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Firm-embedded productivity and cross-country income differences*

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Abstract

We measure the contribution of firm-embedded productivity to cross-country income differences. By firm-embedded productivity we refer to the components of productivity that differ across firms and that can be transferred internationally, such as blueprints, management practices, and intangible capital. Our approach relies on micro-level data on the cross-border operations of multinational enterprises (MNEs). We compare the market shares of the exact same MNE in different countries and document that they are about four times larger in developing than in high-income countries. This finding indicates that MNEs face less competition in less-developed countries, suggesting that firm-embedded productivity in those countries is scarce. We propose and implement a new measure of firm-embedded productivity based on this observation. We find a strong positive correlation between our measure and output per-worker across countries. In our sample, differences in firm-embedded productivity account for roughly a third of the cross-country variance in output per-worker.

Keywords: Development Accounting, TFP, Multinational Enterprises

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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 productivity embedded in individual firms in the form of blue-prints, know-how, management practices, and intangible capital.[2]

This paper introduces a new framework for disentangling firm-embedded productivity from country-embedded factors and decomposing their contributions to cross-country income differences. By 'firm-embedded productivity' we refer to the components of productivity that differ across firms inside a country, and that can be transferred internationally. In contrast, by 'country-embedded factors' we refer to those components that are internationally immobile and affect all firms operating in a country. As noted by Burstein and Monge-Naranjo (2009), separating between these two components is not straightforward, as different combinations of firm-embedded productivity and country-embedded factors can result in the same level of aggregate output per-worker.[3]

Our approach separates these components by exploiting firm-level data on the cross-border operations of multinational enterprises (MNEs). We compare the market shares of the exact same MNE in different countries and document that they are roughly four times larger in developing than in high-income countries. We propose and implement a new measure of firm-embedded productivity based on this observation. Our central idea is that MNEs should have larger market shares in countries where aggregate firm-embedded productivity is relatively scarce, as they face less competition in those countries. The observed differences in MNE market shares are indicative of large differences in the firm-embedded productivity of the competitors that MNEs face in each country.

We develop this logic in a development accounting framework and measure aggregate firm-embedded productivity using market-share data on the foreign affiliates of MNEs

[1] See, for example, Hall and Jones (1999), Acemoglu et al. (2014), or Caselli (2016). Parente and Prescott (2000) refer to these factors as 'dissembodied TFP'.

[2] See, for example, Prescott and Visscher (1980), Klette and Kortum (2004), Atkeson and Kehoe (2005), Bloom and Van Reenen (2007), or McGrattan and Prescott (2009).

[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.

that simultaneously operate in multiple countries. The framework assumes that producers in a country are heterogeneous in their efficiency and quality (what we call 'firm-embedded productivity') but access the same country-embedded factors and set a constant markup over their marginal cost. Thus, the market share of a MNE in a country is driven by its productivity relative to the aggregate firm-embedded productivity in the country.[4] MNEs can transfer their productivity around the world but face different competitors in each country where they operate. Differences in market shares of the same MNE in different countries pin-down the difference in aggregate firm-embedded productivity between those countries. The residual differences in income per-capita across countries can be attributed to differences in country-embedded factors. Our measure of firm-embedded productivity takes into account the fact that MNEs are a selected sample of firms since it compares the market shares of the exact same MNE (in the same sector) in different countries.

Of course, MNEs may not be able to fully transfer their productivity across countries. We allow for imperfect technology transfers by assuming that MNEs can only use a fraction of their productivity when operating abroad. Under this assumption, the market share of an affiliate can be relatively low in a country both if aggregate firm-embedded productivity in that country is high, or if the MNE faces large technology transfer costs.[5] We control for technology transfer costs in two straightforward ways. First, by focusing on the cross-country variation in the market shares of MNE's *foreign* affiliates, we control for MNE-specific costs of transferring technology that are common across foreign destinations. Second, we control for the country-pair specific component of the technology transfer costs using a gravity specification that follows Waugh (2010).[6] If there are destination-specific costs not captured by our gravity controls, and if it is harder for MNEs to transfer technology into developing countries, then our results provide a lower bound to the true cross-country differences in firm-embedded productivity.[7]

[4]The model does not take into account that, given their relatively large market shares, MNEs may be able to set higher markups in developing countries. Higher markups would push down MNEs market shares in these countries, so that the observed market shares would understate the true differences in competition and firm-embedded productivity across countries.

[5]Or equivalently, if there is home-bias in preferences.

[6]The gravity specification models bilateral costs as a function of the distance and other country-pair specific characteristics, and it is common in the International Trade and Multinational Production literature. Waugh (2010) also controls for source-specific costs using fixed effects. See Head and Mayer (2014) for a survey.

[7]If transferring technology into developing countries is relatively harder, foreign MNEs should have low market shares there. Section 5.1 shows how to incorporate data on parent firms to estimate firm-embedded productivity in this case.

We implement our framework using data on MNE revenues from ORBIS, a worldwide dataset maintained by Bureau van Dijk. The main advantage of ORBIS is the scope and accuracy of its ownership information: it details the full list 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 ownership links between affiliates of the same MNE, including cases where 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 focus on destinations for which ORBIS has the best coverage, so that our sample is mainly comprised of Eastern and Western European countries.[8]

We estimate the key structural equation from our model, which states that the log of a MNE market share in a country and sector can be written as the sum of a MNE-sector component, a destination-sector component, and the technology transfer costs. We fit a two-way fixed-effect specification to measure cross-country differences in firm-embedded productivity from the estimated destination-sector fixed-effects.[9] We find that for the average country in our sample, firm-embedded productivity is 0.20 log points lower than in France, our reference country.[10] The relative importance of the differences in firm-embedded productivity vs. country-embedded factors varies considerably across countries. For example, country-embedded factors are similar in Greece and Italy, but firm-embedded productivity in Italy is 0.28 log-points higher than in Greece, accounting for three quarters of the observed differences in output per-worker between these two countries. In contrast, firm-embedded productivity is similar for Greece and Bulgaria, though output per-worker in Greece is 0.5 log points higher than in Bulgaria due to the difference in country-embedded factors between these countries.

We show that there is a strong positive correlation between firm-embedded productivity 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 (firm-embedded productivity) using data on MNE market shares, and

[8]Our sample of destination countries also includes Japan, Korea, and Mexico. In contrast, every country in the world is potentially a source of MNEs in our data.

[9]Destination-sector fixed effects are unbiased estimates of the destination-sector components of the market shares if the assignment of MNEs to countries is not driven by a firm-destination component of the technology transfer costs. We evaluate this assumption and how it affects our results in Section 5.2.

[10]We use France as our reference country since this country has the best coverage among the large rich countries in ORBIS.

show that this component is strongly correlated with independent measures of output per-worker. In fact, differences in firm-embedded productivity account for about one-third of the cross-country variance in output per-worker.

We then study cross-country differences in firm-embedded productivity at the sector level. The cross-country differences in firm-embedded productivity are larger in Manufacturing than in Services, but so are the cross-country differences in output per-worker. Remarkably, the contribution of firm-embedded productivity to the cross-country variance in output per-worker ends up being roughly a third in these two broad sectors. We further show that the foreign output of a country's MNEs is concentrated in sectors where the country's firm-embedded productivity is relatively high. For example, Japan and Finland have a particularly large stock of firm-embedded productivity in Manufacturing, and the foreign output of the MNEs from these countries is concentrated in the Manufacturing sector. In contrast, Latvia and Lithuania have relatively more firm-embedded productivity in Services, and the foreign output of the MNEs from these countries is concentrated in the Service sector.

Finally, we evaluate the sources of the observed cross-country differences in firm-embedded productivity along two dimensions. First, we evaluate if these differences stem from aggregate scale, or variety, effects by focusing on the component of firm-embedded productivity that is orthogonal to a country's population, removing scale effects from our measure. We show that there is still a very strong correlation between this residualized component of firm-embedded productivity and output per-worker. Second, we separately compute differences in firm-embedded productivity across domestic firms and across the foreign affiliates of the MNEs that operate in each country. Differences in firm-embedded productivity across domestic firms account for roughly 88 percent of the observed differences in firm-embedded productivity across countries, while differences across the foreign affiliates of MNEs account for the remaining 12 percent.

Related literature: Our paper is closely related to Burstein and Monge-Naranjo (2009), who separate firm-embedded productivity from country-embedded factors using aggregate data on Foreign Direct Investment (FDI) stocks and the equilibrium conditions of a structural model of MNEs location choices. 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-embedded productivity can be recovered from aggregate data using a non-arbitrage condition that equates after-tax managerial profits across countries. In contrast, our approach treats firm-embedded productivity as a non-rival factor that can be used simultaneously in many countries, and is based on firm-level data on MNE operations in multiple countries rather than on a structural model of MNE's location choices.[11] 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 tease out the role of human-capital in explaining cross-country income differences.

More broadly, our paper is related to the extensive literature on development accounting, which measures directly the contribution of factors of production to cross-country income differences and computes TFP as a residual (see Caselli 2005 for a survey). Like this literature, our approach decomposes cross-country income differences, but provides a direct measure of one of the components of TFP, firm-embedded productivity, using market-share data on MNEs.

Finally, our paper is also related to the large literature studying technology transfers through MNEs. One branch of the literature uses parent-affiliate matched data to estimate how productivity and shocks are transmitted across parties of a MNE (see e.g. Cravino and Levchenko 2017 and Bilir and Morales 2020). In contrast, our focus is on measuring the contribution of firm-embedded productivity vs. country-embedded factors in explaining cross-country income differences. A different branch of the literature parameterizes structural models of location choices of MNEs to measure their contribution to welfare and TFP (see e.g. Ramondo and Rodriguez-Clare 2013, Irarrazabal et al. 2013, Alviarez 2019, or Arkolakis et al. 2018). Our measurement strategy is based on parent-affiliate matched data rather than on the general equilibrium conditions of a structural model.

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 Section 6 concludes.

2 Accounting framework

In this section, we first develop a stylized framework to formalize the distinction between firm-embedded productivity and country-embedded factors, and to illustrate how

[11]This is the standard assumption in the multinational production literature, starting with Markusen (1984), Helpman (1984), and more recently Helpman et al. (2004), among others.

firm-level data on the cross-border operations of MNEs can be used to decompose cross-country income differences into these two components. Next, we present 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 tradable 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 operating 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 shifter for firm ω, which we interpret as product quality. Note that the idiosyncratic quality $Q_{in}(\omega)$ can differ across production locations.

The production function for intermediate goods is

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

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 idiosyncratic to firm ω, and like product quality, can differ across production locations.

It is useful to define $A_{in}(\omega) \equiv [Q_{in}(\omega) \times X_{in}(\omega)]^{\rho-1}$. In what follows, we will refer to

$A_{in}(\omega)$ as "firm-embedded productivity". It captures production, managerial, and marketing know-how that is specific to the firm. In contrast to country-embedded productivity, firm-embedded productivity can be transferred internationally within the boundaries of the firm.

We assume that firm-embedded productivity is transferred imperfectly across countries, so that the productivity of an MNE from country i when it 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 productivity embedded in MNE ω in its home country, and $\kappa_{in}(\omega)$ is a technology transfer cost that captures the degree to which firm-embedded productivity can be moved across countries. If $\kappa_{in}(\omega) = 0$, the MNE can use the same productivity in all the countries where it produces.

Aggregate output and TFP: Aggregate output can be written as

$$Y_n = Z_n \Phi_n^{\frac{1}{\rho-1}} L_n, \tag{4}$$

where

$$\Phi_n \equiv \sum_i \int_{\omega \in \Omega_{in}} A_{in}(\omega)\, d\omega \tag{5}$$

denotes aggregate firm-embedded productivity in country n, which is the sum of the productivity embedded in the firms that produce in country n.

