rho = 14$ for Basic Metals. For Services, estimates range from $\rho = 7$ for Information to $\rho = 15$ for Support Services —Transportation and Storage and Financial and Insurance Services have point estimates that are extremely high with standard errors that are even higher. However, we cannot statistically reject that $\rho = 10$ in most sectors.

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 markup in the United States (see e.g.. Edmond et al. 2018). Using $\rho = 10$, the country variable $\Delta \mathbb{A}_n$ obtained from aggregating the OLS estimates in equation (18), and the restriction in equation (21), we get our baseline estimates of aggregate firm know-how, $\Delta \phi_n$.

[14] We cannot apply the same approach to the TFP data since sectorial data on TFP levels are not available.

Table 1: Estimating the elasticity of substitution ρ.

	All sectors			Manufacturing sectors			Service sectors		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta \mathbb{A}_n^j / \left[1-\alpha^j\right]$	-0.120***	-0.118***	-0.107***	-0.119***	-0.121***	-0.103***	-0.118***	-0.116***	-0.107***
	[0.0170]	[0.0165]	[0.0181]	[0.0236]	[0.0250]	[0.0234]	[0.0252]	[0.0241]	[0.0240]
k_n / y_n		0.365***	0.226		0.483**	0.206		0.174	0.103
		[0.123]	[0.157]		[0.186]	[0.175]		[0.128]	[0.136]
h_n		0.0935	-0.339		0.544	-0.261		-0.203	-0.437
		[0.385]	[0.473]		[0.496]	[0.649]		[0.249]	[0.368]
Rule of law			0.234*			0.415**			0.124
			[0.134]			[0.154]			[0.104]
Observations	430	430	430	151	151	151	154	154	154
R-squared	0.315	0.361	0.398	0.361	0.451	0.568	0.382	0.405	0.423
Implied ρ	9.33	9.47	10.36	9.44	9.29	10.68	9.48	9.65	10.38
s.e. ρ	1.18	1.18	1.59	1.68	1.72	2.19	1.81	1.80	2.11

Notes: OLS estimates from equation (26).

4 Quantitative results

This section combines the estimates from equation (21) 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.[15] 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, $\Delta\phi_n$ ($\Delta\tilde{\phi}_n$), while the blue squares show the differences in country-embedded productivities (country-embedded factors) relative to France, Δz_n ($\Delta\tilde{z}_n$). All the data correspond to the year 2016.

Figure 3a shows our decomposition in terms of TFP. For the average country, aggregate firm know-how is 0.12 log points lower than in France. There is, however, wide variation across countries. Firm know-how is about the same in some of the large developed nations in our sample, such as Germany and Korea, as in France, while in Japan it is somewhat larger (0.05 log-difference). In contrast, firm know-how is quite low in the Baltic countries, such as Lithuania, Latvia, and Estonia.

The relative importance of aggregate firm know-how and country-embedded productivity differences also varies considerably across countries. For example, Italy and Slovenia –both EU members– have similar levels of country-embedded productivity. However, Italy 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 the Netherlands and Greece, though TFP is much higher in the Netherlands due to a large difference in country-embedded productivity. For countries such as Germany and the Netherlands, with roughly the same TFP, our decomposition indicates that while for Netherlands aggregate firm know-how is -0.15 log-point lower than for Germany, that negative difference is compensated by an advantage of equal magnitude in country-embedded productivity.

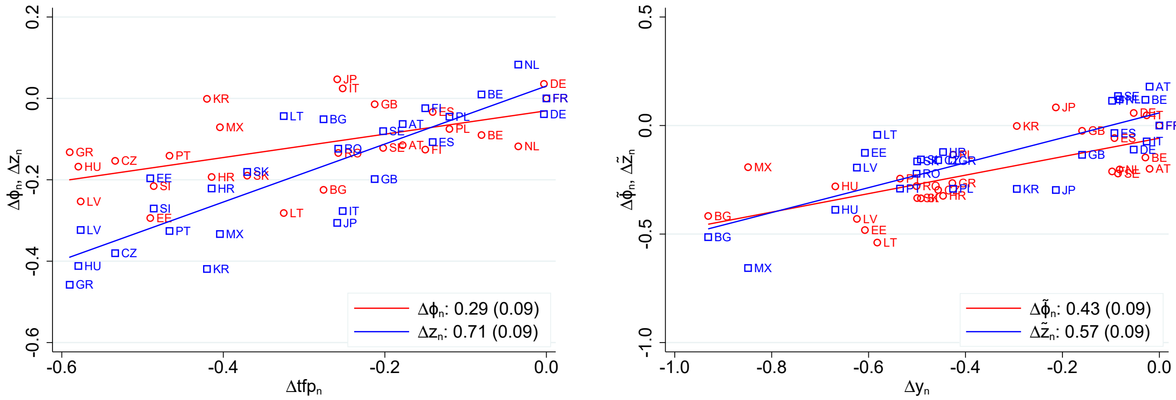
Figure 3b shows our decomposition in terms of output per-worker. For the average country, $\Delta\tilde{\phi}_n$ is 0.21 log points lower than in France, compared to a log-difference in output per-worker relative to France of -0.35, 60 percent of the observed log-point difference in output per-worker. The implied log-difference in country-embedded factors for the average country relative to France, $\Delta\tilde{z}_n$, is -0.15

Figure 11 reveals a strong positive relation between cross-country differences in aggregate

[15] Appendix Table A6 reports the exact numbers underlying this figure.

Figure 3: Dev. accounting: aggregate firm know-how vs country-embedded factors.

(a) TFP (b) Output per-worker



Notes: Each circle (square) represents a country. Figure 3a plots the decomposition in equation (12), 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 equation (13), 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).

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 contrast, our measure of aggregate firm know-how uses data on MNE 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 aggregate firm know-how and country-embedded productivities, 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 almost a third of the cross-country variance in TFP, while differences in $\tilde{\phi}_n$ account for more than 40 percent 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 57 percent of the differences in income per capita.

Correlation with factors: Table 2 evaluates how our measures of aggregate firm know-how, and country-embedded factors correlate with measures of human and physical capital. In particular, we regress sector-level output per-worker, sector level firm-know how, and sector level country embedded factors on a country's capital output ratio and hu-

Table 2: Correlations with factors.

dep var.	Δy_n^j	$\Delta \tilde{\phi}_n^j$	$\Delta \tilde{z}_n^j$
	(1)	(2)	(3)
$\Delta [k_n - y_n]$	0.353*	0.0376	0.315***
	[0.170]	[0.103]	[0.0962]
Δh_n	0.660	0.209	0.451
	[0.418]	[0.276]	[0.286]
Obs.	461	461	461
R-squared	0.176	0.309	0.358

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 (9.1).Sector-level fixed effects are included, and standard errors areclustered at the country-sector level.

man capital.[16] The table shows that differences in aggregate firm know-how for the countries in our sample are uncorrelated with those factors (column 2). Differences in country-embedded factors, in contrast, are significantly correlated with capital-output ratios. These results are reassuring given that, as explained in Section 2.3, cross-country differences in factors should be captured by country-embedded factors, rather than by firm know-how.

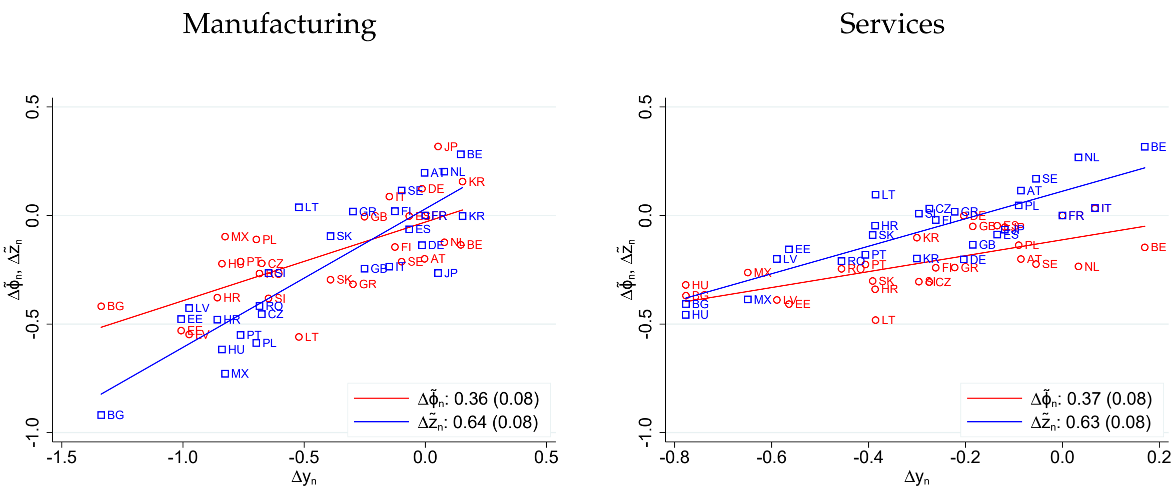
4.1 Sector-level results

We now decompose differences in output per-worker within Manufacturing and Services by aggregating our sectoral estimates of the country effects into those two broad sectoral 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 (-0.18 versus -0.21 log points). However, for the average country, this gap represents more than 40 percent of the observed log-point difference in output per-worker relative to France in Manufacturing, but 75 percent in Services. In turn, country-embedded factors respectively account for 55 and 25 percent of the observed log-point differences in output per worker in Manufacturing and Services. In addition, differences in aggregate firm

[16] We obtain very similar results if we run these regression at the aggregate level, although the number of observations is reduced to 26.

Figure 4: Dev. accounting: Manufacturing and Services.



Notes: Each circle (square) represents a country. The figures plot the decomposition in equation (13) 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) .