In what follows, we use lowercase to denote the log of a variable, and use $y_n \equiv ln[Y_n/L_n]$ to denote the log of output per-worker. Using Equation (4), we can thus write

$$y_n = z_n + \frac{1}{\rho-1}\phi_n. \tag{6}$$

Equation (6) states that cross-country differences in output per-worker arise from differences in country-embedded productivity, z_n, and differences in aggregate firm-embedded productivity, 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 data on market shares. From the demand functions implied by Equation (1), we can write the revenue of MNE ω from country i operating in country n, relative to the sum of the revenues of all firms operating in n, as

$$S_{in}(\omega) \equiv \frac{P_{in}(\omega) Y_{in}(\omega)}{\sum_i \int_{\omega \in \Omega_{in}} P_{in}(\omega) Y_{in}(\omega) d\omega} = \frac{A_{in}(\omega)}{\Phi_n}. \tag{7}$$

A MNE market share in a country depends on its productivity, $A_{in}(\omega)$, relative to the productivity embedded in all firms operating in that country, Φ_n. Intuitively, MNEs should have larger market shares in countries where aggregate firm-embedded productivity is relatively low, since they face less competition in those countries.[12] Importantly, country-embedded productivity Z_n does not affect the MNEs' market share $S_{in}(\omega)$, since it proportionally affects all the firms producing in the same country.[13]

We build on this intuition to identify cross-country differences in Φ_n. Substituting Equation (3) in (7), the market share in logs is

$$s_{in}(\omega) = a_i(\omega) - \kappa_{in}(\omega) - \phi_n. \tag{8}$$

Equation (8) shows that if technology transfer costs do not vary across foreign destinations, $\kappa_{in}(\omega) = \kappa_i(\omega)$, cross-country differences in market shares across affiliates of the same MNE pin-down differences in ϕ_n. In this case, one could regress firm-level market shares on MNE- and destination-level dummies, and use the destination dummies to recover cross-country differences in ϕ_n. The MNE-level dummies would capture differences in $a_i(\omega) - \kappa_i(\omega)$ across MNEs, 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 z_n can be computed as residuals from Equation (6). This two-way fixed-effect approach constitutes the basis of our estimation strategy described in Section

[12] Note that, in our model, the allocation of resources is not distorted across firms. If, as documented by Bento and Restuccia (2017) and Fattal Jaef (2020), size-dependent distortions are more prevalent in less developed countries -for example if larger firms are taxed more or have higher markups in developing countries-, our procedure would underestimate the contribution of firm-embedded productivity to cross country income differences.

[13] Section 5.2 and Appendix B show that our assumption that Z_n and $X_{in}(\omega)$ enter log-linearly into the production function provides a good approximation of the data.

3.2.

In the more general case where technology transfer costs vary across destinations, differences in market shares across affiliates of the same MNE are not enough to identify differences in aggregate firm-embedded productivity. As Equation (8) makes clear, this is because the market share of an affiliate can be relatively low in country n if either firm-embedded productivity is relatively large in country n, high ϕ_n, or if the costs to transfer technology are large, high $\kappa_{in}(\omega)$. Section 3.2 shows how, if we observe market shares forMNE 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 International 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

$$Y_n = \prod_j \left[Y_n^j\right]^{\theta_n^j}, \tag{9}$$

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,

$$Y_n^j = \left[\sum_i \int_{\omega \in \Omega_{in}^j} \left[Q_{in}^j(\omega)\, Y_{in}^j(\omega)\right]^{\frac{\rho^j - 1}{\rho^j}} d\omega\right]^{\frac{\rho^j}{\rho^j - 1}}, \tag{10}$$

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 product quality of firm ω from country i in sector j.

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

$$Y_{in}^j(\omega) = Z_n^j X_{in}^j(\omega) \left[H_n L_{in}^j(\omega)\right]^{1-\alpha^j} K_{in}^j(\omega)^{\alpha^j}, \tag{11}$$

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.[14]

As in the previous section, we define $A^j_{in}(\omega) \equiv \left[Q^j_{in}(\omega) \times X^j_{in}(\omega)\right]^{\rho^j-1}$ with

$$A^j_{in}(\omega) = A^j_i(\omega) \times exp\left(-\kappa^j_{in}(\omega)\right). \tag{12}$$

Aggregate output in each sector satisfies

$$Y^j_n = Z^j_n \left[\Phi^j_n\right]^{\frac{1}{\rho^j-1}} \left[H_n L^j_n\right]^{1-\alpha^j} \left[K^j_n\right]^{\alpha^j},$$

where $\Phi^j_n \equiv \sum_i \int_{\omega\in\Omega^j_{in}} A^j_{in}(\omega)\, d\omega$ is the aggregate firm-embedded productivity in sector j and country n. Output per-worker in sector j can be written as

$$\frac{Y^j_n}{L^j_n} = \tilde{Z}^j_n \tilde{\Phi}^j_n, \tag{13}$$

where $\tilde{Z}^j_n \equiv \left[Z^j_n\right]^{\frac{1}{1-\alpha^j}} H_n \left[\frac{K^j_n}{Y^j_n}\right]^{\frac{\alpha^j}{1-\alpha^j}}$, $\tilde{\Phi}^j_n \equiv \left[\Phi^j_n\right]^{\beta^j}$, and $\beta^j \equiv \frac{1}{1-\alpha^j}\frac{1}{\rho^j-1}$. In an abuse of notation, in what follows we will refer both to $\tilde{\Phi}^j_n$ and Φ^j_n as firm-embedded productivity. We refer to $\tilde{Z}^j_n$ as country-embedded factors, as it includes physical and human capital, in addition to the country-embedded productivity Z^j_n.

Aggregate output per worker can be written as

$$\frac{Y_n}{L_n} = \tilde{Z}_n \tilde{\Phi}_n, \tag{14}$$

with $\tilde{\Phi}_n \equiv \prod_j \left[\tilde{\Phi}^j_n\right]^{\theta^j_n \frac{\beta_n}{\beta^j} \frac{\rho_n-1}{\rho^j-1}}$, $\beta_n \equiv \frac{1}{1-\alpha_n}\frac{1}{\rho_n-1}$, $\alpha_n \equiv \sum_j \theta^j_n \alpha^j$, $\rho_n \equiv \sum_j \theta^j_n \rho^j$ and $\tilde{Z}_n \equiv \bar{\theta}_n H_n \left[\frac{K_n}{Y_n}\right]^{\frac{\alpha_n}{1-\alpha_n}} \prod_j \left[Z^j_n\right]^{\frac{\theta^j_n}{1-\alpha_n}}$.[15]

Applying logs in Equation (14), we can thus write

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

[14] Appendix C shows that our approach and results do not change if we incorporate intermediate inputs in production, and recalibrate the model's parameters accordingly.

[15] $\bar{\theta}_n \equiv \prod_j \left[\theta^j_n \left[\frac{1-\alpha^j}{1-\alpha_n}\right]^{1-\alpha^j} \left[\frac{\alpha^j}{\alpha_n}\right]^{\alpha^j}\right]^{\frac{\theta^j_n}{1-\alpha_n}}$ is a country-specific constant.

We can compute the terms in Equation (15) following steps analogous to those described in Section 2.2. In particular, the (log) market-share of MNE ω operating in country n and sector j is

$$s_{in}^{j}(\omega) = a_{i}^{j}(\omega) - \kappa_{in}^{j}(\omega) - \phi_{n}^{j}, \tag{16}$$

A MNE share in a sector depends on its productivity, $a_i^j(\omega)$, relative to the productivity of all firms in the sector, ϕ_n^j. As explained in the previous section, we can use differences in sectorial market 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 to obtain $\tilde{\phi}_n = \sum_j \theta_n^j \frac{\beta_n}{\beta^j} \frac{\rho_n - 1}{\rho^j - 1} \tilde{\phi}_n^j$. Once $\tilde{\phi}_n$ is calculated, $\tilde{z}_n$ can be computed as a residual from Equation (15).

Finally, our development-accounting exercise evaluates the contribution of firm-embedded productivity to the cross-country variance of output per-worker. We follow the variance decomposition in Klenow and Rodriguez-Clare (1997) and compute

$$\frac{cov(y_n, \tilde{z}_n)}{var(y_n)} + \frac{cov(y_n, \tilde{\phi}_n)}{var(y_n)} = 1. \tag{17}$$

The next section explains how we implement this variance decomposition in our data.[16]

3 Data and empirical strategy

3.1 Data description

This section describes our data. We refer the reader to Appendix A for details.

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 fam-

[16] The decomposition in Equation (17) follows from $Var(y_n) = Cov(y_n, y_n) = Cov(y_n, \tilde{z}_n) + Cov(y_n, \tilde{\phi}_n)$.

ily. This information allows us to build links between affiliates of the same MNE, 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.

The main variable used in our analysis is the revenue (turnover) of each firm. We use data for the year 2016, which is the year with the largest coverage in ORBIS. We focus on a subset of destination countries for which aggregate revenues by foreign-firms in ORBIS account for at least 25 percent of the aggregate revenues by foreign-firm reported by OECD/Eurostat.[17] In addition, we exclude Ireland, Luxembourg, and Switzerland from our sample as MNEs revenues in these countries are particularly sensitive to profit-shifting strategies. In contrast, every country in the world is a potential source country for the MNEs in ORBIS, so that our sample of source countries is much larger than our sample of destination countries.[18] 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-firm revenues as reported by OECD/Eurostat.

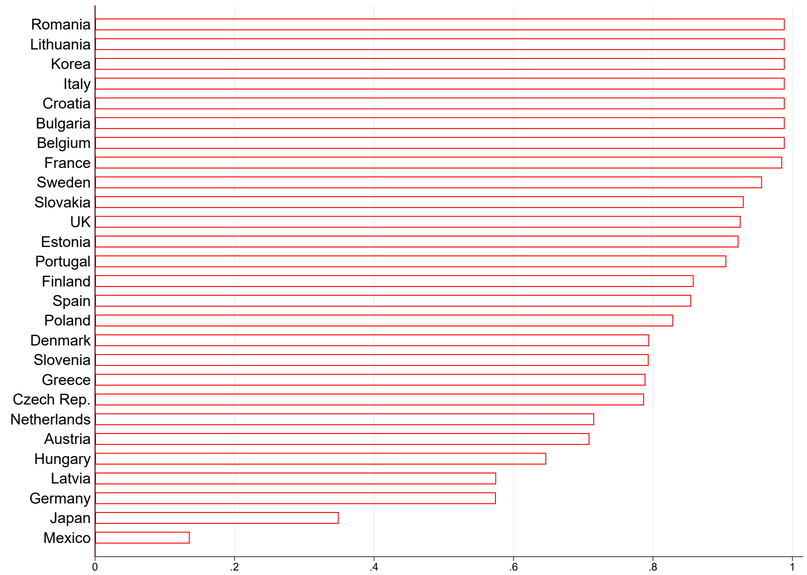
The original unit of observation in ORBIS is a tax-identification number. Often, affiliates or plants, located in different addresses within the same country and belonging to the same corporate group, are registered with different tax identification numbers. We aggregate revenues of all firms in ORBIS that belong to the same corporate group and that operate in the same country and 2-digit NAICS sector. Our unit of observation is then a corporate group-country-sector triplet. For example, ORBIS shows multiple tax-ids belonging to Renault in Germany in the Transportation and Equipment sector. We aggregate the revenues of those affiliates to obtain the Renault's total revenues in this sector in Germany. We then compute market shares by dividing the revenues of each corporate group-country-sector by the aggregate revenues in each country-sector. Data on aggregate revenues are from EU KLEMS and OECD, since ORBIS not always covers the population of firms in each country-sector pair. Finally, we define a MNE as all the tax id's that belong to the same corporate group. Our procedure compares affiliates of the MNE 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.

We obtain output per-worker, physical capital, and human capital directly from the Penn

[17]OECD Activity of Multinational Enterprises (AMNE) database and the Eurostat Foreign Affiliate Statistics database.

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

Figure 1: Data coverage: foreign-MNE 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.

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

3.2 Empirical strategy

This section describes how we measure cross-country differences in firm-embedded productivity using firm-level data on the activity of MNEs across countries. Our strategy builds on Equation (16) and imposes structure on the technology transfer costs following a long tradition in International Economics that approximates trade and multinational production costs using observable variables.

We assume that technology transfer costs are given by

$$\kappa_{in}^{j}(\omega) = O_i^j + D_n^j + B_{in}^j + \varepsilon_{in}^j(\omega). \tag{18}$$

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 MNE-destination specific component, $\varepsilon_{in}^j(\omega)$. In addition, we assume that the bilateral component is symmetric and a log-linear function of observable characteristics, such as bilateral distance and sharing a language, $B^j_{in} = \chi^j_d dist_{in} + \chi^j_l lang_{in}$.

Substituting Equation (18) into (16), we obtain the estimating equation

$$s^j_{in}(\omega) = \delta^j_i(\omega) + \mathbb{A}^j_n + \psi^j_d dist_{in} + \psi^j_l lang_{in} + \epsilon^j_{in}(\omega)\,. \tag{19}$$

Here, $\delta^j_i(\omega)$ are MNE-sector fixed effects. $\mathbb{A}^j_n$ denotes a set of dummies that take the value of 1 if the destination country is n and the sector is j. We estimate Equation (19) by Ordinary Least Squared (OLS) using the sample of the foreign affiliates of MNEs in the ORBIS data -MNEs in their home country are not included. The regression identifies the MNE-sector fixed effect, $\delta^j_i(\omega)$, from the within-MNE average market share across destinations, in each sector j, controlling for destination characteristics and the bilateral component of the technology transfer costs. Similarly, the destination effects $\mathbb{A}^j_n$ are identified from the average market shares of the foreign affiliates that operate in each country n and sector j, controlling for within-MNE characteristics and the bilateral component of the technology transfer costs. The residual $\epsilon^j_{in}(\omega)$ is (the negative of) the MNE-destination-sector specific component of the technology transfer costs.

The OLS estimates of the destination-sector-specific components of the market shares, $\mathbb{A}^j_n$, are unbiased if the assignment of MNEs to destination countries is exogenous with respect to the error term, $\epsilon^j_{in}(\omega)$. This is the case in the workhorse models of multinational production in the tradition of Helpman et al. (2004), where selection is driven by firm characteristics (e.g. productivity) and by destination-country characteristics (e.g. market size), not by firm-destination characteristics.

For the reminder of this section, we assume that MNEs do not select into countries based on firm-destination characteristics, $\varepsilon^j_{in}(\omega)$. In Section 5.2, we show that our main results are robust to reestimating Equation (19) using subsamples of MNEs that are more likely to satisfy this exogeneity assumption.

3.3 Cross-country differences in MNE market shares

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. Using data on sectorial expenditure shares in each country, θ^j_n, our OLS estimates of $\Delta\mathbb{A}^j_n$, and defining $\Delta x_n \equiv \sum_j \theta^j_n \Delta x^j_n$

as the aggregate across sectors, we compute the aggregate destination-country effects as

$$\Delta\mathbb{A}_n \equiv \sum_j \theta_n^j \Delta\mathbb{A}_n^j. \tag{20}$$

The aggregate country effect, $\Delta\mathbb{A}_n$, captures the (log of the) average MNE market share in each destination relative to France, after controlling for the MNE-sector fixed effects and the bilateral variables. Figure 2 reports $exp(\Delta\mathbb{A}_n)$. On average, MNE market shares are larger in less developed countries. Differences between developed and developing countries are enormous: MNEs market shares are about three and a half times larger in Greece and Portugal, and about twelve times larger in Estonia and Lithuania, compare to their market shares in France. In contrast, MNEs have similar market shares in the UK, Germany, and France.

Appendix Figure A1 reports standard errors for our estimates of $\Delta\mathbb{A}_n$, and show that these dummies are tightly estimated and exhibit substantial variation across countries.[19] The figure also shows that we obtain very similar estimates if we use data on employment shares or value-added shares as the dependent variables in our estimation.[20]

3.4 Interpreting differences in MNE market shares

We calculate the differences in $\Delta\phi_n^j$ using our estimated country effects, $\Delta\mathbb{A}_n^j$. In our model, these effects correspond to

$$\Delta\mathbb{A}_n^j = -\left[\Delta\phi_n^j + \Delta D_n^j\right], \tag{21}$$

which conflates firm-embedded productivity $\Delta\phi_n^j$ and the destination effects of the technology transfer costs ΔD_n^j. For our baseline results, the identification strategy follows Waugh (2010), and assumes that costs have an origin-specific, but not destination-specific, component, $\Delta D_n^j = 0$. In that case, the country dummies can be interpreted as $\Delta\mathbb{A}_n^j = -\Delta\phi_n^j$. But what if this identification assumption is not satisfied, $\Delta D_n^j \neq 0$? If ΔD_n^j is high

[19] Appendix Table A1 reports the OLS coefficients on bilateral distance and common language, ψ_d^j and ψ_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 (19), while the MNE-sector dummies $\delta_i^j(\omega)$ account for 0.45. The R-squared of the regression is 0.72. Appendix B presents additional statistics on our two-way fixed effect estimator.

[20] In the model, revenue shares, employment shares, and value-added shares coincide, so that in theory any of these shares can be used for our purposes. We use revenue shares for our baseline estimates since ORBIS has a more complete coverage of revenues than of employment and value-added. But using employment data alleviates concerns about profit-shifting strategies by MNEs.

Figure 2: Market shares of foreign MNE affiliates, relative to France.

Note: The figure shows $exp(\Delta\mathbb{A}_n)$, calculated using Equation (20) and the OLS estimates of Equation (19). The x-axis reports the output per-worker of each country, relative to France, from Penn World Tables (9.1).

for low income countries (i.e. it is harder to transfer technology into less developed countries), then $cov(\Delta y_n, \Delta D_n^j) \leq 0$. This implies that our baseline estimates of $\Delta\phi_n^j$ based on Equation (21) will understate the contribution of aggregate firm-embedded productivity to the cross-country variance of output per-worker,

$$cov\left(\Delta y_n, -\Delta\mathbb{A}_n^j\right) = cov\left(\Delta y_n, \Delta\phi_n^j + \Delta D_n^j\right) \leq cov\left(\Delta y_n, \Delta\phi_n^j\right). \tag{22}$$

Section 5 presents a robustness exercise that allows for $\Delta D_n^j > 0$. These results are remarkably similar to our baseline results.

3.4.1 Parameterization

Finally, as shown in Section 2.3, to evaluate the contribution of aggregate firm-embedded productivity to cross-country income differences we need to aggregate our sectoral estimates and assign values to the model parameters. Taking logs on Equation (13), and using our baseline identification assumption so that $\Delta\mathbb{A}_n^j = -\Delta\phi_n^j$, yields

$$\Delta y_n^j = -\,\beta^j \Delta\mathbb{A}_n^j + \Delta\tilde{z}_n^j.$$

Here $\beta^j \equiv \left[\left[\rho^j - 1\right]\left[1 - \alpha^j\right]\right]^{-1}$ is a composite elasticity and can be estimated from an OLS regression of Δy_n^j on $\Delta\mathbb{A}_n^j$. 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 policies that encourage accumulation of country-embedded factors, captured by $\Delta\tilde{z}_n^j$, would also improve firm-embedded productivity, $\Delta\phi_n^j$. One way to deal with this concern is to control for factors included in $\Delta\tilde{z}_n^j$ that simultaneously affect the accumulation of firm-embedded productivity, such as human capital and the capital-output ratio in country n. In particular, we estimate

$$\Delta y_n^j = b_0^j + b_1^j \Delta\mathbb{A}_n^j + b_2^j \Delta C_n + u_n^j, \tag{23}$$

where C_n is a vector of controls that captures differences in human- and physical capital across countries.

Table 1 reports these estimates. Columns (1), (3) and (5) respectively show the results for the pooled sample of sectors, Manufacturing sectors, and Services sectors, estimated under the restriction that b_1 is the same in all sectors (see Appendix Table A2 for results on estimating b_1^j for each sub-sector in Manufacturing and Services). The coefficients on b_1 are precisely estimated around -0.20 in the three samples. As shown in Columns (2), (4), (6), we estimate very similar values when we control for the (log of the relative) capital-output ratio and the (log of the relative) average years of schooling. Overall, we cannot reject the null hypothesis that $\beta = 0.2$ in any of these samples. For a labor share of $1 - \alpha = 2/3$, our estimate implies a value of $\rho = 8.5$, which is within the range of estimates used to match the average markup in the United States (see e.g. Edmond et al. 2018 or Baqaee and Farhi 2020). Using $\beta = 0.2$ and the restriction that $\Delta D_n^j = 0$, we get our baseline estimates of aggregate firm-embedded productivity as $\Delta\tilde{\phi}_n = \beta\Delta\mathbb{A}_n$, where $\Delta\mathbb{A}_n$ is obtained from aggregating the OLS estimates in Equation (19) according to Equation (20).[21] We calculate $\Delta\tilde{z}_n$ as a residual using data on income per worker.

[21] In a one sector model, estimating Equation (23) without controlling for ΔC_n would yield $\beta = -\frac{cov(\Delta\mathbb{A}_n, \Delta y_n)}{var(\Delta\mathbb{A}_n)}$. Using this expression to calculate $\Delta\tilde{\phi}_n = -\beta\Delta\mathbb{A}_n$, the second term of the variance decomposition in Equation (17) would boil down to $\frac{cov(\Delta y_n, \Delta\tilde{\phi}_n)}{var(\Delta y_n)} = -\beta\frac{cov(\Delta y_n, \Delta\mathbb{A}_n)}{var(\Delta y_n)} = \frac{cov(\Delta\mathbb{A}_n, \Delta y_n)cov(\Delta y_n, \Delta\mathbb{A}_n)}{var(\Delta\mathbb{A}_n)var(\Delta y_n)}$, which corresponds to the R-squared of a regression of Δy_n on $\Delta\mathbb{A}_n$, and which does not depend on the model's parameters. Rather than focusing exclusively on this R-squared, we parameterize β to evaluate the decomposition for each individual country in our sample.

Table 1: Estimating the composite elasticity β.

	All sectors		Manufacturing sectors		Service sectors	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\mathbb{A}_n^j$	-0.194***	-0.199***	-0.189***	-0.203***	-0.193***	-0.194***
	[0.0267]	[0.0261]	[0.0338]	[0.0372]	[0.0342]	[0.0342]
$\Delta[k_n - y_n]$		0.381***		0.496**		0.195
		[0.115]		[0.165]		[0.122]
Δh_n		0.244		0.774		-0.0915
		[0.385]		[0.494]		[0.301]
Observations	445	445	158	158	161	161
R-squared	0.334	0.393	0.397	0.513	0.420	0.447

Notes: The table reports the OLS estimates from Equation (23). $\Delta\left[k_n - y_n\right]$ denotes the capital-output ratio and Δh_n denotes human capital. Both are in logs, relative to France, and computed with data from Penn World Tables (9.1). Sector fixed-effects are included and standard errors are clustered by country and sector (in parentheses).

4 Quantitative results

This section combines the estimates from Equation (21) with our elasticity estimates to decompose differences in output per-worker across countries into country-embedded factors and aggregate firm-embedded productivity. Figure 3 plots the result of this decomposition (see Appendix Table A5 for the exact numbers). The x-axis shows the log-difference in output per-worker in each country relative to France, Δy_n. In the y-axis, the red circles show the difference in firm-embedded productivity in each country relative to France, $\Delta\tilde{\phi}_n$, while the blue squares show the differences in country-embedded factors relative to France, $\Delta\tilde{z}_n$.

For the average country, firm-embedded productivity is 0.20 log points lower than in France. There is, however, wide variation across countries. For some of the large developed nations in our sample, such as Germany and Korea firm-embedded productivity is the same as in France, whereas in Japan it is somewhat larger (0.09 log-difference). In contrast, firm-embedded productivity is quite low in the Baltic Republics of Lithuania, Latvia, and Estonia.

The relative importance of the differences in firm-embedded productivity and country-embedded factors also varies considerably across countries. For example, Italy and Slovenia –both EU members– have similar levels of country-embedded factors. However, Italy has more firm-embedded productivity, which generates significant differences in output per-worker between these two countries. In contrast, firm-embedded productivity is similar for Slovenia and Bulgaria, though output per-worker is much higher in Slovenia due to a large difference in country-embedded factors between these two countries. For countries such as Spain and the Netherlands, with roughly the same level of output per-worker, our decomposition indicates that while for Netherlands firm-embedded productivity is 0.15 log-point lower than for Spain, that negative difference is compensated by an advantage of equal magnitude in country-embedded factors.