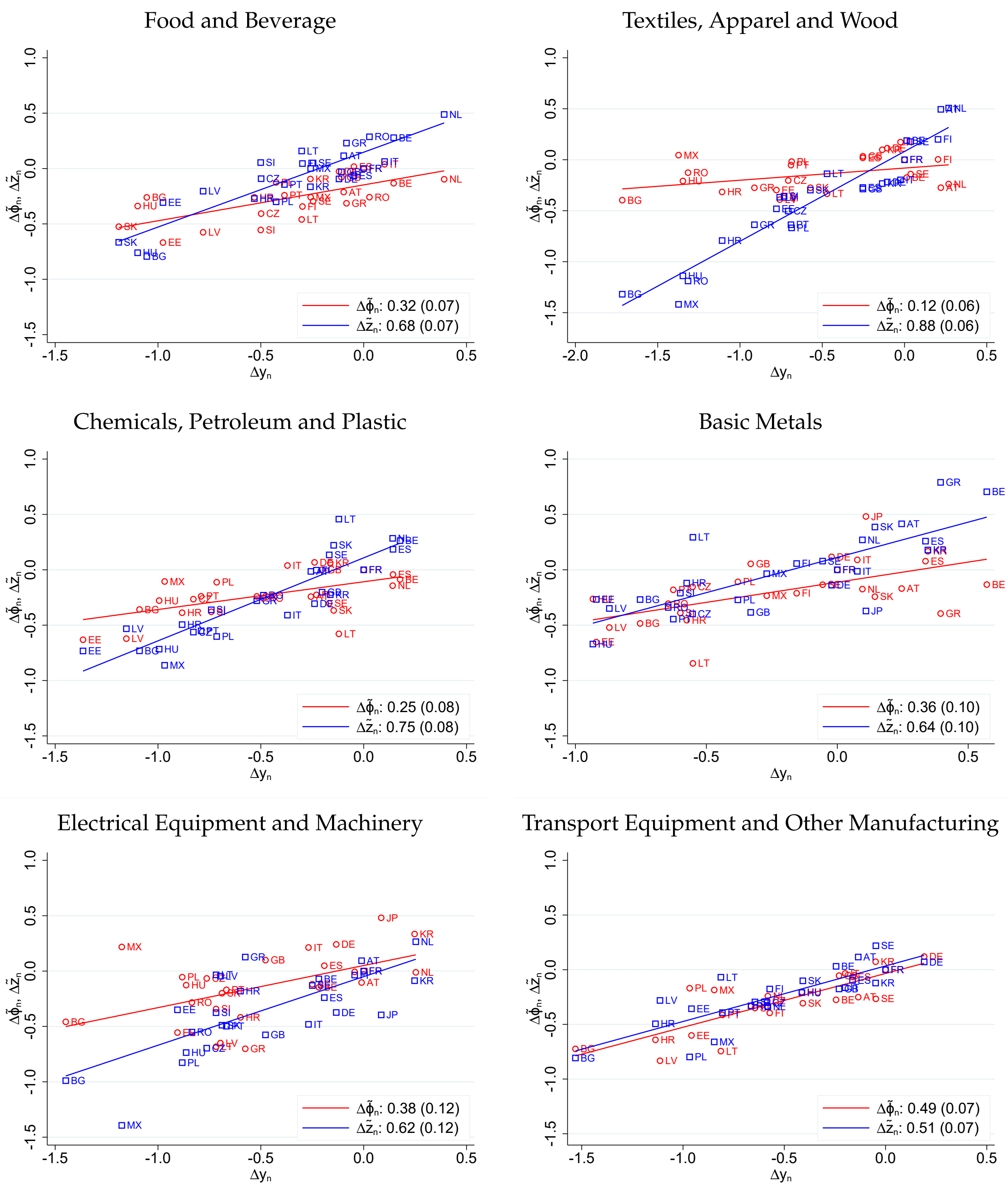
know-how account for about the same share of the cross-country variance in output per worker in Manufacturing and in Services (0.36 versus 0.37).

We can further decompose differences in output per-worker within each sub-sector in Manufacturing and each sub-sector in Services. Figures 5 and 6 show the results. Starting with Manufacturing, the contribution of aggregate firm know-how to differences in output per-worker across countries, in each sector, range from 0.12 (Textiles, Apparel and Wood) to 0.49 (Transportation Equipment and Other Manufacturing). That is, aggregate firm know-how play a small role, relative to country-embedded factors, in explaining cross-country differences in output per-worker in Textiles, Apparel and Wood, while it plays an equally important role in the Transportation Equipment and Other Manufacturing.

Within Services, differences in the importance of aggregate firm know-how in accounting for cross-country differences in output per worker across sub-sectors are smaller, ranging from 0.18 for Transportation and Storage, to 0.35 for Support Services.

There is some interesting heterogeneity in terms of the countries that exhibit the highest or lowest aggregate firm know-how, relative to France, in different sectors — that is, rankings differ across sectors. For instance, Greece is the country with the highest output per-worker in Transportation and Storage and Accommodation and Recreation. Their aggregate firm know-how in those two sectors, however, is not much higher than

Figure 5: Dev. accounting: Manufacturing sectors.



Notes: Each circle (square) represents a country. The figures plot the decomposition in equation (13) 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 $j =$ two-digit manufacturing sectors.

in other Services and Manufacturing sectors where they have lower output per-worker; differences are almost exclusively driven by differences in country-embedded factors. In contrast, the high output per-worker observed in many sectors for Japan is mainly derived from high aggregate firm know-how, relative to France.

Differences in aggregate firm know-how within and between sectors: Differences in aggregate firm-know can arise from within-sector differences, or from differences in sectoral shares across countries. We proceed by computing a measure of aggregate firm know-how that aggregates sectoral differences using the output shares from France $\Delta\phi_n^w \equiv \sum_j \theta_r^j \Delta\phi_n^j$. 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 sectoral shares. Figure 7 plots these two measures against 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 sectoral 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.

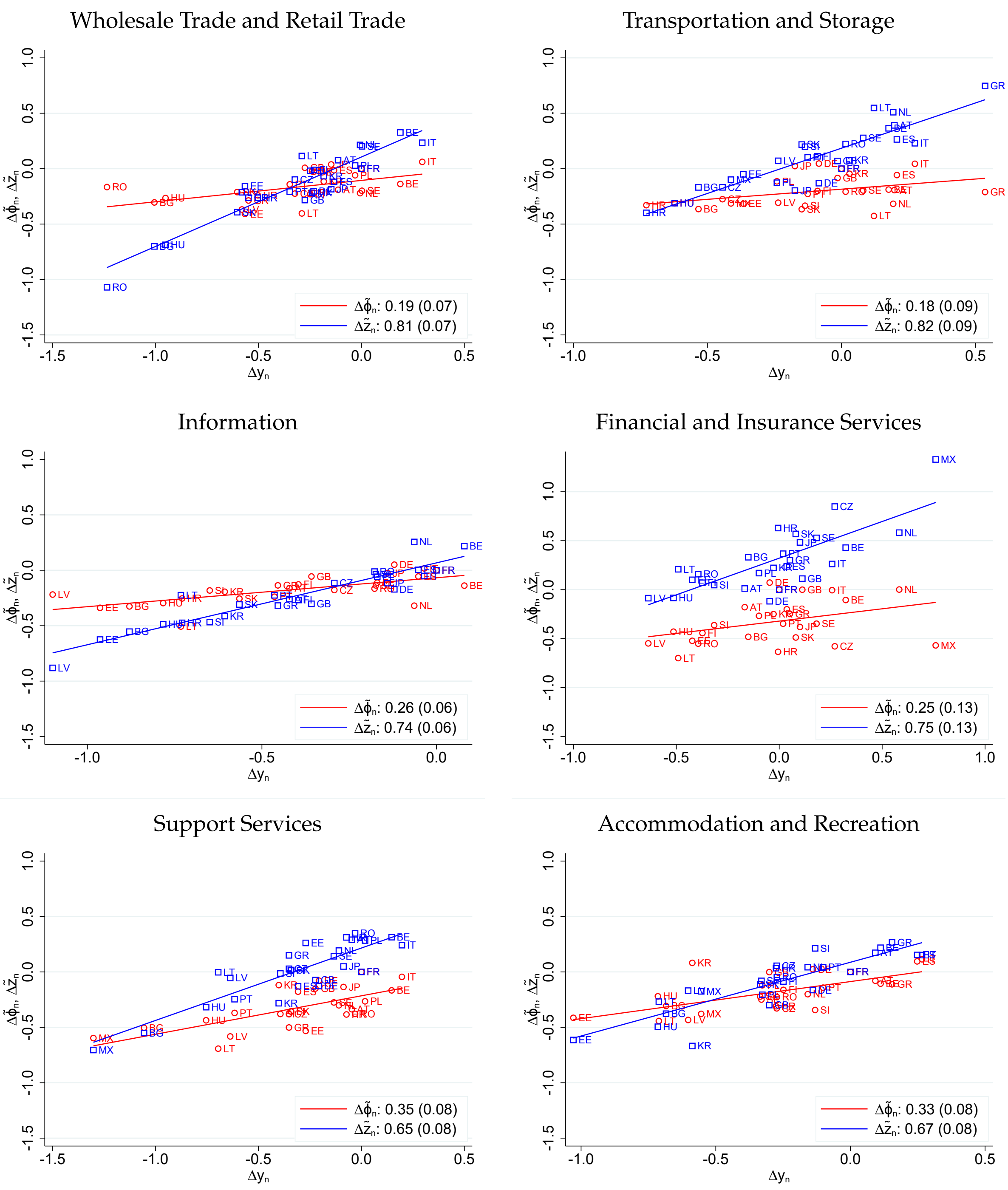
4.2 Contribution of domestic and foreign firms

Cross-country differences in aggregate firm know-how $\Delta\phi_n$ may arise both from cross-country differences in the aggregate know-how of domestic firms, and from differences in the aggregate know-how of the foreign affiliates operating in each country. 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

$$\left[\Phi_n^j\right]^{\rho-1} = \left[\Phi_{nn}^j\right]^{\rho-1} + \left[\Phi_{Fn}^j\right]^{\rho-1}, \tag{27}$$

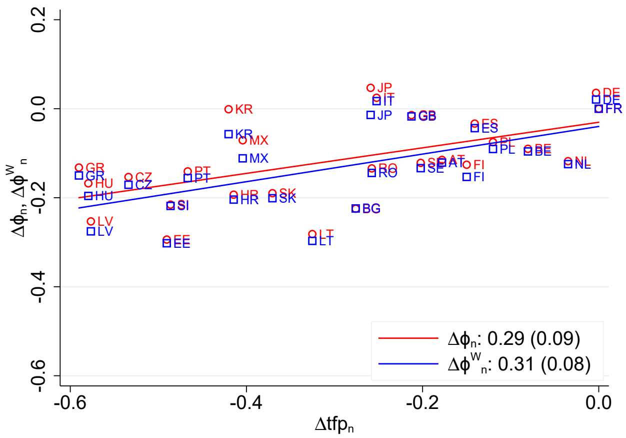
where $\left[\Phi_{nn}^j\right]^{\rho-1} \equiv \int_{\Omega_{nn}^j} A_{nn}^j(\omega)^{\rho-1} d\omega$ denotes the aggregate know-how of the domestic firms, and $\left[\Phi_{Fn}^j\right]^{\rho-1} \equiv \sum_{i\neq n} \int_{\Omega_{in}^j} A_{in}^j(\omega)^{\rho-1} d\omega$ is the aggregate know-how of foreign MNEs in country n. Since we are interested in decomposing cross-country differences in

Figure 6: Dev. accounting: Service sectors.



Notes: Each circle (square) represents a country. The figures plot the decomposition in equation (13) 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 = two-digit manufacturing sectors.

Figure 7: Differences in aggregate firm know-how within and between sectors.



Notes: The figure plots the decomposition in equation (12), where Δtfp_n is plotted in the x-axis and $\Delta\phi_n^w \equiv \sum_j \theta_r^j \Delta\phi_n^j$ 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 $\Delta\phi_n$ (rest. $\Delta\phi_n^w$) on Δtfp_n. Each circle (square) represents a country.