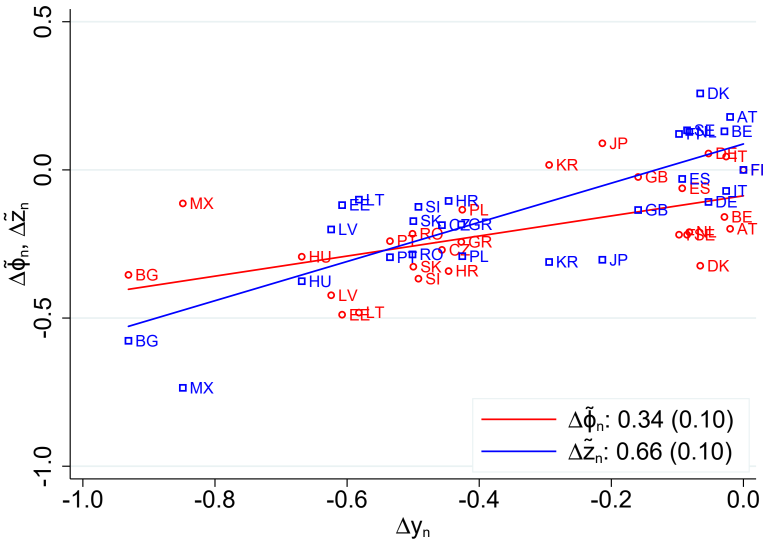
Our measure of aggregate firm-embedded productivity is strongly correlated with output per-worker. As we noted in the Introduction, while the development accounting literature documents a positive correlation between TFP and output per-worker, it computes TFP as a residual using output per-worker data. In contrast, we directly measure one component of TFP (firm-embedded productivity) and show that this component is strongly correlated with independent measures of output per-worker.[22] Furthermore, we compute the share of the cross-country variance in output per-worker accounted for aggregate firm-embedded productivity and country-embedded factors, in the spirit of Klenow and Rodriguez-Clare (1997). The contribution of aggregate firm-embedded productivity corresponds to the slope of a bivariate OLS regression of $\Delta\tilde{\phi}_n$ on Δy_n, which is reported in Figure 3. Differences in $\Delta\tilde{\phi}_n$ account for roughly a third of the cross-country variance in output per-worker; differences in country-embedded factors account for the remaining two thirds.

Correlation with factors: Table 2 evaluates how our measures of firm-embedded productivity and country-embedded factors correlate with measures of human and physical capital. In particular, we regress output per-worker, firm-embedded productivity, and country-embedded factors on a country's capital-output ratio and human capital.[23] The table shows that differences in firm-embedded productivity are uncorrelated with those factors (Column 2). In contrast, differences in country-embedded factors are significantly correlated with human capital and capital-output ratios (Column 3), a significant correlation inherited by income per-worker (Column 1). These results are reassuring since, as explained in Section 2.3, cross-country differences in factors should be captured by our measure of country-embedded factors, and not by our measure of firm-embedded pro-

[22] Our findings are reminiscent of the results in Bloom and Van Reenen (2007), who document a strong positive correlation between managerial practices and income per capita. Their measure of managerial practices is calculated with survey data created from interviews with managers around the world.

[23] We obtain very similar results if we run the regressions in Table 2 at the aggregate level, although the number of observations is reduced to 26.

Figure 3: Dev. accounting: firm-embedded productivity vs country-embedded factors.



Notes: Each circle (square) represents a country's firm-embedded productivity (country-embedded factors) relative to France. The figure plots the decomposition in Equation (15), where Δy_n is plotted in the x-axis and $\Delta \tilde{z}_n$ and $\Delta \tilde{\phi}_n$ are plotted in the y-axis. The legend reports the slopes of a bivariate OLS regression of $\Delta \tilde{\phi}_n$ on Δy_n.

ductivity.

4.1 Sector-level decompositions

We now decompose differences in output per-worker in Manufacturing and Services by aggregating our sectoral estimates of the country effects into those two broad sectoral categories.

Figure 4 reports the results. Even though firm-embedded productivity for the average country (relative to France) is similar for Manufacturing and Services (-0.18 vs -0.20 log-points), the cross-country differences are larger in Manufacturing. The cross-country differences in output per-worker are also larger in Manufacturing than in Services, so the contribution of firm-embedded productivity to cross-country income differences ends up being roughly a third for both sectors. There is substantial variation across countries. For example, Japan, Korea, and Germany have relative high levels of firm-embedded productivity in Manufacturing, but their firm-embedded productivity in Services is similar to that of other developed countries. Firm-embedded productivity is lower than country-embedded factors, relative to France, in Services sectors for all countries, except for Ger-

Table 2: Correlations with factors.

dep. var.	Δy_n^j	$\Delta\tilde{\phi}_n^j$	$\Delta\tilde{z}_n^j$
	(1)	(2)	(3)
$\Delta\left[k_n - y_n\right]$	0.379**	-0.045	0.428***
	[0.179]	[0.094]	[0.127]
Δh_n	0.772*	-0.019	0.792**
	[0.424]	[0.274]	[0.350]
Obs.	27	27	27
R-squared	0.201	0.007	0.358

Notes: $\Delta\left[k_n - y_n\right]$ denotes the capital-output ratio and Δh_n denotes human capital. Both are in logs, relative to France, and computed with data from Penn World Tables (9.1). Robust standard errors in parentheses.

many, Mexico, and Hungary. Manufacturing presents much more heterogeneity, with less developed countries having higher firm-embedded productivity than more developed countries, and vice-versa.

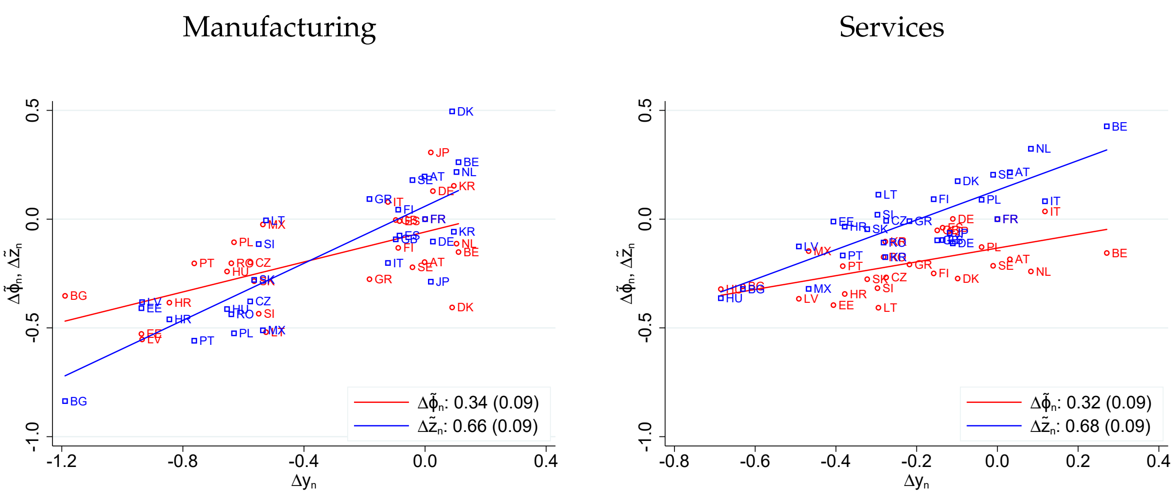
We can further decompose differences in output per-worker within each sub-sector in Manufacturing and each sub-sector in Services. Appendix Figures A2 and A3 show these results. The figures show a very strong correlation between our sectoral measures of firm-embedded productivity and output per-worker at the sector level.

Finally, we evaluate if the observed differences in aggregate firm-embedded productivity arise from differences in the sectoral composition of output across countries. With this in mind, we compute a measure of aggregate firm-embedded productivity that aggregates sectoral differences using the output shares of our reference country (France), $\Delta\tilde{\phi}_n^w \equiv \sum_j \theta_r^j \Delta\tilde{\phi}_n^j$. Figure 5 shows that this measure and our baseline measure are very close to each other, indicating that cross-country differences in aggregate firm-embedded productivity are not driven by cross-country differences in sectoral output shares. Within-sector differences in firm-embedded productivity across countries overwhelmingly create the observed aggregate differences.

4.2 Firm-embedded productivity and comparative advantage

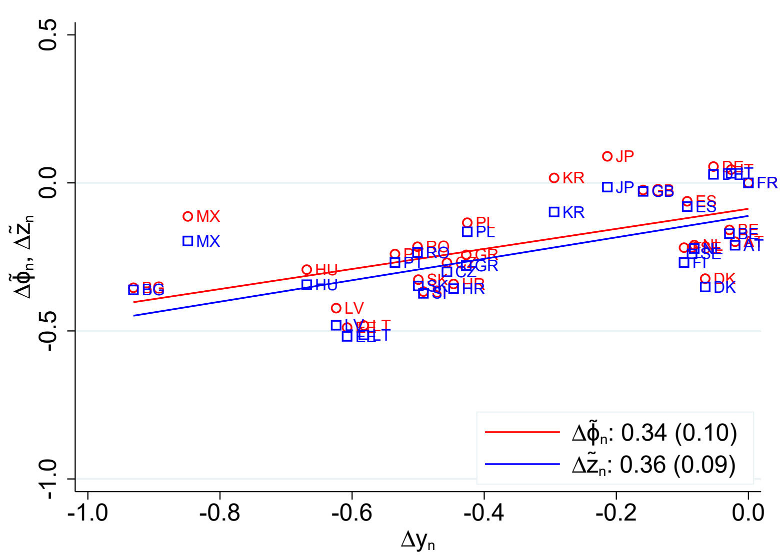
An extensive literature in International Trade studies the sources of comparative advantage by relating the sectorial concentration of a country's exports to factor endowments,

Figure 4: Dev. accounting: Manufacturing and Services



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

Figure 5: Differences in firm-embedded productivity within and between sectors.



Notes: The figure plots the decomposition in equation (15), where Δy_n is plotted in the x-axis and $\Delta\tilde{\phi}_n^w \equiv \sum_j \theta_r^j \Delta\tilde{\phi}_n^j$ and $\Delta\tilde{\phi}_n \equiv \sum_j \theta_n^j \Delta\tilde{\phi}_n^j$ are plotted in the y-axis. The legend reports the slopes of a bivariate OLS regression of $\Delta\tilde{\phi}_n$ (rest. $\Delta\tilde{\phi}_n^w$) on Δy_n. Each circle (square) represents a country.

technologies, financial conditions, or institutions.[24] In this section, we evaluate how sectorial differences in firm-embedded productivity and in country-embedded factors shape the sectorial concentration of the foreign output of a country's MNEs. The notion that MNEs can use their idiosyncratic productivity around the world while country embedded factors are immobile suggests that only the former should affect the activities of MNEs when producing abroad.

With this in mind, we correlate sectoral differences in firm-embedded productivity in a country with the sectoral concentration of the foreign output of the MNEs from that country (referred to as 'outward MNE sales'). We measure this sectoral concentration using a Revealed Comparative Advantage (RCA) index for outward MNE sales. With this in mind, let $R^j_{n,row}$ ($R^j_{r,row}$) denote the total revenues of MNEs from country n (reference country, r) in the rest of the world.[25] We define the RCA index for outward MNE sales as

$$\Delta rca^j_n \equiv ln\left(\frac{R^j_{n,row}/\sum_{j'} R^{j'}_{n,row}}{R^j_{r,row}/\sum_{j'} R^{j'}_{r,row}}\right). \tag{24}$$

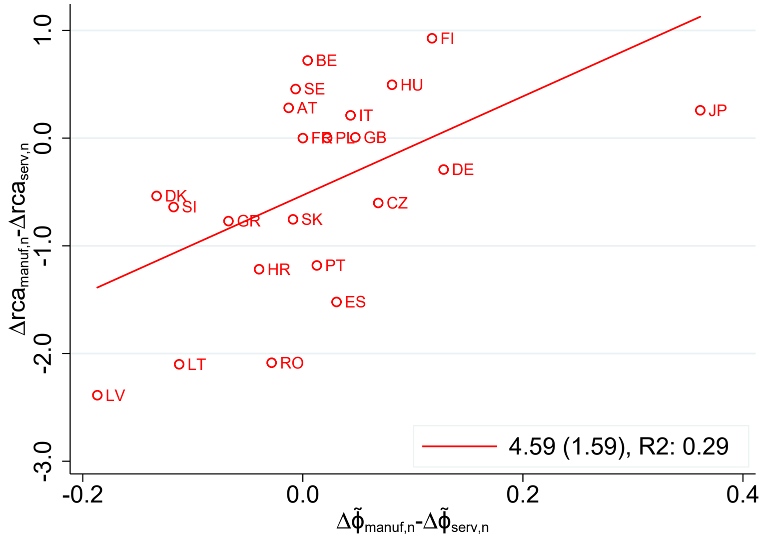
Like $\Delta\tilde{\phi}^j_n$, Δrca^j_n is defined in logs and takes France as the reference country. Thus, $\Delta rca^j_n > 0$ when the share of sector j in outward MNE sales is larger for MNEs from country n than for MNEs from France. Note that, while $\Delta\tilde{\phi}^j_n$ is measured with data on market shares of foreign MNEs in country n, Δrca^j_n is measured with data on sales of country n's MNEs in foreign countries, so that the two measures do not need to be correlated.

Figure 6 compares the relative differences in firm-embedded productivity in manufacturing vs. services, $\Delta\tilde{\phi}^{man}_n - \Delta\tilde{\phi}^{serv}_n$, to the differences in relative comparative advantage in manufacturing and services for outward MNE sales, $\Delta rca^{man}_n - \Delta rca^{serv}_n$. There is a strong positive relation between differences in firm-embedded productivity and differences in the RCA index for outward MNE sales across countries. For example, Japan and Finland have a particularly large stock of firm-embedded productivity in Manufacturing, and the outward sales of the MNEs from these countries are concentrated in the Manufacturing sector. In contrast, Latvia and Lithuania have relatively more firm-know how in Services, and the sales of the MNEs from these countries in the rest of the world are also concen-

[24] A non-exhaustive list of recent papers includes Bernhofen and Brown (2004), Romalis (2004), Levchenko (2007), Nunn (2007), Costinot et al. (2012), Levchenko and Zhang (2016), and Hanson et al. (2015).

[25] Using the notation from Section 2 these revenues correspond to $R^j_{n,row} \equiv \sum_{n'\neq n}\int_{\omega\in\Omega^j_{nn'}} P^j_{nn'}(\omega)\, Y^j_{nn'}(\omega)\, d\omega$.

Figure 6: Sectorial firm-embedded productivity and outward MNE sales.



Notes: The x-axis reports the difference in our measure of firm-embedded productivity in manufacturing vs. services, relative to France. The y-axis reports the difference in the Δrca_n^j index defined in Equation (24), between $j =$ Manufacturing and $j =$ Services.

trated in the Service sector.

We observe similar patterns across disaggregated 2-digit sectors. Table 3 shows the results of regressing our sectorial measure of comparative advantage, Δrca_n^j, on our measures of sectorial firm-embedded productivity and country embedded factors, $\Delta\tilde{\phi}_n^j$ and $\Delta\tilde{z}_n^j$. Columns (1), (4) and (7) show a strong correlation between a country's sectorial firm-embedded know how and its comparative advantage.[26] In contrast, Columns (2), (5) and (8) show no correlation between sectorial country-embedded factors and a country's comparative advantage. Columns (3), (6), and (9) reports similar results when country-embedded factors and firm-embedded productivity are simultaneously included in the regression.

These results highlight that firm-embedded productivity is transferable across countries and a source of advantage for MNEs operating abroad.[27] Country embedded factors, which are immobile across countries, do not appear to shape the sectorial concentration of a country's MNEs.

[26] This result is in line with the findings in Alviarez (2019), who using sectoral-level data shows a positive correlation between the bilateral sales of affiliates in a sector and the RCA index of sectoral TFP in the source country of the MNE.

[27] In the same spirit, Arkolakis et al. (2018) show that more outward MNE activity is correlated with a comparative advantage in innovation activities.

Table 3: Sectorial firm-embedded productivity and comparative advantage.

dep. var. Δrca_n^j	All sectors			Manufacturing sectors			Service sectors		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta\tilde{\phi}_n^j$	2.63***		3.23***	4.14**		5.48***	3.07**		2.84**
	[0.663]		[0.836]	[1.326]		[1.075]	[0.906]		[0.812]
$\Delta\tilde{z}_n^j$		0.17	0.83		1.51	2.49**		-0.76	-0.19
		[0.469]	[0.501]		[0.927]	[0.823]		[0.527]	[0.645]
Observations	313	313	313	121	121	121	132	132	132
R-squared	0.072	0.001	0.094	0.138	0.056	0.274	0.063	0.023	0.064

Notes: Each j corresponds to a NAICS 2-digit sector. 'All sectors' include sectors those in Manufacturing, Services, and others. Standard errors are clustered by country and sector (in parentheses).

4.3 Contribution of domestic and foreign firms

This section further decomposes the sources of the cross-country differences in firm-embedded productivity by considering the origin of the firms in each country. In particular, differences in firm-embedded productivity may arise both from cross-country differences in the productivity embedded in all domestic firms, and from differences in the productivity embedded in all foreign affiliates operating in each country.

We write the market share of domestic firms in country n and in sector j as

$$S_{nn}^j \equiv \int_{\Omega_{nn}^j} S_{nn}^j(\omega)d\omega = \frac{\Phi_{nn}^j}{\Phi_n^j}, \tag{25}$$

where $\Phi_{nn}^j \equiv \int_{\Omega_{nn}^j} A_{nn}^j(\omega)\, d\omega$ is the productivity embedded in domestic firms in country n. Similarly, the market share of foreign firms in country n is given by

$$S_{Fn}^j \equiv \sum_{i\neq n} \int_{\Omega_{in}^j} S_{in}^j(\omega)d\omega = \frac{\Phi_{Fn}^j}{\Phi_n^j}, \tag{26}$$

where $\Phi_{Fn}^j \equiv \sum_{i\neq n} \int_{\Omega_{in}^j} A_{nn}^j(\omega)\, d\omega$ denotes the productivity embedded in foreign firms operating in country n. From the definition of Φ_n^j, and using lowercase to denote logs, we can write the first-order approximation

$$\Delta\phi_n^j = S_{rr}^j \Delta\phi_{nn}^j + \left[1 - S_{rr}^j\right] \Delta\phi_{Fn}^j, \tag{27}$$

where S^j_{rr} refers to the the market share of domestic firms in the reference country r (and sector j).

Finally, aggregating across sectors we obtain

$$\Delta\tilde{\phi}_n = \underbrace{\sum_j \theta^j_n S^j_{rr} \Delta\tilde{\phi}^j_{nn}}_{\Delta\tilde{\phi}_{nn}} + \underbrace{\sum_j \theta^j_n \left[1 - S^j_{rr}\right] \Delta\tilde{\phi}^j_{Fn}}_{\Delta\tilde{\phi}_{Fn}}, \tag{28}$$

where $\Delta\tilde{\phi}^j_{nn} \equiv \beta^j \Delta\phi^j_{nn}$ and $\Delta\tilde{\phi}^j_{Fn} \equiv \beta^j \Delta\phi^j_{Fn}$.

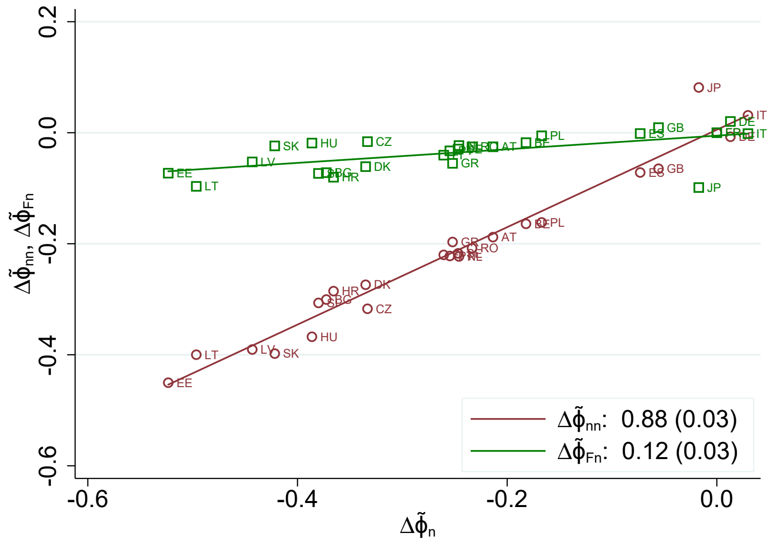
Equation (28) shows the contributions of domestic firms ($\Delta\tilde{\phi}_{nn}$) and foreign firms ($\Delta\tilde{\phi}_{Fn}$) to the observed differences in aggregate firm-embedded productivity ($\Delta\tilde{\phi}_n$). To measure these contributions, we first use domestic shares S^j_{nn} from the data, our estimates of $\Delta\tilde{\phi}^j_n$, and Equation (25) to compute $\Delta\tilde{\phi}^j_{nn}$. Similarly, we use the revenue share of foreign firms in country n, S^j_{Fn}, together with the estimates of $\Delta\tilde{\phi}^j_n$, and Equation (26), to compute $\Delta\tilde{\phi}^j_{Fn}$. We then aggregate across sectors using sectoral shares θ^j_n and the reference-country sectoral revenue share for their domestic firms, S^j_{rr}.

Figure 7 shows the two terms in the right-hand side of Equation (28). The average country has a 0.21 log-point difference relative to France regarding domestic firm-embedded productivity, while the gap for foreign firms is only 0.04. Differences in aggregate firm-embedded productivity for domestic firms account for 88 percent of the cross-country differences in aggregate firm-embedded productivity. Differences in the productivity embedded in the foreign affiliates of MNEs are very small across countries, with some developing countries having better foreign MNE affiliates than developed countries. Countries such as Latvia, Estonia, and Slovakia have less productivity embedded in domestic firms than most of the more developed countries in our sample. However, they host foreign firms that are as productive as the ones located in Finland, the Netherlands, or Austria. Finally, this decomposition attributes, for instance, all the difference in aggregate firm-embedded productivity between France and Poland, observed in Figure 3, to domestic firms.

4.4 Firm-embedded productivity and scale effects

A recurring theme in the International Trade and Growth/Development literatures is that aggregate scale or variety effects may be important for TFP (see e.g. Krugman 1980, Jones

Figure 7: Aggregate firm-embedded productivity: domestic vs foreign firms.



Notes: Brown circles and green squares, respectively, report $\Delta\tilde{\phi}_{nn}$ and $\Delta\tilde{\phi}_{Fn}$ defined in Equation (28).

1995, and Hsieh and Klenow 2009). In this section we decompose cross-country differences in aggregate firm-embedded productivity that arise from differences in the average productivity embedded in each firm, from differences in the number of firms across countries. In particular, we can write the differences in firm-embedded productivity as

$$\Delta\tilde{\phi}_n = \underbrace{\beta\Delta m_n}_{Scale} + \underbrace{\Delta\bar{\phi}_n}_{Average}, \tag{29}$$

where Δm_n denotes the log-difference in the aggregate number of firms across sectors, and $\Delta\bar{\phi}_n \equiv \Delta\tilde{\phi}_n - \beta\Delta m_n$ is the log-difference in the average firm-embedded productivity relative to France.

Computing the scale term in Equation (29) is not straightforward, since comparable data on the number of firms across countries are not readily available.[28] This problem is compounded by the fact that, in our framework, a firm corresponds to all the tax-identification numbers belonging to the same ultimate owner. In contrast, in most existing datasets, establishments and firms are not recorded by their ultimate owner. Notice that this challenge cannot be overcome by counting the firms in our dataset, since ORBIS does not cover the population of firms in each country and the coverage differs across countries.

[28]The definition of what constitutes a 'firm' differs across country-sources. For example, the minimum number of employees for an establishment or firm to be counted in surveys varies across countries.

With this in mind, we assume that there is a log-linear relation between the scale effect and the population in a country,

$$\Delta m_n = \lambda \times \Delta pop_n, \tag{30}$$

where we continue to use lowercase to denote logs, and where pop_n is the log of the population population in country n. This relation is a standard feature of many models of scale economies, such as Krugman (1980). Replacing Equation (30) into (29), we fit the regression given by

$$\Delta\tilde{\phi}_n = b \times \Delta pop_n + \varepsilon_n.$$

Under the assumption that the average firm-embedded productivity $\Delta\bar{\phi}_n$ is orthogonal to the population of the country, the error term can be interpreted as $\varepsilon_n = \Delta\bar{\phi}_n$. If the average firm-embedded productivity in a country increases with population, the residual ε_n would understate the differences in average firm-embedded productivity across countries, since it would capture only the part of average firm-embedded productivity that is orthogonal to population.