Φ_n, we first note that we can write aggregate firm know-how relative to France as

$$\Delta\phi_n = \sum_j \theta_n^j S_{rr}^j \Delta\phi_{nn}^j + \sum_j \theta_n^j \left[1 - S_{rr}^j\right] \Delta\phi_{Fn}^j = \Delta\phi_{nn} + \Delta\phi_{Fn}, \tag{28}$$

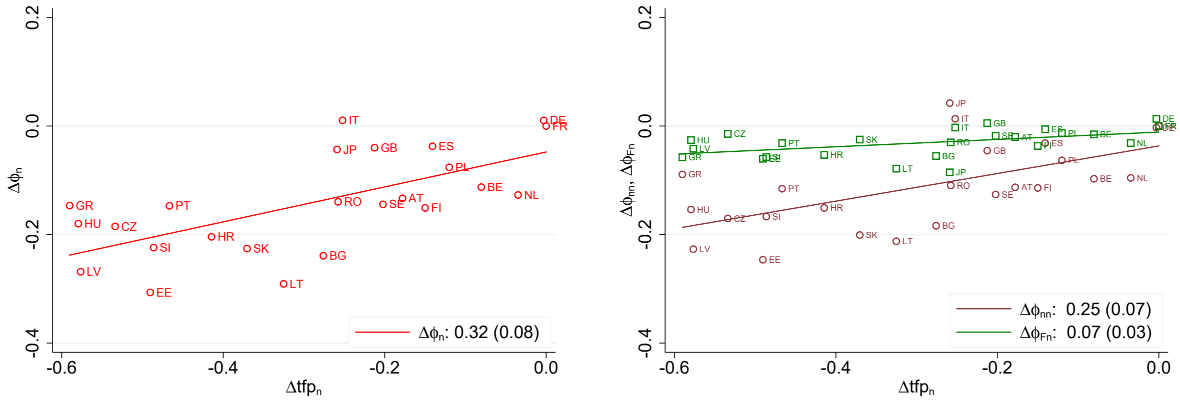
where

$$S_{nn}^j \equiv \int_{\Omega_{nn}^j} S_{nn}^j(\omega) d\omega = \left[\frac{\Phi_{nn}^j}{\Phi_n^j}\right]^{\rho-1} \tag{29}$$

denotes the revenue share of from n in country n, in sector j. We use the domestic share S_{nn}^j from the data, our estimates of $\Delta\Phi_n^j$, and equation (29) to compute $\Delta\Phi_{nn}^j$. Similarly, we use the revenue share of foreign firms in country n, S_{Fn}^j, together with the estimates of $\Delta\Phi_n^j$, to compute $\Delta\Phi_{Fn}^j$. Lastly, we use equation (28), and our sectoral estimates of $\Delta\phi_{nn}^j$, $\Delta\phi_{Fn}^j$, θ_n^j, and S_{rr}^j in order to compute county n's aggregate firm know-how relative to France $\Delta\phi_n$.

Figure 8 shows the two terms in the last equality of equation (28). 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 for domestic firms (brown) account for more than 70 percent of the cross-country differences in aggregate firm know-how (0.21 vs 0.29). Differences in the know-how embedded in the foreign affiliates of MNEs (green) are very small across countries, with some developing

Figure 8: Aggregate firm know-how: Domestic vs foreign firms.



Notes: Each circle (square) represents a country. The left panel shows $\Delta\phi_n$ (y-axis), and Δtfp (x-axis), as in Figure 3. The right panel plots the two terms in (28) (y-axis) and Δtfp (x-axis). Mexico and Korea are not included since data on sectorial revenues by domestic firms (S^j_{nn}) are not available for these countries.

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 Latvia, Estonia, and Slovakia 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 Finland, the Netherlands, or Austria. Finally, this decomposition attributes, for instance, all the difference in aggregate firm know-how between Great Britain and Sweden observed in Figure 3 to domestic firms: While domestic and foreign firms in Great Britain have very similar aggregate know-how (relative to their counterparts in France), Swedish domestic firms have much lower aggregate know-how than British domestic firms.

5 Robustness and extensions

This section presents several robustness results for our baseline estimates of aggregate firm know-how. Additionally, we present two extensions of the baseline model and show how our procedure to estimate firm know-how remains unchanged.

5.1 Alternative assumptions on the technology transfer costs

Our baseline estimates for $\Delta\phi_n$ were derived under the assumption that technology transfer costs could have an origin-specific, but not a destination-specific component, $\Delta D_n = 0$, as specified in equation (21). As explained in Section 3.2, if this assumption does not hold and it is harder to transfer technology to less developed countries, $cov\left(D_n, tfp_n\right) < 0$, 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 equation (23), 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 $cov\left(O_n, tfp_n\right) < 0$, these estimates will overstate the contribution of aggregate firm know-how to the cross-country variance of TFP.

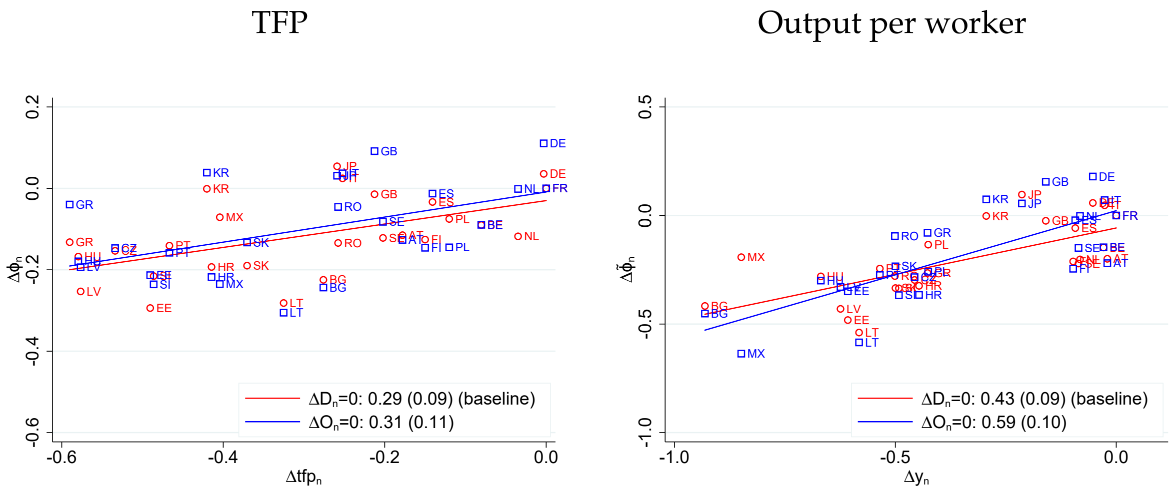
Figure 9 compares the estimates based on equations (21) and (23). The two alternative assumptions yield similar estimates for aggregate firm know-how, relative to France, for each country. For the alternative estimates of $\Delta\phi_n$ in Figure 9, $\Delta\phi_n$ ranges between -0.10 and -0.12, for the average country, while for $\Delta\tilde{\phi}_n$ in Figure 9, the range is between -0.21 and -0.19. In both figures, excluding Mexico, one of the largest differences is observed for the Netherlands where aggregate firm know-how, relative to France, ranges from -0.25 and 0. For Japan, Italy, and Belgium, estimates are virtually the same. The contribution of firm know-how to TFP differences across countries is very similar -and statically indistinguishable- regardless of the estimate of $\Delta\phi_n$ used (0.29 vs 0.31). The difference in the contribution of aggregate firm know-how to cross-country differences in output per-worker has a larger range across our two alternative estimates of $\Delta\tilde{\phi}_n$ (0.43 vs 0.59).

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 $\mathbb{A}_n^j$.

To assess the severity of this potential bias, we follow the literature on two-way matching

Figure 9: Alternative assumptions on the technology transfer costs.



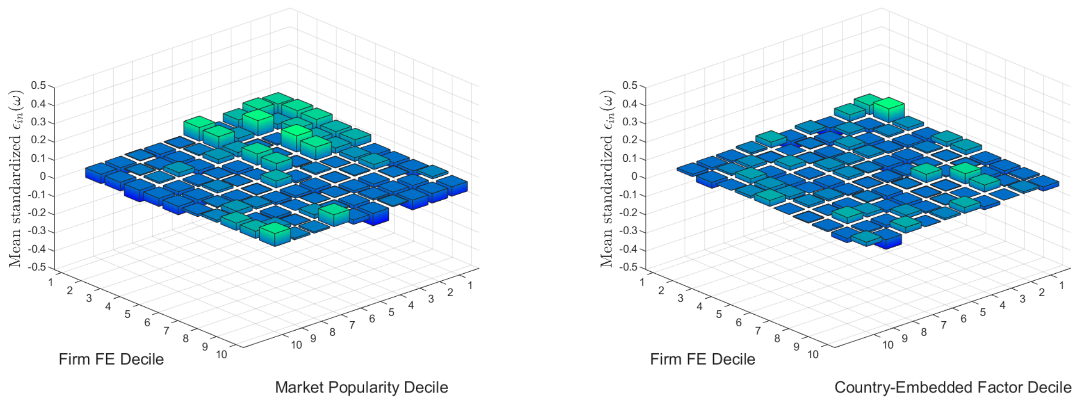
Notes: Each circle (square) represents a country. The figure plots the decomposition in equation (13), where Δtfp_n (Δy_n) is plotted in the x-axis and $\Delta\phi_n$ ($\Delta\tilde{\phi}_n$) is plotted in the y-axis. The legends report the slopes of a bivariate OLS regression of $\Delta\phi_n$ ($\Delta\tilde{\phi}_n$) on Δtfp_n (Δy_n) under the assumption that $\Delta D_n = 0$ (baseline) and $\Delta O_n = 0$. Standard errors are in parenthesis.

(see Abowd et al., 1999) and analyze the residuals from estimating our baseline specification in equation (18) by OLS. If the assignment of MNEs to countries is driven by firm-destination specific transfer costs, we should expect these costs to be lower—low $\varepsilon^j_{in}(\omega)$—on average for low-productivity firms in unattractive markets —. In contrast, highly productive firms are more likely to enter these markets irrespective of their $\varepsilon^j_{in}(\omega)$. If this is the case, our specification should underestimate revenue shares, as it does not take into account that the $\varepsilon^j_{in}(\omega)$'s can systematically vary with firm productivity among the firms that choose to enter any given market.

We evaluate this implication in Figure 11a, which plots the mean standardized residuals, $\hat{\epsilon}^j_{in}(\omega) = \frac{s^j_{in}(\omega)-\hat{s}^j_{in}(\omega)}{\sigma_s}$, against deciles of estimates of the firm-sector fixed effects, $\delta^j(\omega)$, and deciles of market popularity. Our measure of market popularity is calculated using data from OECD-Eurostat on the number of foreign firms in a destination-sector pair. Indeed, we tend to see positive residuals for the less productive firms (decile 1 of the firm-sector fixed effect) in less popular markets (decile 1 of market popularity). In contrast, we overestimate the revenue shares of the most productive firms (decile 10 of the firm-sector fixed effect) in these markets. 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.

A related concern with our baseline estimation is related to complementarities between

Figure 10: OLS Residuals.



(a) By firm-sector and market popularity. (b) By firm-sector and country-embedded factor.

Notes: Deciles are calculated within sectors. Market popularity refers to the number of foreign firms in a country-sector pair, from OECD-Eurostat. Country-sector embedded factors refers to estimates of $\tilde{Z}_n^j$.

firm-embedded and country embedded productivity. That is, we assume a production function that is log-linear in firm know-how $A(\omega)$ and country-embedded productivity Z_n. This separability is inherited by the aggregate production function, which is log-linear in Z_n and aggregate firm know-how Φ_n. But if, for instance, high productivity firms do relatively better in countries with high country-embedded productivity, the assumption would not longer hold and our procedure would underestimate revenue shares for high know-how firms in markets with high Z_n.

We evaluate this implication in Figure 11b, which plots the mean standardized residuals, $\hat{\epsilon}_{in}^j(\omega) = \frac{s_{in}^j(\omega)-\hat{s}_{in}^j(\omega)}{\sigma_s}$, against deciles of estimates of the firm-sector fixed effects, $\delta^j(\omega)$, and deciles of estimates of the country-embedded factor $\tilde{Z}_n$. Indeed, we tend to see positive residuals for the less productive firms (decile 1 of the firm-sector fixed effect) in markets with lower $\tilde{Z}_n$ (decile 1 of country-embedded factors). We overestimate the revenue shares of the most productive firms (decile 10 of the firm-sector fixed effect) in these markets. The residuals are very close to zero in the remaining bins of the figure, indicating that the lo-linearity assumption is not systematically violated in those bins.

With this in mind, we proceed to re-estimate equation (18) using alternative subsamples, restricted to exclude the firms at the extreme of the know-how distribution. Concretely, we 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 firm fixed effect distribution within a sector.

Table 3 shows the contribution of $\Delta\phi_n$ ($\Delta\tilde{\phi}_n$) to the cross-country variance in tfp_n (y_n) in

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

	$\frac{cov(\Delta tfp_n, \Delta\phi_n)}{var(\Delta tfp_n)}$	$\frac{cov(\Delta y_n, \Delta\tilde{\phi}_n)}{var(\Delta y_n)}$
Baseline	0.29 (0.09)	0.43 (0.09)
2nd to 9th Decile	0.27 (0.08)	0.40 (0.09)
3rd to 8th Decile	0.28 (0.09)	0.38 (0.10)
4th to 7th Decile	0.28 (0.09)	0.37 (0.10)
5th to 6th Decile	0.32 (0.12)	0.49 (0.14)

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, for each sector, from estimating equation 18 by OLS. Standard errors are in parenthesis.

each of these restricted samples. The table shows that the contribution of firm know-how to the cross-country variance is very similar to the estimates in our baseline. If anything, focusing on the narrow middle of the distribution increases slightly the importance of aggregate firm know-how in accounting for TFP (output per worker) differences across countries.

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 the contribution of $\Delta\phi_n$ ($\Delta\tilde{\phi}_n$) to the cross-country variance in tfp_n (y_n) , when we apply our estimation procedure to subsamples of firms of different size. We rank affiliates by their revenue size in each destination country, and repeat our estimation for firms below and above the 50th percentile of the size distribution, as well as for the smallest (below 20th percentile) and largest (above 80th percentile) affiliates. We find a positive correlation between aggregate firm know-how and TFP and output per worker in all our sub-samples of firms. The resulting contribution of aggregate firm know-how to differences in TFP and output per-worker across countries would be larger if only smaller affiliates were considered in the estimation, while estimates would be smaller when larger affiliates were considered. Another (related) firm characteristic that is worth exploring is the number of markets where the firm operates. When we apply our procedure to MNEs that operate in at least 3, 5, or 10 markets, the contribution of aggregate firm know-how to differences in TFP (output per-worker) across countries decreases as we increase the number of markets. The effect on TFP is reduced by half only when we consider firms that operate in at least 10 markets; all the other cases are close to the baseline estimates.

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

	$\frac{cov(\Delta tfp_n,\Delta\phi_n)}{var(\Delta tfp_n)}$	$\frac{cov(\Delta y_n,\Delta\tilde{\phi}_n)}{var(\Delta y_n)}$
Baseline	0.29 (0.09)	0.43 (0.09)
I. Dropping firms:		
below 50th pc size	0.23 (0.08)	0.31 (0.08)
above 50th pc size	0.33 (0.10)	0.46 (0.11)
above 20th pc size	0.35 (0.12)	0.53 (0.14)
below 80th pc size	0.17 (0.07)	0.28 (0.08)
II. Keeping firms operating in at least		
3 countries	0.26 (0.08)	0.37 (0.09)
5 countries	0.22 (0.07)	0.32 (0.08)
10 countries	0.16 (0.07)	0.34 (0.08)
III. Narrow industries:		
4-digit SIC	0.32 (0.10)	0.48 (0.10)

Notes: Slopes of a bivariate OLS regression of $\Delta\phi_n$ (resp. $\Delta\tilde{\phi}_n$) on Δtfp_n (resp. Δy_n). I. refers to percentiles of the size distribution of affiliates. II. refers to firms that have affiliates in at least x countries. Standard errors are in parenthesis.

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, in our procedure we include 4 digit, rather than 2-digit, industry fixed effects, interacted with firm and country fixed effects. Table 4 shows that these alternative estimates imply a higher contribution of differences in aggregate firm know-how to differences in TFP and output per-worker across countries, but still these estimates are close to our baseline estimates.

5.4 Estimation using employment and value-added data

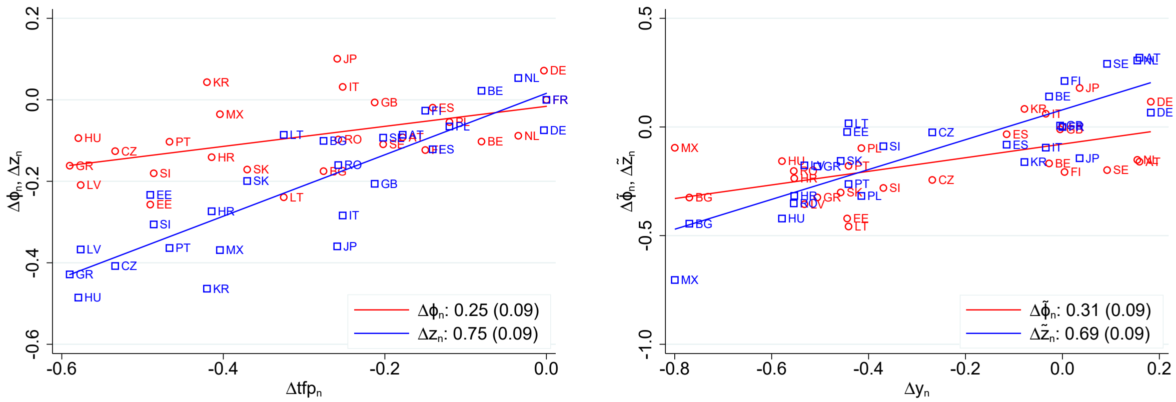
Equation (18) shows how data on revenue shares can be used to compute differences in aggregate firm know-how. Since in the model revenue shares and employment shares coincide, we could have used data on employment shares to compute these differences. We re-estimate equation (18) using data on log-employment shares as the dependent variable. The resulting estimates of the country are in Appendix Figure A4, and are remarkably close to our baseline. Figure 11 shows our decomposition using employment rather than sales data. In that case, aggregate firm-embedded productivity would explain 0.25 of the cross-country TFP differences and 0.31 of differences in income per-worker. The contribution of aggregate firm know-how to cross-country TFP differences when we use employment data is very similar to our baseline estimates of 0.29. For output per-worker, differences are slightly larger (0.31 vs 0.43). We use the estimation with the revenue data as our baseline specification since those data are available for a much larger set of firms in ORBIS.[17]

A similar argument and procedure can be applied to value added. We re-estimate equation (18) using data on log-value-added shares as the dependent variable, as calculated in ORBIS. Value-added data is only available for 20 countries in our sample. Appendix Figure A4 shows that the resulting country effects are similar to our baseline. Results for our development-accounting exercise are in Figure 12. The contribution of aggregate know-how to cross country differences in TFP (output per-worker) is 0.22 (0.35), very similar to our baseline calculation of 0.29 (0.43) based on firm revenues.

[17] Appendix Figure A5 shows the calculations for Manufacturing and Services separately.

Figure 11: Dev. accounting: Employment data.

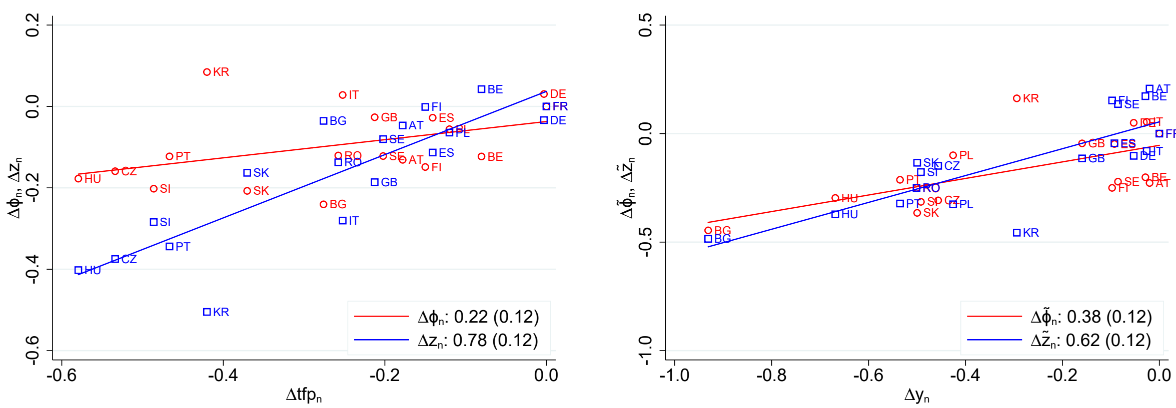
(a) TFP (b) Output per-worker



Notes: Each circle (square) represents a country. Figure (11a) plots the decomposition in equation (12), where Δtfp_n is plotted in the x-axis and Δz_n and $\Delta \phi_n$ are plotted in the y-axis. Figure (11b) plots the decomposition in equation (13), 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).

Figure 12: Dev. accounting: Value added data.

(a) TFP (b) Output per-worker



Notes: Each circle (square) represents a country. Figure (12a) plots the decomposition in equation (12), where Δtfp_n is plotted in the x-axis and Δz_n and $\Delta \phi_n$ are plotted in the y-axis. Figure (12b) plots the decomposition in equation (13), 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).

5.5 Other measurement issues

Mis-measurement of 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

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

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 equation (1). 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 that, despite this bias, it is still possible to use equation (7) 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.

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

$$\frac{R_{in}}{R_n} = \left[\frac{\Phi_{in} exp\left(-\kappa_{in}\right)}{\Phi_n}\right]^{\rho-1}, \tag{30}$$

where $\Phi_{in} \equiv \left[\int_{\omega\in\Omega_{in}} A^j(\omega)^{\rho-1} d\omega\right]^{\frac{1}{\rho-1}}$, and we omit country subscripts from $A(\omega)$ since the technology transfer costs κ_{in} in equation (30) are factored-out. Taking logs we obtain

$$s_{in} = [\rho - 1]\left[\phi_{in} - \phi_n - \kappa_{in}\right]. \tag{31}$$

This equation differs from equation (7) because it expresses aggregate shares rather than firm-level shares. The variable ϕ_{in} varies across $n's$ as long as 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 contaminates the estimates of ϕ_n if we were to use aggregate data and equation (31). This result implies that to recover cross-country differences in aggregate firm know-how using equation (31) and aggregate data one needs to model selection explicitly.