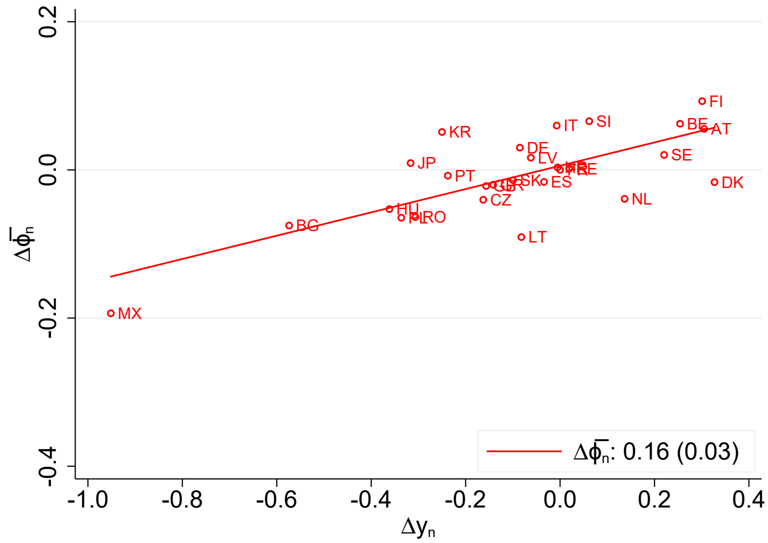
Figure 8 shows a very strong correlation between our measure of average firm-embedded productivity $\Delta\bar{\phi}_n$ and output per-worker, where output per-worker is also residualized by population.[29] The slope is flatter than the slope in Figure 3, though it is more precisely estimated. The cross-country variation in firm-embedded productivity that is not driven by the country's scale accounts for 16 percent of the cross-country variance in income per-worker, almost half of the variation accounted for our aggregate measure of firm-embedded productivity $\Delta\tilde{\phi}_n$.

5 Robustness

This section presents several robustness exercises. First, we show how to estimate firm-embedded productivity under alternative assumptions on the technology transfer costs. Second, we evaluate potential selection concerns and the log-linearity assumption in our production function. Finally, we repeat our analysis using alternative samples, sectoral disaggregations, and gravity controls.

[29] The slope of this relation thus corresponds to the slope of a regression of Δy_n on $\Delta\tilde{\phi}_n$ that also controls for Δpop_n.

Figure 8: Dev. accounting: average firm-embedded productivity.



Notes: Each circle represents a country. The y-axis plots the residual of a regression of firm-embedded productivity, $\Delta\tilde{\phi}_n$, on the log of population. The x-axis plots the residual of a regression of the log of income per capita, y_n, on the log of population.

5.1 Alternative assumptions on the technology transfer costs

Our baseline estimates for $\Delta\phi_n^j$ were derived under the assumption that technology transfer costs could have an origin-specific, but not a destination-specific component, $\Delta D_n^j = 0$, as specified in Equation (21). As explained in Section 3.2, if this assumption does not hold, and if it is harder to transfer technology to less developed countries, our baseline estimates would understate the contribution of firm-embedded productivity to the cross-country variance of output per-worker.

We now show how to estimate $\Delta\phi_n^j$ when $\Delta D_n^j \neq 0$. We use data on market shares of both affiliates and parent firms of MNEs, and assume that costs have a destination-specific, but no origin-specific, component, $\Delta O_n^j = 0$, as in Eaton and Kortum (2002). In particular, we estimate

$$s_{in}^j(\omega) = \delta_i^j(\omega) + \mathbb{A}_n^j + \mathbb{P}_n^j + \psi_d^j dist_{in} + \psi_l^j lang_{in} + \epsilon_{in}^j(\omega). \tag{31}$$

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, $i \neq n$, in sector j, 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. In this specification, the dummies $\mathbb{A}^j_n$ are still given by Equation (21), while the dummies $\mathbb{P}^j_n$ are

$$\Delta\mathbb{P}^j_n = -\left[\Delta\phi^j_n - \Delta O^j_n\right]. \tag{32}$$

If $\Delta O^j_n = 0$, $\Delta\mathbb{P}^j_n$ can be interpreted as the inverse of the firm-embedded productivity in country n relative to France. If the assumption is not satisfied and the origin-specific component of the transfer cost is higher for low income countries, $cov(\Delta y^j{}_n, \Delta O^j_n) \leq 0$, estimates based on Equation (32) would overstate the contribution of firm-embedded productivity to the cross-country variance of output per-worker,

$$cov\left(\Delta y_n, -\Delta\mathbb{P}^j_n\right) = cov\left(\Delta y_n, \Delta\phi^j_n - \Delta O^j_n\right) \geq cov\left(\Delta y_n, \Delta\phi^j_n\right). \tag{33}$$

While our baseline estimates yield a lower bound to the contribution of differences in firm-embedded productivity to cross-country differences in income, this alternative specification yields an upper bound to that contribution.

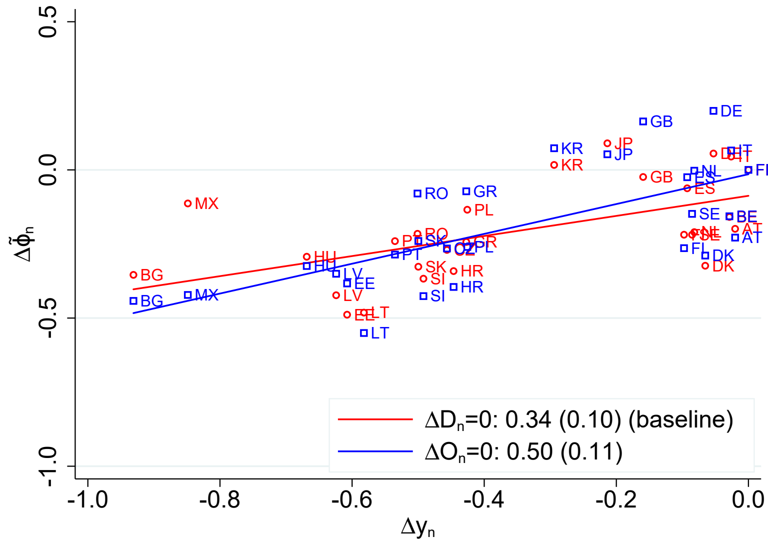
Figure 9 compares our baseline estimates with those based on Equations (32) and (31) and the restriction that $\Delta O^j_n = 0$. The two alternative identification assumptions on transfer costs yield similar estimates for aggregate firm-embedded productivity, relative to France, for each country. Appendix Figure (A4) shows that the OLS estimates from Equation (31) are less precise than our baseline estimates, as the number of MNE foreign affiliates in our data far exceeds the number of MNE parent firms. For the average country, this alternative estimate of $\Delta\phi_n$ is -0.19 log-points, relative to France, while our baseline estimate is -0.20. One of the largest differences is observed for Mexico where aggregate firm-embedded productivity, relative to France, is estimated in -0.42 when we assume that $\Delta O^j_n = 0$ and in -0.11 for $\Delta D^j_n = 0$.

5.2 Selection: MNE-destination specific technology transfer costs

Section 3.2 noted that our OLS estimates of the country effects are biased if MNE-destination specific transfer costs drive the assignment of MNEs to countries -that is, if selection is based on match-specific effects-. If the relatively unproductive MNEs enter unattractive locations only when their MNE-destination specific component of the transfer cost $\varepsilon^j_{in}(\omega)$ is low, then the average of $\varepsilon^j_{in}(\omega)$ across the MNEs that choose to enter each destination would vary across n and thus it would be captured by the country effects $\mathbb{A}^j_n$.

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.

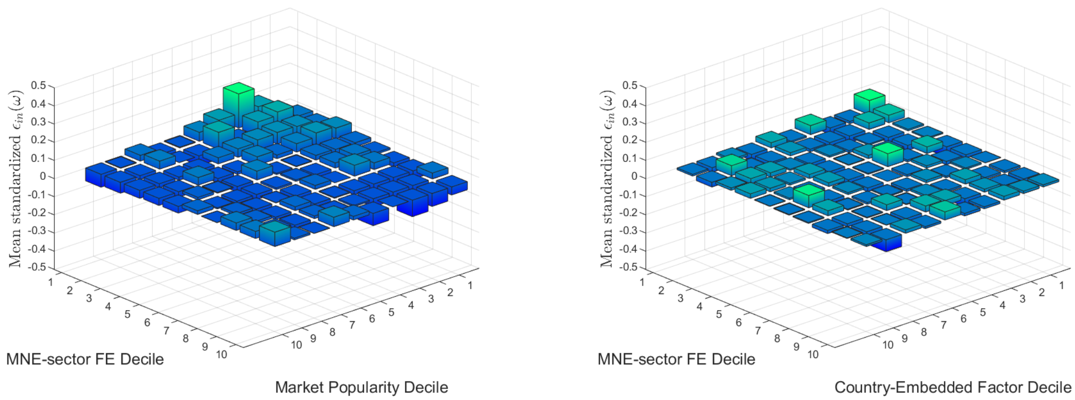


Notes: Each circle (square) represents a country. The figure plots the decomposition in Equation (15), where Δy_n is plotted in the x-axis and $\Delta\tilde{\phi}_n$ is plotted in the y-axis. The legends report the slopes of a bivariate OLS regression of $\Delta\tilde{\phi}_n$ on Δy_n under the assumption that $\Delta D_n^j = 0$ (baseline) and $\Delta O_n^j = 0$. Standard errors are in parenthesis.

(see Abowd et al., 1999) and analyze the residuals from estimating our baseline specification in Equation (19) by OLS. If the assignment of MNEs to countries is driven by MNE-destination specific transfer costs, we should expect these costs to be on average lower -low $\varepsilon_{in}^j(\omega)$- for low-productivity MNEs in unattractive markets. In contrast, highly productive MNEs are more likely to enter these markets irrespective of their $\varepsilon_{in}^j(\omega)$. If this is the case, our specification should underestimate market shares for low-productivity MNEs in unattractive markets, as it does not take into account that the $\varepsilon_{in}^j(\omega)$'s can systematically vary with firm productivity among the MNEs that choose to enter any given market.

We evaluate this implication in Figure 11a, 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 MNE-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 MNEs operating in a country-sector pair. Indeed, we tend to see positive residuals for the less productive MNEs (decile 1 of the MNE-sector fixed effect) in less popular markets (decile 1 of market popularity). In contrast, we overestimate the market shares of the most productive MNEs (decile 10 of the MNE-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

Figure 10: OLS Residuals.



(a) By MNE-sector and market popularity.

(b) By MNE-sector and country-embedded factors.

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

systematically across MNEs and locations in those bins.

A related concern with our baseline estimation is related to complementarities between firm-embedded productivity and country-embedded factors. That is, our model assumes a production function that is log-linear in firm-embedded productivity and the country embedded factors. This separability is inherited by the aggregate production function, which is log-linear in $\tilde{Z}_n$ and aggregate firm-embedded productivity $\tilde{\Phi}_n$. But if, for instance, high productivity MNEs do relatively better in countries with high country-embedded productivity, the assumption would not longer hold, and our procedure would underestimate market shares for high productivity MNEs in markets with high $\tilde{Z}_n$.

We evaluate this implication in Figure 11b, 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 MNE-sector fixed effects, $\delta^j(\omega)$, and deciles of estimates of the country-embedded factors $\tilde{Z}^j_n$. We see positive residuals for the less productive MNEs (decile 1 of the MNE-sector fixed effect) in countries with lower $\tilde{Z}^j_n$ (decile 1 of country-embedded factors). We actually overestimate the market shares of the most productive MNEs (decile 10 of the MNE-sector fixed effect) in these countries. The residuals are very close to zero in the remaining bins of the figure, indicating that the log-linearity assumption is not systematically violated in those bins. Appendix B presents additional test that support our linearity assumption.

With these concerns in mind, we proceed to re-estimate Equation (19) using alternative

Table 4: Contribution of firm-embedded productivity, restricted samples.

	$\frac{cov(\Delta y_n, \Delta\tilde{\phi}_n)}{var(\Delta y_n)}$
Baseline	0.34 (0.10)
I. Keeping MNEs with MNE-sector FE belonging to:	
2nd to 9th Decile	0.32 (0.10)
3rd to 8th Decile	0.31 (0.11)
4th to 7th Decile	0.31 (0.11)
5th to 6th Decile	0.37 (0.12)
II. Keeping MNEs operating in:	
at least 3 countries	0.32 (0.10)
at least 5 countries	0.28 (0.08)
at least 10 countries	0.32 (0.08)

Notes: Slopes of a bivariate OLS regression of $\Delta\tilde{\phi}_n$ on Δy_n. MNE-sector fixed effect, for each sector, estimated using Equation 19 by OLS. Standard errors are in parenthesis.

subsamples, restricted to exclude the MNEs at the extremes of the productivity distribution. Concretely, we restrict the sample to subsets of MNEs that lie within the 2nd to 9th, 3rd to 8th, 4th to 7th deciles, or 5th and 6th deciles, of the MNE-sector fixed effect distribution within a sector. Alternatively, we also apply our estimation procedure to subsamples of MNEs that operate in at least 3, 5, or 10 countries. These are large MNEs that are unlikely to select into destination markets due to the MNE-destination specific component of the technology transfer costs. Table 4 shows that the contribution of firm-embedded productivity to the cross-country variance in output per-worker is very similar to our baseline in all these subsamples.