5.6 Extensions

5.6.1 Intermediate Inputs

This section shows how to extend our framework to allow for intermediate inputs in production. In particular, we assume that the final good can be used as an input, and that the production function for intermediate goods is

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

Here the parameter β is the value-added share in sector j and $M_{in}^{j}(\omega)$ are the intermediate inputs used by producer ω in sector j and country n. The aggregate production function is

$$\mathcal{Y}_n \;=\; Z_n^{imp} \Phi_n^{\frac{1}{\beta_n}} \left[H_n L_n \right]^{1-\alpha_n} \left[K_n \right]^{\alpha_n},$$

where $\beta_n = \sum_j \beta^j \theta_n^j$, $\alpha_n = \sum_j \frac{\beta^j}{\beta_n} \theta_n^j \alpha^j$, $Z_n^{inp} = \left[\bar{\theta}_n^{inp} \right]^{\frac{1}{\beta_n}} \prod_j \left[Z_n^j \right]^{\frac{\theta_n^j}{\beta_n}}$ and $\bar{\theta}_n^{inp} \equiv \beta_n \prod_j \left[\theta_n^j \left[\left[\frac{1-\alpha^j}{1-\alpha_n} \right]^{1-\alpha^j} \left[\frac{\alpha^j}{\alpha_n} \right]^{\alpha^j}\right.\right.$

We can write the log of TFP and value added per worker as

$$tfp_n = z_n^{inp} + \phi_n^{inp}, \tag{32}$$

and

$$y_n = \tilde{z}_n^{inp} + \tilde{\phi}_n^{inp}, \tag{33}$$

where $\phi_n^{inp} \equiv \frac{1}{\beta}\phi_n$, $\tilde{\phi}_n^{inp} = \frac{1}{1-\alpha_n}\phi_n^{inp}$ and $\tilde{z}_n^{inp} = \frac{1}{1-\alpha_n}z_n^{inp} + ln\left[H_n\left[\frac{K_n}{Y_n}\right]^{\frac{\alpha_n}{1-\alpha_n}}\right]$.

We show next how to obtain aggregate firm know-how, ϕ_n^{inp}, in this setup. Note that in this economy, the revenue, employment, and the value-added shares coincide and are given by equation (14). We can thus use equation (18) and the procedure described in Section 3.2 to estimate $\Delta\mathbb{A}_n$, which under our baseline assumption on technology-transfer costs corresponds to $\Delta\mathbb{A}_n = [1-\rho]\,\Delta\phi_n$.

The last step is to reestimate ρ in a way that is consistent with equation (33). In particular, with intemediate inputs the equation is written as

$$\Delta y_n^j = b_0^j + b_1^{inp}\frac{\Delta\mathbb{A}_n^j}{\beta^j\left[1-\alpha^j\right]} + b_2 C_n + u_n^j,$$

so the sectorial coefficients in Table A2 are $b_1^{j,inp} = \beta^j b_1^j$. In the special case where β and ρ do not vary across sectors, we obtain $b_1^{inp} = \beta b_1$. We can then compute $\phi_n^{inp} \equiv \frac{1}{\beta}\phi_n = \frac{1}{\beta}\frac{\Delta\mathbb{A}_n}{1-\rho^{inp}} = b_1\Delta\mathbb{A}_n$, which coincides with the estimate used in our baseline analysis.

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. 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 not strongly correlated to income per-capita.

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APPENDIX

Table A1: Estimates of gravity coefficients.

	Distance		Common Language	
	Coeff	S.E	Coeff	S.E
Other goods				
Agriculture and Mining	-0.885	0.186	-0.056	0.392
Electricity	-0.777	0.147	0.061	0.460
Construction	-0.409	0.168	0.615	0.295
Manufacturing				
Food and Beverage	-0.144	0.132	0.556	0.073
Textiles, Apparel and Wood	-0.186	0.099	-0.079	0.288
Chemicals, Petroleum and Plastic	-0.241	0.061	0.165	0.107
Basic Metals	-0.294	0.092	0.241	0.102
Electrical Equipment and Machinery	-0.083	0.062	0.276	0.109
Transport Equipment and Other Manufacturing	-0.259	0.098	-0.052	0.197
Services				
Wholesale Trade and Retail Trade	-0.258	0.067	0.229	0.098
Transportation and Storage	-0.191	0.096	0.271	0.205
Information	-0.297	0.117	0.592	0.128
Financial and Insurance Services	-0.508	0.104	1.006	0.190
Support Services	-0.265	0.055	0.342	0.159
Accommodation and Recreation	-0.155	0.124	0.242	0.187
Non-Market Economy				
Education	0.251	0.520	0.605	0.545
Health	0.192	0.440	0.141	0.404
Real Estate	-0.125	0.112	0.333	0.161

Notes: This table reports OLS coefficients on distance, β_d^j, and common language, β_l^j, from estimating equation (18).

Table A2: Estimating sectoral elasticities of substitution ρ.

	$\Delta\mathbb{A}_n^j$		$+k_n/y_n + h_n$		$+Rule of Law$	
	Implied ρ	S.E	Implied ρ	S.E	Implied ρ	S.E
Other goods						
Agriculture and Mining	19.19	9.25	19.28	8.47	21.72	12.52
Construction	10.28	1.81	10.66	1.95	11.87	2.77
Electricity	25.5	9.25	25.95	8.51	31.32	13.49
Manufacturing						
Food and Beverage	9.31	1.66	9.13	1.49	10.11	2.08
Textiles, Apparel and Wood	5.68	0.77	5.58	0.67	5.98	0.86
Chemicals, Petroleum and Plastic	7.25	1.06	7.22	1.16	7.73	1.35
Basic Metals	12.07	2.24	12.45	2.84	14.31	3.96
Electrical Equipment and Machinery	9.49	1.31	9.32	1.13	10.22	1.29
Transport Equipment and Other Manufacturing	7.45	0.79	7.60	0.81	7.93	0.91
Services						
Wholesale Trade and Retail Trade	8.03	1.69	7.89	1.54	8.72	2.05
Transportation and Storage	45.17	53.47	52.87	76.83	442.35	5918.56
Information	6.27	0.88	6.36	0.97	6.77	1.27
Financial and Insurance Services	68.98	90.01	78.36	110.93	416.11	3595.86
Support Services	12.36	2.00	12.86	2.07	14.76	3.35
Accommodation and Recreation	9.36	2.02	9.78	2.28	11.26	3.68
Non-Market Economy						
Real Estate	10.49	2.43	10.68	2.77	11.79	3.71
Health	7.11	1.24	7.29	1.24	8.01	1.66
Education	53.16	86.77	36.47	40.90	19.32	7.57

Notes: OLS estimates from equation (26) by 2-digit sector.

Table A3: R^2, number of observations, and mean squared errors.

	N	R^2	MSE
Baseline			
Sales	68,801	0.72	1.46
I. Other outcome variables			
Employment	57,054	0.77	1.35
Value Added	36,466	0.76	1.33
II. Dropping firms:			
below 50th pc size	28,049	0.77	0.98
above 50th pc size	27,362	0.80	1.00
above 20th pc size	6,343	0.89	0.74
below 80th pc size	9,805	0.80	0.80
III. Keeping firms:			
2nd to 9th Decile	50,823	0.75	1.07
3rd to 8th Decile	34,315	0.82	0.80
4th to 7th Decile	19,541	0.90	0.55
5th to 6th Decile	7,064	0.97	0.28
IV. Keeping firms operating			
at least in 3 countries	40,746	0.66	1.46
at least in 5 countries	27,156	0.62	1.44
at least in 10 countries	11,824	0.59	1.35
V. Narrow industries:			
4-digit SIC	85,890	0.62	1.62

Notes: Number of observations, R^2, and mean squared errors for the firm-level OLS regressions specified in each row. I. refers to alternative firm's outcome variables. II. refers to dropping firms below or above a given percentiles of the size distribution of affiliates. III. refers to keeping firms within a range of the percentiles of the size distribution of affiliates. IV. refers to keeping firms that have affiliates in as many countries as reflected by the threshold. Standard errors are in parenthesis.

Table A4: Contribution of aggregate firm know-how. Additional robustness.

	$\frac{cov(\Delta tfp_n, \Delta\phi_n)}{var(\Delta tfp_n)}$	$\frac{cov(\Delta y_n, \Delta\tilde{\phi}_n)}{var(\Delta y_n)}$
Baseline	0.29 (0.09)	0.43 (0.09)
Excluding non-market economy	0.28 (0.09)	0.41 (0.09)
Constant sample firms (2010-2016)	0.26 (0.08)	0.43 (0.09)
Controlling for differences in GDP pc between HQ and host country	0.29 (0.09)	0.43 (0.09)
Excluding gravity variables	0.26 (0.10)	0.37 (0.11)

Notes: 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.

Table A5: Contribution of aggregate firm know-how (by year).

	All firms		Countries (#)	Constant Sample		Countries (#)
	$\frac{cov(\Delta tfp_n, \Delta\phi_n)}{var(\Delta tfp_n)}$	$\frac{cov(\Delta y_n, \Delta\tilde{\phi}_n)}{var(\Delta y_n)}$		$\frac{cov(\Delta tfp_n, \Delta\phi_n)}{var(\Delta tfp_n)}$	$\frac{cov(\Delta y_n, \Delta\tilde{\phi}_n)}{var(\Delta y_n)}$	
2006	0.28 (0.14)	0.27 (0.16)	17			
2007	0.29 (0.11)	0.31 (0.11)	24	0.17 (0.10)	0.24 (0.11)	16
2008	0.27 (0.09)	0.34 (0.08)	25	0.23 (0.08)	0.27 (0.08)	24
2009	0.28 (0.08)	0.38 (0.08)	25	0.24 (0.07)	0.31 (0.07)	24
2010	0.33 (0.09)	0.42 (0.09)	25	0.30 (0.08)	0.36 (0.09)	24
2011	0.30 (0.09)	0.44 (0.10)	25	0.26 (0.08)	0.38 (0.09)	24
2012	0.28 (0.09)	0.48 (0.11)	25	0.24 (0.08)	0.41 (0.10)	24
2013	0.28 (0.09)	0.38 (0.10)	26	0.24 (0.08)	0.41 (0.09)	24
2014	0.29 (0.09)	0.42 (0.10)	26	0.25 (0.08)	0.42 (0.09)	24
2015	0.30 (0.09)	0.40 (0.10)	26	0.26 (0.08)	0.43 (0.09)	24
2016	0.29 (0.09)	0.43 (0.09)	26	0.26 (0.08)	0.43 (0.09)	24
2017	0.28 (0.09)	0.42 (0.10)	26	0.25 (0.09)	0.45 (0.10)	24

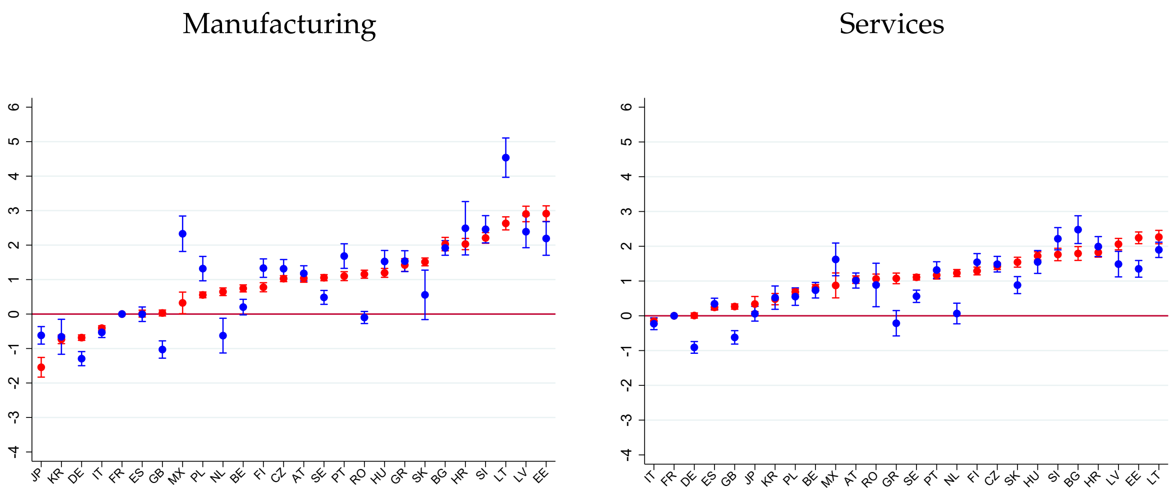
Notes: Slopes of a bivariate OLS regression of $\Delta\phi_n$ (resp. $\Delta\tilde{\phi}_n$) on Δtfp_n (resp. Δy_n). A country is required to have estimates of firm know-how in at least 10 sectors to construct the aggregate firm know-how $\Delta\phi_n$. Each sector is required to have observations of three or more foreign affiliates. The last two columns use only firms (BVDIDs) that are available in ORBIS in every year from 2010 to 2016.

Table A6: TFP, output per worker, and aggregate firm know-how, by country.

Country	ISO	Δtfp_n	Δy_n	$1-\alpha_n$	$\Delta\phi_n$	$\Delta\tilde{\phi}_n^{all}$	$\Delta\tilde{\phi}_n^{manuf}$	$\Delta\tilde{\phi}_n^{serv}$
Austria	AT	-0.18	-0.02	0.58	-0.11	-0.20	-0.20	-0.20
Belgium	BE	-0.08	-0.03	0.61	-0.09	-0.15	-0.14	-0.15
Bulgaria	BG	-0.28	-0.93	0.54	-0.22	-0.42	-0.42	-0.37
Czech Rep.	CZ	-0.53	-0.46	0.52	-0.15	-0.30	-0.22	-0.31
Germany	DE	0.00	-0.05	0.62	0.04	0.06	0.12	0.00
Estonia	EE	-0.49	-0.61	0.61	-0.29	-0.48	-0.53	-0.41
Spain	ES	-0.14	-0.09	0.58	-0.03	-0.06	0.00	-0.05
Finland	FI	-0.15	-0.1	0.59	-0.13	-0.21	-0.15	-0.24
France (ref)	FR	0	0	0.63	0	0	0	0
UK	GB	-0.21	-0.16	0.59	-0.01	-0.02	-0.01	-0.05
Greece	GR	-0.59	-0.43	0.50	-0.13	-0.27	-0.32	-0.24
Croatia	HR	-0.41	-0.45	0.60	-0.19	-0.32	-0.38	-0.34
Hungary	HU	-0.58	-0.67	0.60	-0.17	-0.28	-0.22	-0.32
Italy	IT	-0.25	-0.03	0.52	0.02	0.05	0.09	0.03
Japan	JP	-0.26	-0.21	0.56	0.05	0.10	0.32	-0.05
Korea	KR	-0.42	-0.29	0.52	0.00	0.00	0.16	-0.10
Lithuania	LT	-0.33	-0.58	0.52	-0.28	-0.54	-0.56	-0.48
Latvia	LV	-0.58	-0.62	0.59	-0.25	-0.43	-0.55	-0.39
Mexico	MX	-0.40	-0.85	0.37	-0.07	-0.19	-0.10	-0.26
Netherlands	NL	-0.03	-0.08	0.58	-0.12	-0.20	-0.12	-0.23
Poland	PL	-0.12	-0.43	0.56	-0.08	-0.13	-0.11	-0.14
Portugal	PT	-0.47	-0.54	0.58	-0.14	-0.24	-0.21	-0.23
Romania	RO	-0.26	-0.50	0.48	-0.13	-0.28	-0.27	-0.25
Sweden	SE	-0.20	-0.09	0.55	-0.12	-0.22	-0.21	-0.22
Slovenia	SI	-0.49	-0.49	0.64	-0.22	-0.34	-0.38	-0.30
Slovakia	SK	-0.37	-0.50	0.57	-0.19	-0.33	-0.30	-0.30

Notes: TFP, output per-worker and the GDP share of labor compensation $(1-\alpha_n)$ are from PWT (9.1).

Figure A1: Estimated country effects.



Note: Red (blue) dots are OLS estimates of $\Delta\mathbb{A}_n$ ($\Delta\mathbb{P}_n$) from equation (18). Bars reflect 95-percent confidence intervals, clustered at the country level.

A Data Appendix

Firm level data: In this section we describe the construction of our sample using ORBIS dataset. We start by dropping those firms with revenues below 100k USD. We also drop firms that only report information from consolidated accounts, as well as firms with “limited financials” (LF) only.[1] From the remaining sample, we exclude firms operating in “Public Administration”, "Extraterritorial Organizations", and "Activity of Households" sectors. The time span of our dataset is 2006-2017, but our baseline analysis uses information for 2016 since it is the latest year with the largest number of firms in ORBIS historical.[2]

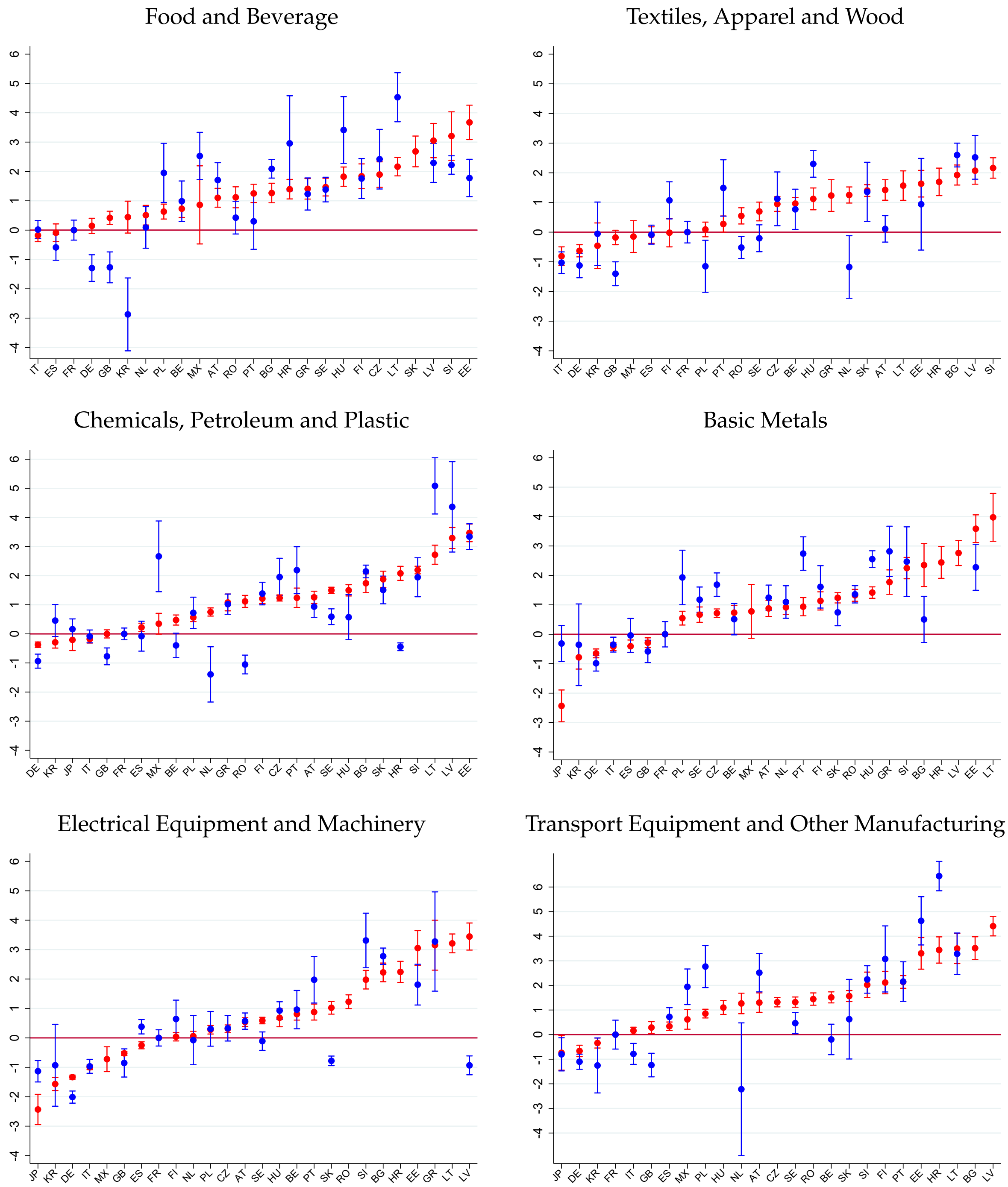
A multinational is defined as a company exerting above 50 percent of the control rights on affiliates located in more than one country. Crucially for our analysis, a multinational company is defined within a given sector. Thus, a company owning affiliates in multiple locations, but none of them in the same sector, will ultimately be excluded from our sample. In order to define a company as a multinational, we use the NAICS sector classification at three different levels of disaggregation, NAICS2 (18 industries), NAICS3 (99 industries) and NAICS4 (336 industries).[3] Information on revenues, employment, and

[1] The latest vintage of ORBIS historical data has significantly increased its coverage in the U.S., China, Australia, Chile, Colombia, among others. But most of these affiliates only present limited financial information, and are labeled as “LF”. The financial information provided for these companies shows several inconsistencies, and thus were excluded from our final sample.

[2] Table A5 shows that our results hold for any year in the period 2006-2017, whether using all available firms for a given year or using only firms available in every year between 2010-2016, which accounts for 24.1% of all firms in our sample. Notice that further restricting the sample to firms available through the entire period, 2007-2016, results in a reduction of the sample to less than 2% of all firms.

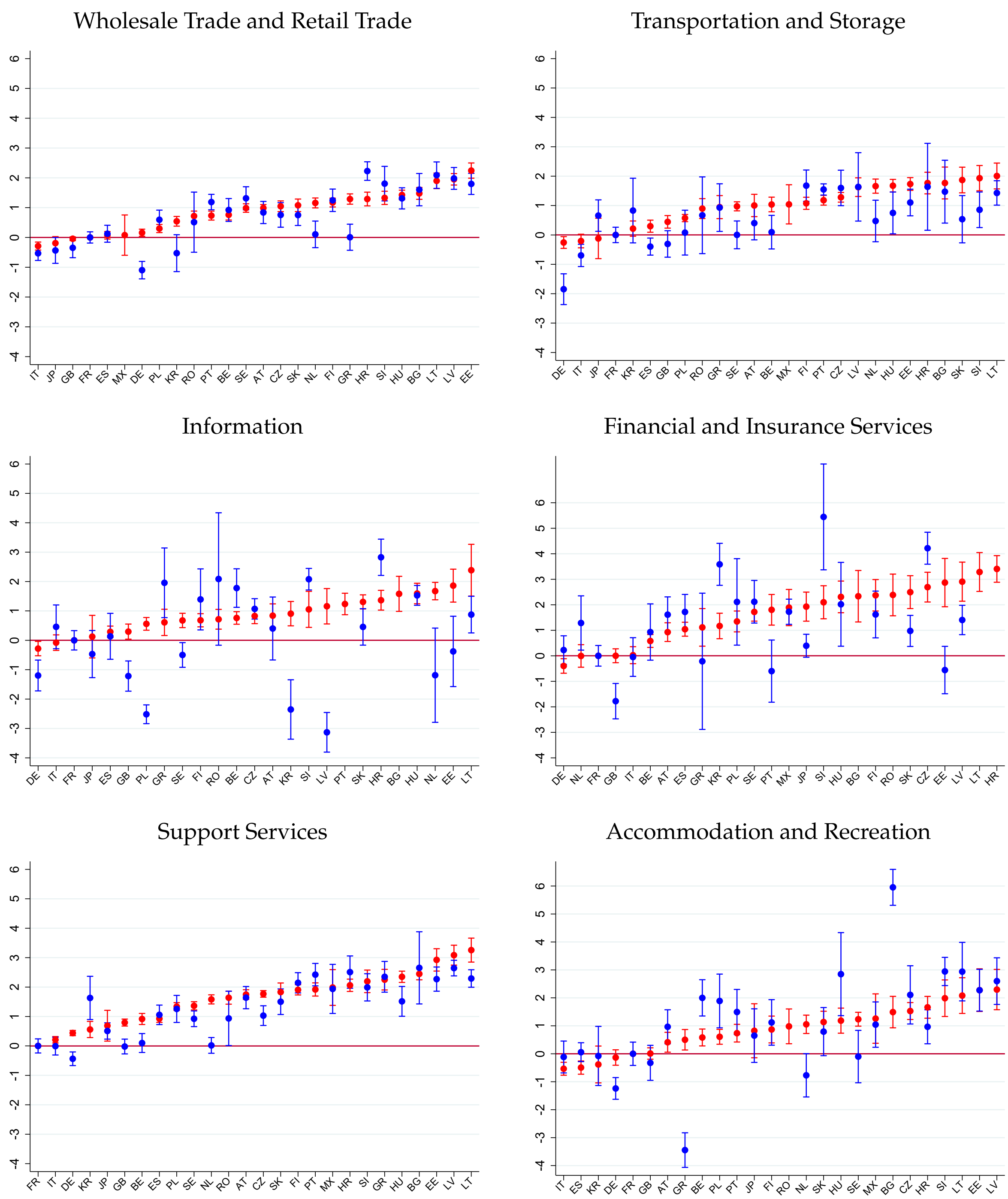
[3] Notice that the latest vintage of ORBIS historical does not longer provide NAICS6 sector for each firm