5.3 Additional robustness exercises

This section briefly describes additional robustness exercises, which are collected in Table 5. First, we define sectors at the 4-digit NAICS (336 sectors), rather than the 2-digit NAICS classification. Second, we exclude the Health, Education, and Real Estate sectors from our sample, as the government has a large participation on theses sectors in some countries in our sample. Third, we repeat our analysis for firms that appear in ORBIS in every year between 2010 and 2016, as these are arguably the years when the ORBIS data are of

Table 5: Contribution of firm-embedded productivity, additional robustness.

	$\frac{cov(\Delta y_n, \Delta\tilde{\phi}_n)}{var(\Delta y_n)}$
Baseline	0.34 (0.10)
Aggregation at 4-digit NAICS industries	0.38 (0.11)
Excluding Real Estate, Health, and Education	0.32 (0.10)
Excluding MNEs that do not appear in ORBIS every year between 2010-2016	0.39 (0.09)
Controlling for differences in GDP per-worker between source and host country	0.34 (0.10)
Excluding gravity variables	0.29 (0.11)

Notes: Slopes of a bivariate OLS regression of $\Delta\tilde{\phi}_n$ on Δy_n. Standard errors are in parenthesis.

the highest quality (see Appendix Table A4 for results by year). Fourth, we include the difference between the income per-capita of the home and the host country among our gravity controls. Finally, we repeat our analysis without any gravity control. The results of our decomposition for all these alternative specifications are remarkably close to our baseline result.

6 Conclusion

This paper sheds light on the determinants of TFP by decomposing cross-country differences in output per-worker into differences in firm-embedded productivity and differences in country-embedded factors. Our key insight is that, if MNEs can use their idiosyncratic productivity around the world but they must use the factors from the countries where they produce, then differences in the market shares of the same MNE across countries can be used to measure cross-country differences in firm-embedded productivity. We implement this idea in an accounting framework that includes MNEs and measure firm-embedded productivity using firm-level revenue data from ORBIS.

Our results indicate that cross-country differences in firm-embedded productivity are large, accounting for roughly a third of the observed differences in output per-worker across the countries in our sample. Our robustness results further suggest that a plausible range for this contribution goes from one-fifth to a half of the observed variance in output per-worker.

Our decomposition suggests that policies that help to close the gap in firm-embedded productivity across countries can go a long way in reducing cross-country income differences. For example, governments can design policies such as tax incentives for R&D, patent boxes, and research grants to stimulate firm innovation and firm embedded-productivity (Bloom et al. 2019). A caveat with our analysis is that, due to data availability, our sample of developing countries is limited to those in Eastern Europe and Mexico. Our procedure and decomposition, however, can be easily applied to other developing and poorer countries as new affiliate-parent matched data become available.

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ONLINE APPENDIX

Table A1: Estimates of gravity coefficients.

	Distance		Common Language	
	Coef.	S.E.	Coef.	S.E.
Other goods				
Agriculture and Mining	-0.702	0.215	-0.078	0.327
Electricity	-0.754	0.138	0.069	0.481
Construction	-0.491	0.222	0.740	0.277
Manufacturing				
Food and Beverage	-0.214	0.165	0.597	0.090
Textiles, Apparel and Wood	-0.285	0.125	-0.144	0.277
Chemicals, Petroleum and Plastic	-0.191	0.075	0.161	0.085
Basic Metals	-0.202	0.097	0.261	0.089
Electrical Equipment and Machinery	-0.030	0.074	0.272	0.112
Transport Equipment and Other Manufacturing	-0.278	0.114	0.004	0.211
Services				
Wholesale Trade and Retail Trade	-0.278	0.064	0.212	0.103
Transportation and Storage	-0.123	0.088	0.233	0.201
Information	-0.340	0.116	0.559	0.114
Financial and Insurance Services	-0.423	0.101	1.013	0.178
Support Services	-0.276	0.058	0.335	0.149
Accommodation and Recreation	-0.075	0.147	0.245	0.218
Other Sectors				
Education	0.081	0.511	0.678	0.592
Health	0.099	0.569	0.240	0.511
Real Estate	-0.296	0.129	0.279	0.176

Notes: This table reports OLS coefficients on distance, ψ_d^j, and common language, ψ_l^j, from estimating Equation (19).

Table A2: Estimates of sectoral elasticities β^j.

	no controls		$+k_n/y_n + h_n$	
	Coef.	S.E	Coef.	S.E
Other goods				
Agriculture and Mining	-0.08	0.04	-0.09	0.04
Construction	-0.21	0.04	-0.21	0.04
Electricity	-0.12	0.02	-0.13	0.02
Manufacturing				
Food and Beverage	-0.18	0.03	-0.19	0.03
Textiles, Apparel and Wood	-0.26	0.05	-0.29	0.05
Chemicals, Petroleum and Plastic	-0.22	0.04	-0.23	0.04
Basic Metals	-0.12	0.02	-0.12	0.03
Electrical Equipment and Machinery	-0.21	0.03	-0.21	0.03
Transport Equipment and Other Manufacturing	-0.31	0.03	-0.32	0.03
Services				
Wholesale Trade and Retail Trade	-0.18	0.05	-0.20	0.04
Transportation and Storage	-0.06	0.05	-0.07	0.05
Information	-0.28	0.05	-0.29	0.05
Financial and Insurance Services	0.05	0.03	0.04	0.02
Support Services	-0.15	0.03	-0.15	0.02
Accommodation and Recreation	-0.20	0.05	-0.22	0.04
Other Sectors				
Real Estate	-0.18	0.04	-0.19	0.04
Health	-0.16	0.04	-0.15	0.04
Education	-0.04	0.05	-0.05	0.06

Notes: OLS estimates from Equation (23) by 2-digit sector. Standard errors in parentheses.

Table A3: Number of observations, R-squared, and mean squared errors.

	N	R^2	MSE
Baseline	49,811	0.70	1.43
I. Other outcome variables			
Employment	41,697	0.76	1.31
Value Added	27,271	0.75	1.30
II. Alternative assumption on technology transfer costs	70,353	0.72	1.46
III. Keeping MNEs with firm-sector FE belonging to:			
2nd to 9th Decile	38,652	0.74	1.06
3rd to 8th Decile	27,275	0.81	0.80
4th to 7th Decile	16,218	0.89	0.55
5th to 6th Decile	6,120	0.97	0.28
IV. Keeping MNEs operating in:			
at least 3 countries	38,709	0.66	1.43
at least 5 countries	26,298	0.62	1.42
at least 10 countries	11,682	0.58	1.34
V. Other Robustness:			
Aggregation at 4-digit NAICS industries	59,088	0.63	1.54
Excluding Real Estate, Health, and Education	47,584	0.70	1.43
Excluding MNEs that do not appear in ORBIS every year between 2010-2016	32,396	0.72	1.34
Controlling for differences in GDP per-worker between source and host country	48,955	0.70	1.43
Excluding gravity variables	50,649	0.70	1.44

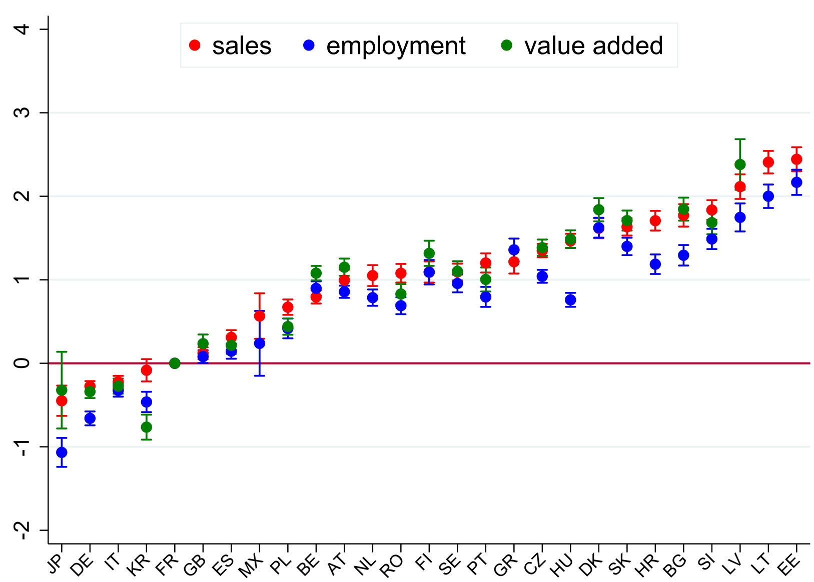
Notes: Number of observations, R^2, and mean squared errors for the regression presented in the paper. I. refers to alternative firm's outcome variables. II. refers to our alternative specification in Equation (31), which includes data from parent firms. III. refers to keeping firms in the specified deciles of the distribution of the MNE-sector fixed effects. IV. refers to keeping firms that have affiliates in at least as many countries as reflected by the threshold. V. corresponds to the additional roburstness in Section 5.3. Standard errors are in parenthesis.

Table A4: Contribution of aggregate firm-embedded productivity, by year.

	All firms	Countries (#)	Constant Sample	Countries (#)
	$\frac{cov(\Delta y_n, \Delta\tilde{\phi}_n)}{var(\Delta y_n)}$		$\frac{cov(\Delta y_n, \Delta\tilde{\phi}_n)}{var(\Delta y_n)}$	
2006	0.28 (0.15)	15		
2007	0.35 (0.10)	24	0.20 (0.11)	15
2008	0.32 (0.09)	25	0.24 (0.08)	24
2009	0.34(0.08)	25	0.26 (0.08)	24
2010	0.36 (0.10)	25	0.31 (0.09)	24
2011	0.35 (0.10)	25	0.29 (0.09)	24
2012	0.38 (0.11)	25	0.31 (0.10)	24
2013	0.28 (0.11)	27	0.33 (0.09)	24
2014	0.32 (0.10)	27	0.34 (0.09)	24
2015	0.33 (0.10)	27	0.37 (0.09)	24
2016	0.34 (0.10)	27	0.39 (0.09)	24
2017	0.34 (0.10)	27	0.41 (0.09)	24

Notes: Slopes of a bivariate OLS regression of $\Delta\tilde{\phi}_n$ on Δy_n. A country is required to have estimates of firm-embedded productivity in at least 10 sectors to construct the aggregate firm-embedded productivity $\Delta\phi_n$. 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.

Figure A1: Estimated country effects.



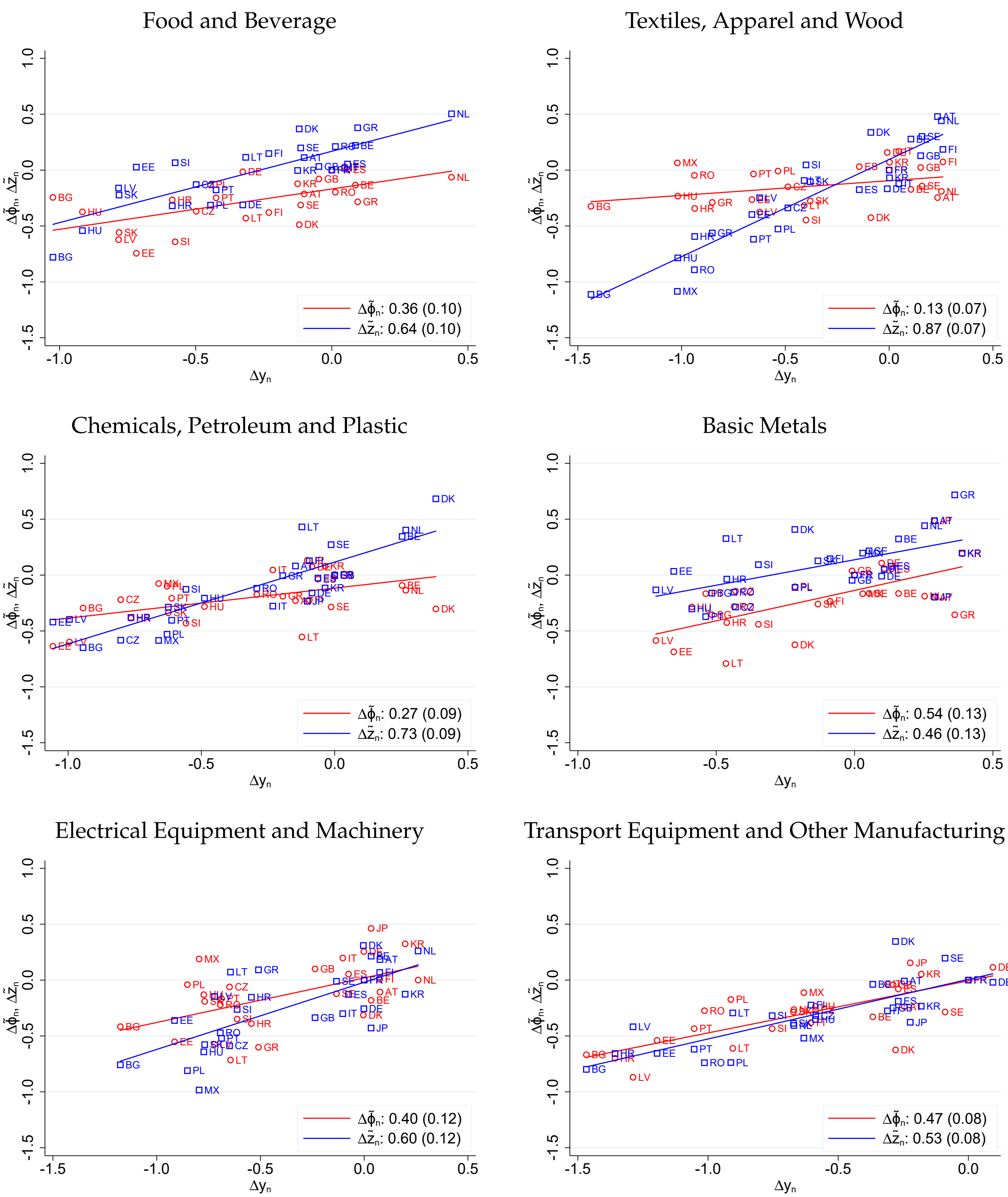
Note: Red dots are OLS estimates of $\Delta\mathbb{A}_n$ from Equation (19) using data on revenue shares. Blue and Green dots are OLS estimates of $\Delta\mathbb{A}_n$ using employment and value added shares, respectively. Bars reflect 95-percent confidence intervals, clustered at the country level.