Figure A2: Estimated country effects (Manufacturing).



Note: Red (blue) dots are OLS estimates of $\Delta\mathbb{A}_n$ ($\Delta\mathbb{P}_n$) from equation (18). Bars reflect 95-percent confidence intervals, clustered at the country level.

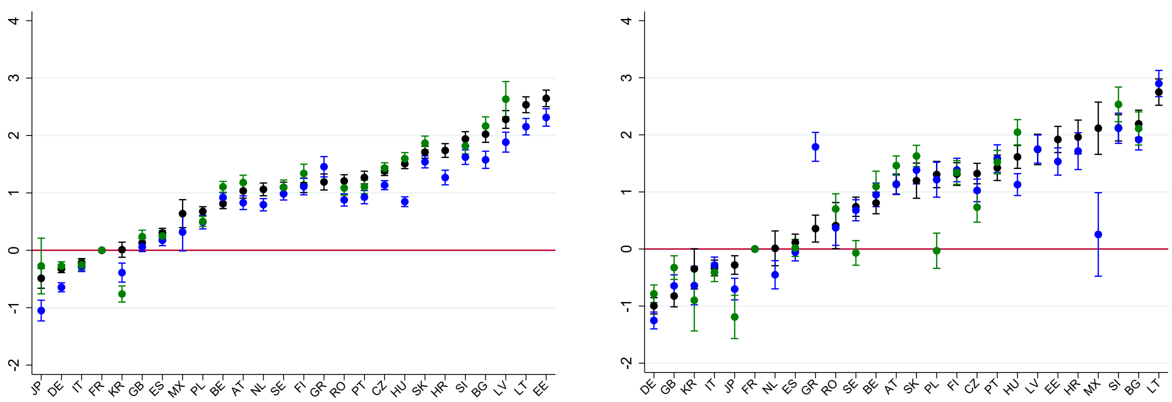
Figure A3: Estimated country effects (Services).



Note: Red (blue) dots are OLS estimates of $\Delta\mathbb{A}_n$ ($\Delta\mathbb{P}_n$) from equation (18). Bars reflect 95-percent confidence intervals, clustered at the country level.

Figure A4: Estimated country effects: Sales, Employment and Value Added.

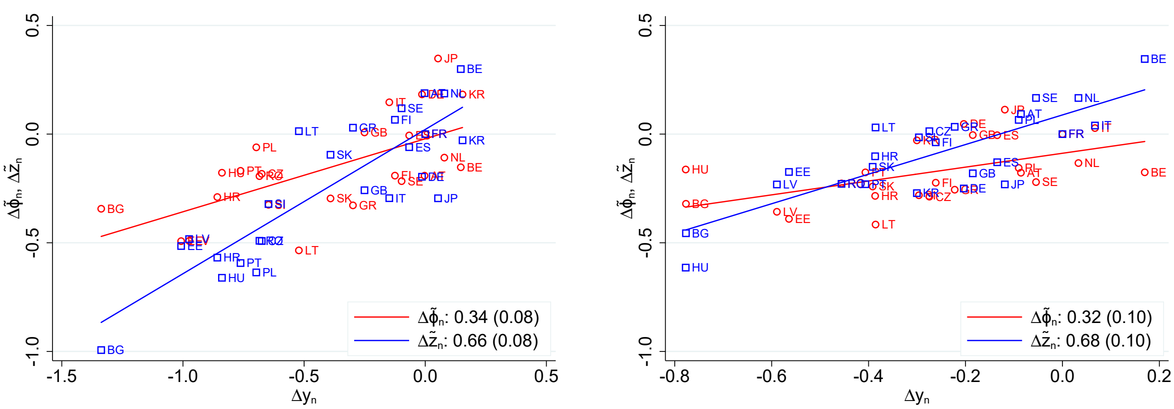
$\Delta\mathbb{A}_n$ (baseline) $\qquad\qquad$ $\Delta\mathbb{P}_n$



Note: Black, blue and green dots correspond to the OLS estimates of $\Delta\mathbb{A}_n$ (left panel) and $\Delta\mathbb{P}_n$ (right panel), for sales, employment and value added, respectively. Bars reflect 95-percent confidence intervals, clustered at the country level.

Figure A5: Dev. accounting: Manufacturing and Services (Employment).

Manufacturing $\qquad\qquad$ Services



Notes: Each circle (square) represents a country. The figures plot the decomposition in equation (13) 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) .

Table A7: Number of affiliates and parents (by NAICS2).

	Foreign Affiliates			Parents		
	Sales	Emp.	VA	Sales	Emp.	VA
Other goods						
Agriculture and Mining	498	394	242	154	117	69
Construction	1,353	996	615	463	325	202
Electricity	655	354	260	181	109	73
Manufacturing						
Food and Beverages	1,181	1,046	824	268	242	194
Textiles, Apparel and Wood	1,220	1,094	758	422	385	236
Chemicals, Petroleum and Plastic	3,499	3,124	2,474	775	678	520
Basic Metals	1,936	1,674	1,296	583	510	351
Electrical Equipment and Machinery	3,550	3,217	2,254	921	816	533
Transport Equipment and Other Manufacturing	1,625	1,426	1,104	353	313	217
Services						
Wholesale Trade and Retail Trade	19,900	17,052	10,857	3,136	2,606	1,468
Transportation and Storage	2,601	2,215	1,438	659	571	372
Information	1,582	1,304	772	287	236	139
Financial and Insurance Services	1,511	1,123	456	315	245	91
Support Services	11,562	9,603	5,427	2,573	2,052	1,109
Accommodation and Recreation	1,425	1,224	741	350	280	162
Non-Market Economy						
Real Estate	2,234	1,066	766	552	252	173
Health	253	224	164	71	62	41
Education	110	88	47	34	22	16

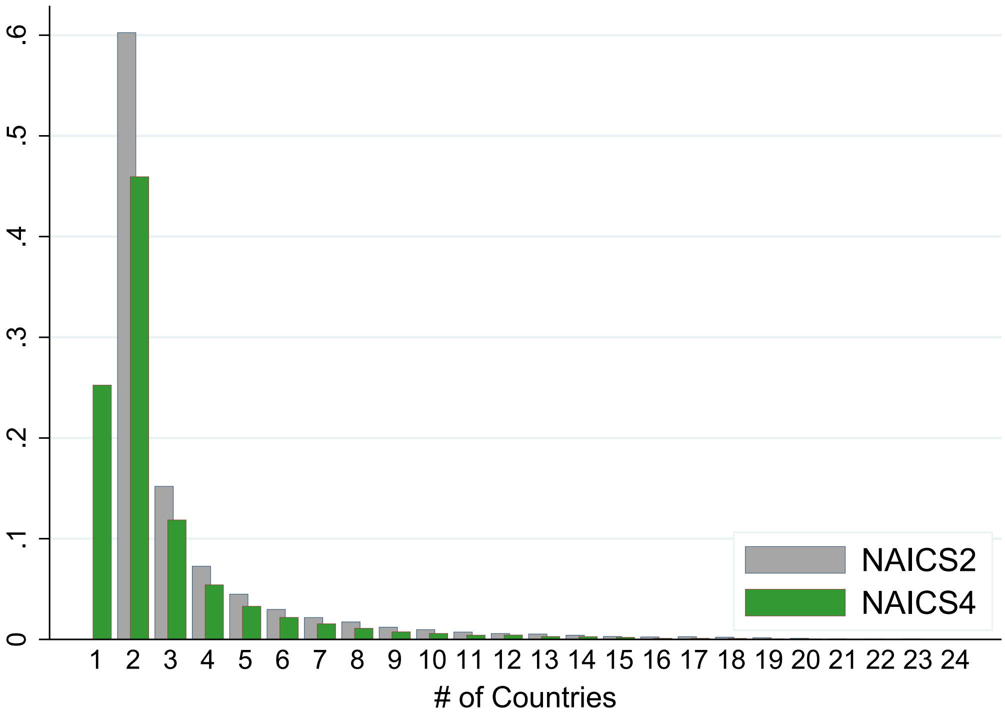
Notes: A foreign affiliate is a majority-owned firm by a company with operations in multiple countries within a given sector. In this table sectors roughly correspond to the 2-digit NAICS classification.

value added are aggregated for all BVDIDs in ORBIS belonging to the same corporate group and operating in the same country and sector. Therefore, in our analysis an affiliate is defined as a corporate group-country-sector triplet in which the country of location differs from the country where the headquarter is located, whereas a parent is defined as a triplet located at the headquarter's country. Table A7 shows the number of affiliates and the number of parent firms in each NAICS2 sectors in our sample, including affiliates in "Other Goods" as well as in "Non-Market Economy" sectors. Each column of Table A7 shows the number of affiliates and parents according to the availability of information on firm's revenues, employment and value added.

Table A8 and Table A9 show the number of affiliates and the number of parents in each country in our sample, according to the available information from sales, employment and value added. The numbers are shown for manufacturing, services, and for the overall

in the dataset. Earlier versions of this paper using previous ORBIS vintages show that our results are robust to this more granular sectoral definition.

Figure A6: Percentage of corporate groups by number of host countries.



Note: An affiliate is defined as a corporate group-country-sector triplet where the country of location differs from the country where the headquarter is located.

economy.

When reproducing our results within more narrowly defined sectors, we potentially limit the number of countries in which a corporate group operates, reducing the variation we rely on in order to identify firm embedded productivity. A corporate group may not longer be consider a multinational when analyzing more granular sectors, if within each detailed sector the corporation does not operates in more than one country. In order to explore the variation across countries within a corporate group at different levels of sectoral disaggregation, we calculate within each NAICS2 and NAICS4, the number of countries in which a corporation operates and take the maximum for each corporate group. Figure A6 shows the distribution of the maximum number of countries where corporate groups operate for NAICS2 and NAICS4 classifications. As revealed by the green bars, 25 percent of the corporations are not classified as multinationals under NAICS4, since they operate in at most one country within each sector. As a consequence the fraction of multinationals operating in two or more countries is lower for NAICS4 relative to NAICS2, as showed by a the smaller green bars for two or more countries. Nevertheless, Table4 shows that our results are robust to using the NAICS4 classification.

Aggregate firm know-how at the country level, $\Delta\phi_n$, is constructed by calculating the weighted average of the sector level firm-know how, using country-sector level expendi-

Table A8: Number of foreign affiliates (by country and sector).

Country	Sales			Employment			Value Added		
	All	Mfg.	Services	All	Mfg.	Services	All	Mfg.	Services
Austria	1,668	329	1,252	1,297	294	948	934	240	642
Belgium	2,937	575	2,101	2,637	558	1,915	1,779	432	1,231
Bulgaria	853	154	591	790	148	563	607	124	428
Czech Rep.	2,896	819	1,781	2,647	790	1,668	1,514	555	842
Germany	4,048	1,187	2,571	3,810	1,148	2,421	2,600	918	1,511
Estonia	872	159	630	768	141	578	-	-	-
Spain	4,697	964	3,324	4,278	940	3,064	3,999	898	2,810
Finland	1,623	287	1,197	1,236	239	916	624	135	450
France	5,198	1,212	3,589	3,857	1,051	2,627	3,390	1,017	2,213
UK	5,500	1,407	3,639	4,812	1,340	3,156	2,527	873	1,500
Greece	520	76	404	503	76	394	-	-	-
Croatia	994	144	725	903	137	682	-	-	-
Hungary	1,370	350	865	1,222	342	787	562	206	296
Italy	5,054	1,322	3,282	4,509	1,271	3,000	3,551	1,121	2,233
Japan	198	50	144	181	49	128	11	4	7
Korea	1,005	343	641	763	298	451	380	178	198
Lithuania	499	80	361	467	72	343	-	-	-
Latvia	856	82	670	794	78	637	21	2	17
Mexico	152	59	78	57	28	21	-	-	-
Netherlands	1,188	271	843	1,028	256	725	-	-	-
Poland	3,945	1,062	2,468	1,092	349	648	1,904	628	1,126
Portugal	2,248	358	1,633	2,060	352	1,535	2,018	328	1,484
Romania	2,687	689	1,643	2,396	642	1,522	1,413	465	815
Sweden	2,855	453	2,164	2,547	431	1,963	1,228	201	950
Slovenia	741	134	552	666	130	498	338	66	253
Slovakia	2,098	445	1,433	1,911	421	1,331	1,100	319	685

Notes: An affiliate is defined as a corporate group-country-sector triplet in which the country of location differs from the country where the headquarter is located. The "All" column includes sectors "Manufacturing", "Services", as well as in "Others" and "Non-market Economy".

Table A9: Number of parents (by country and sector).

Country	Sales			Employment			Value Added		
	All	Mfg.	Services	All	Mfg.	Services	All	Mfg.	Services
Austria	599	170	345	495	159	279	320	114	164
Belgium	600	160	353	440	139	262	353	121	198
Bulgaria	53	8	42	49	7	39	17	4	12
Czech Rep.	422	39	331	353	31	288	163	19	125
Germany	1381	459	783	1156	409	662	753	308	385
Estonia	194	13	149	143	9	112		-	-
Spain	1095	222	687	909	200	583	844	186	542
Finland	507	140	304	401	117	243	149	50	80
France	1506	413	885	1173	355	693	1075	344	614
UK	953	178	670	775	164	553	430	105	295
Greece	86	19	52	74	15	47	-	-	-
Croatia	76	7	60	60	7	48	-	-	-
Hungary	157	22	106	131	20	90	50	7	35
Italy	1430	604	670	1182	542	561	867	406	405
Japan	892	400	456	828	381	419	312	219	86
Korea	108	50	52	88	40	44	52	30	19
Lithuania	95	7	76	86	5	70	-	-	-
Latvia	70	5	56	64	5	50	-	-	-
Mexico	12	5	5	7	4	2	-	-	-
Netherlands	224	33	161	167	29	122	-	-	-
Poland	152	35	100	87	27	51	36	5	26
Portugal	235	45	151	191	41	129	191	37	127
Romania	37	6	25	31	6	20	19	6	11
Sweden	944	242	608	716	199	467	258	73	167
Slovenia	123	19	89	107	16	77	21	8	10
Slovakia	148	21	104	110	17	79	56	9	40

Notes: A parent is defined as a corporate group-country-sector triplet located in the headquarter country. The "All" column includes sectors "Manufacturing", "Services", as well as in "Others" and "Non-market Economy".

ture shares as weights, $\Delta\phi_n = \sum_j \Delta\phi_n^j$. We request to have estimates of the sector level firm know-how for at least 10 sectors in each country in order to compute the weighted average, and the weights are re-weighted to express the relative importance of the sectors for which we could estimate $\Delta\phi_n^j$. Similarly, we request to have least 4 (out of 6 sectors) to construct aggregate firm know-how for both manufacturing and services. Notice that this restriction is satisfied by all countries in the sample, in our baseline and in most of the robustness exercises. Finally, we only use sectoral firm know-how estimates, $\Delta\phi_n^j$, for which there are three or more foreign affiliates with available financial information.

Aggregate level data:

We use aggregate level information to measure production, employment, value added, productivity, and the activity of foreign affiliates for each country-sector in our sample. To construct firm's sales, employment and value added shares, we use information from KLEMS and OECD on gross output, gross value added and the number of employees at the country-sector level, in million of current dollars and thousands of employees, respectively. The KLEMS dataset corresponds to the statistical national accounts from their latest release in 2019. The OECD statistics come from the Dataset for Structural Analysis (STAN) and we convert the sectoral ISIC revision 4 to the sectoral classification used in KLEMS. To ensure we have aggregate information for all countries and sectors in our sample, we sacrifice some sectoral disaggregation. In particular, we combine into the following categories: Agriculture and Mining; Textiles, Apparel and Woods; Chemicals, Petroleum and Plastic; Electrical Equipment and Machinery; Transport Equipment and Other Manufacturing; and Accommodation and Recreation

We obtain aggregate measures of productivity from Penn World Tables (PWT). We use the TFP level at current purchasing power parity (PPP) to measure total factor productivity and the real GDP at chained PPPs in 2011 US dollars over total employment to measure output per worker in each country. To construct measures of output per-worker at the sectoral level we use gross value added per worker from the KLEMS-OECD dataset that we convert to international dollars using the PPP conversion factor for GDP, measured in units of local currency per international dollars. We obtain the GDP PPP conversion factor and the share of employees compensation in value added from PWT.

Finally, we obtain information for the activity of foreign affiliates for each country-sector pair in our sample from the OECD Activity of Multinational Enterprises (AMNE) dataset and the Eurostat Foreign Affiliates Statistics (FATS), for which we harmonize the sectoral classification into the 18 sectors used in our dataset.

B Additional statistics on the two-way fixed effect estimation

Connectivity: To be able to identify country-sector fixed effects firms need to connect countries in the sample. Since we only consider multinationals, by definition all corporations contribute in connecting the countries where they keep operations, overcoming the usual problem of "limited mobility bias" that plagues most two-way fixed effect exercises in the labor literature.[4] Since country fixed effects are estimated relative to a reference country, estimation has to be performed on the largest connected set. In our case, the largest connected set (LCS) is comprised of all 26 countries in our sample, whether using sales or employment, NAICS2 or NAICS4 sector classification. Nonetheless, it is possible that countries are poorly connected, even within the LCS, if only few corporations link them together. When only a handful of corporate groups connect countries in the sample the variance of the fixed effects will be over-estimated and spurious negative correlations can appear between country and corporation fixed effects (Andrews et al. 2008). The literature has illustrated three ways in which connectivity can be improved. The first method consists in performing the estimation on the "leave-one-out" set, which is defined as the set of countries that remain connected even after any individual corporation is removed from the sample (Kline et al. 2020). Notice that all countries in our sample stay connected regardless of which multinational is dropped from the set. The second method comes from Bonhomme et al. (2019), who group firms using k-means clustering based on the distribution of affiliates' market shares in each country. This method enhances connectivity by reducing the number of country fixed effect that must be estimated. The third method, proposed by Andrews et al. (2008), consists in restricting the sample to countries hosting corporations that also operate elsewhere. Since we only work with multinationals, this restriction is always satisfied in our sample.

To judge the connectedness of the countries in our sample within each sector, we construct the global connectivity of the induce network, λ_2, proposed by Jochmans and Weidner (2019).[5] Table A10 shows the mean and standard deviation of λ_2 across sectors. Connectivity is fairly high, almost 60%, for the largest connected and leave-one-out sets. As expected, both methods deliver the same value for λ_2 since for both sets, all 26 countries stay in the sample. Restricting the dimensionality to five clusters of countries further increases connectivity. However, as we have pointed out, our strategy relies in using the high dimensional entities (country-sectors). Nontheless, the k-mean clustering can be used to test the underlying additivity assumption as we discuss in the next section.

Linearity: In section 5.2 we show the standarized residuals are mostly flat across the firm fixed effects and country-embedded factors decile-bins. We also show that our results are robust to excluding deciles at the top and bottom of the firm fixed effect dis-

[4] In the labor literature identification is achieved by workers who switch employers over their careers Abowd et al. (1999).

[5] Jochmans and Weidner (2019) show that a the amount of excess variance in the teacher fixed effect estimates will be bounded from above by λ_2, which takes values between zero and one, with one indicating full connectivity.

Table A10: Global connectivity of the induce network, λ_2

		μ_{λ_2}	σ_{λ_2}
Largest connected set	Abowd et al. (1999)	0.59	0.11
Leave-out set	Kline et al. 2020	0.59	0.11
K-means clusters	Bonhomme et al. (2019)	0.97	0.02

Notes: The global connectivity measure is constructed on firm's sales and 18 sectors. We allocate all firms in our data to k = 5 with similar sales's share structures using k-means cluster analysis.

Table A11: Contribution to $Var\left(s^j_{in}(\omega)\right)$

Variance Decomp	Baseline	k-means (linear)	Interaction
$\Delta\mathbb{A}^j_k$	0.27	0.26	
$\delta^j(\omega)$	0.45	0.45	
R^2	0.72	0.70	0.76

Notes: In the second and third columns, k corresponds to the group FE (K = 5).

tribution. A different approach to assessing the additive separability assumption comes from Bonhomme et al. (2019), where each pairing of corporation and country-group is allowed to have a differential effect. This new specification replaces the additive country and firm fixed effects with an interaction between country-group and firm fixed effect. If country-firm "match effects" are relevant in determining the assignment of corporations to countries, then there is a potential for bias given that the error term could be correlated with the country fixed effects. Table A11 shows the share of the variance explained by the country fixed effects. Our results indicate that an additive model provides a very good approximation to our data; allowing interactions between corporations and country-group yields a small increase in R^2. Also notice that the individual contributions of firm and country effects to overall affiliates' shares variance remain almost unchanged in the additive model using individual countries (baseline) or country groups.