Table A5: Output per-worker and firm-embedded productivity by country.

Country	ISO	Δy_n	$\Delta\tilde{\phi}_n$	$\Delta\tilde{\phi}_n^{manuf}$	$\Delta\tilde{\phi}_n^{serv}$
Austria	AT	-0.02	-0.20	-0.20	-0.18
Belgium	BE	-0.03	-0.16	-0.15	-0.16
Bulgaria	BG	-0.93	-0.35	-0.35	-0.31
Czech Rep.	CZ	-0.46	-0.27	-0.20	-0.27
Germany	DE	-0.05	0.06	0.13	0.00
Denmark	DK	-0.07	-0.32	-0.41	-0.27
Estonia	EE	-0.61	-0.49	-0.53	-0.40
Spain	ES	-0.09	-0.06	-0.01	-0.04
Finland	FI	-0.10	-0.22	-0.13	-0.25
France (ref)	FR	0.00	0.00	0.00	0.00
UK	GB	-0.16	-0.02	0.00	-0.05
Greece	GR	-0.43	-0.24	-0.28	-0.21
Croatia	HR	-0.45	-0.34	-0.38	-0.34
Hungary	HU	-0.67	-0.29	-0.24	-0.32
Italy	IT	-0.03	0.04	0.08	0.04
Japan	JP	-0.21	0.09	0.31	-0.05
Korea	KR	-0.29	0.02	0.15	-0.10
Lithuania	LT	-0.58	-0.48	-0.52	-0.41
Latvia	LV	-0.62	-0.42	-0.55	-0.37
Mexico	MX	-0.85	-0.11	-0.02	-0.15
Netherlands	NL	-0.08	-0.21	-0.11	-0.24
Poland	PL	-0.43	-0.13	-0.11	-0.13
Portugal	PT	-0.54	-0.24	-0.20	-0.22
Romania	RO	-0.50	-0.22	-0.20	-0.17
Sweden	SE	-0.09	-0.22	-0.22	-0.21
Slovenia	SI	-0.49	-0.37	-0.43	-0.32
Slovakia	SK	-0.50	-0.33	-0.29	-0.28

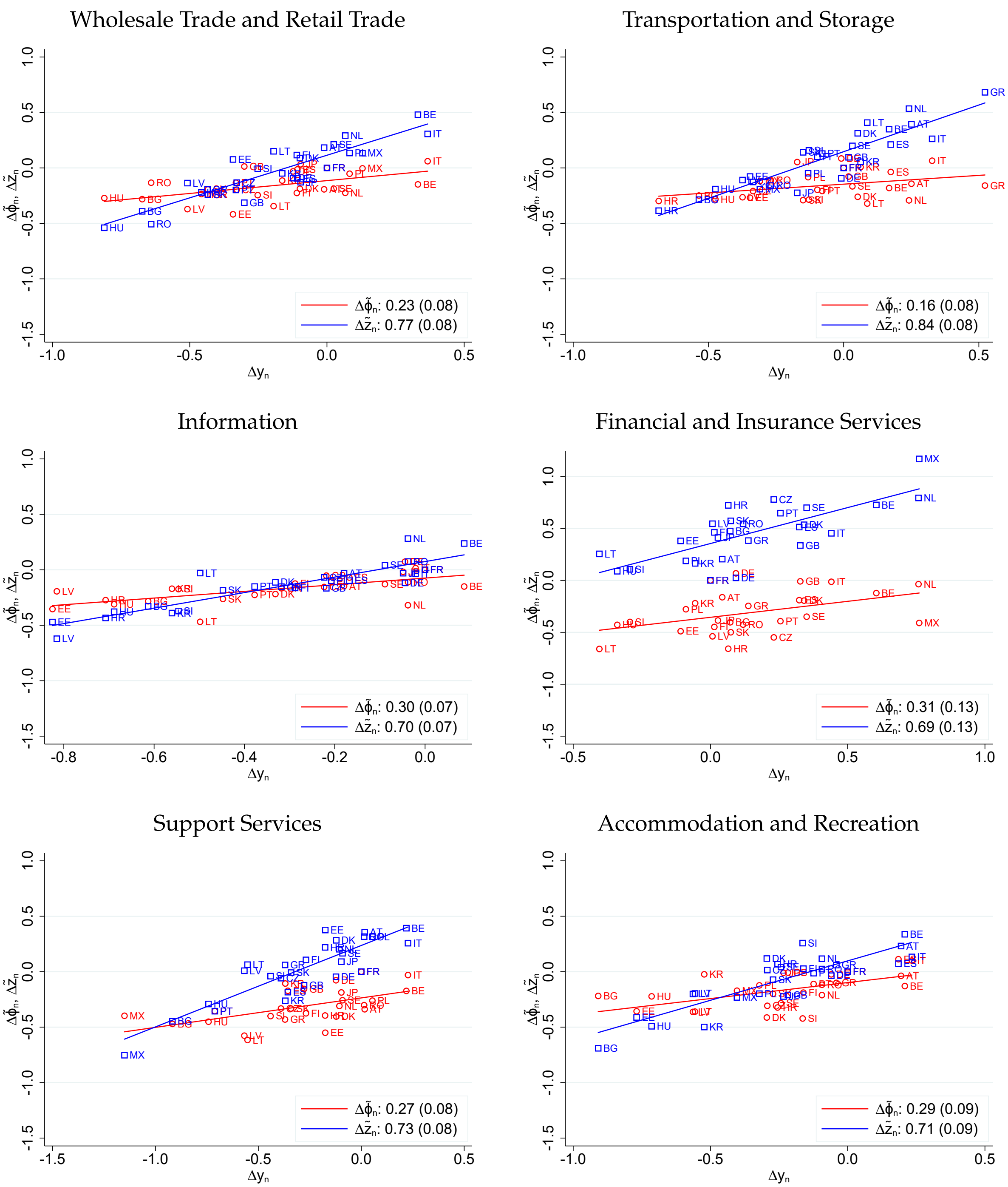
Notes: Numbers underling Figures 3 and 4. Column 3 of the Table shows the country's output per worker relative to France, Δy_n, and Column 4 shows the country's aggregate firm-embedded productivity, $\Delta\tilde{\phi}$, and Columns 5 and 6 show the country's firm-embedded productivity for the Manufacturing and the Service sector, respectively.

Figure A2: Dev. accounting: Manufacturing sectors.



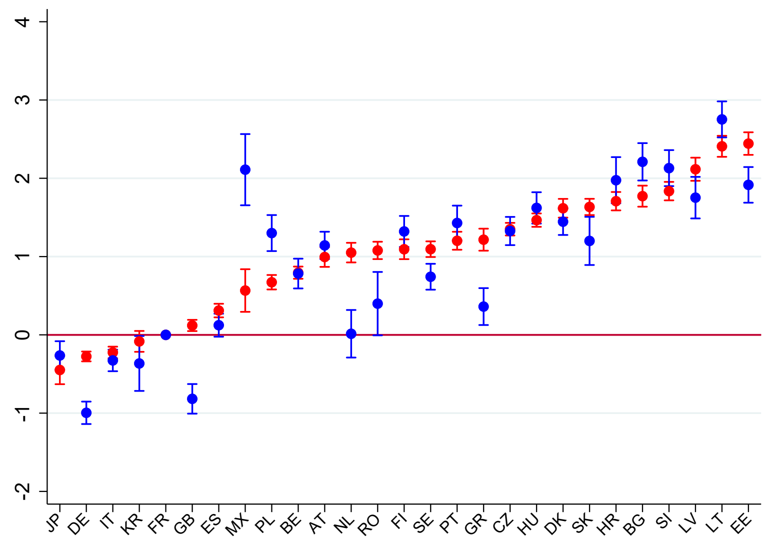
Notes: Each circle (square) represents a country. The figures plot the decomposition in Equation (15) at the sectoral level. Δy_n^j is plotted in the x-axis and $\Delta\tilde{z}_n^j$ and $\Delta\tilde{\phi}_n^j$ are plotted in the y-axis for j = two-digit manufacturing sectors.

Figure A3: Dev. accounting: Service sectors.



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

Figure A4: Country effects: Alternative specification of the technology transfer costs



Note: Red dots are our baseline OLS estimates of $\Delta\mathbb{A}_n$. Blue dots are the OLS estimates of $\Delta\mathbb{P}_n$ from Equation (31). 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. We start by dropping those firms with revenues below 100,000 USD. We also drop firms that only report information from consolidated accounts, as well as firms with "limited financials" information (LF) only. 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.

A multinational company 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 countries, but each operating in a different 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). Information on revenues, employment, and value-added are aggregated for all tax identification numbers 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 A6 shows the number of affiliates and the number of parent firms in each NAICS2

Table A6: Number of affiliates and parents, by NAICS2.

	Foreign Affiliates			Parents		
	Sales	Emp.	VA	Sales	Emp.	VA
Other goods						
Agriculture and Mining	407	354	246	43	37	30
Construction	1,041	843	583	125	113	92
Electricity	557	344	273	73	65	57
Manufacturing						
Food and Beverages	1,061	964	794	118	116	99
Textiles, Apparel and Wood	965	886	699	127	126	109
Chemicals, Petroleum and Plastic	3,104	2,861	2,375	307	301	260
Basic Metals	1,550	1,401	1,178	160	158	124
Electrical Equipment and Machinery	3,019	2,828	2,195	327	321	270
Transport Equipment and Other Manufacturing	1,445	1,309	1,082	139	136	105
Services						
Wholesale Trade and Retail Trade	18,513	16,434	11,429	1,245	1,184	868
Transportation and Storage	2,265	2,004	1,417	237	231	192
Information	1,499	1,298	882	115	111	86
Financial and Insurance Services	1,402	1,104	555	147	138	80
Support Services	10,329	9,015	5,817	959	894	702
Accommodation and Recreation	1,218	1,098	774	105	99	75
Other Sectors						
Real Estate	1,969	1,132	910	192	145	112
Health	204	187	151	21	21	19
Education	96	84	49	5	4	4

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

sectors in our sample, including affiliates in "Other Goods" as well as in other sectors. Each column of Table A6 shows the number of affiliates and parents according to the availability of information on firm's revenues, employment and value-added.

Table A7 and Table A8 report 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 all sectors.

Aggregate firm-embedded productivity at the country level is constructed by calculating the weighted average of the sector level firm-know how, using country-sector level expenditure shares as weights. If a country has less than three foreign MNEs affiliates in a particular sector, we exclude the country from that sector, and reweigh the remaining sectors accordingly to compute the aggregate $\Delta\tilde{\phi}_n$ of that country. Table A9 reports the country-sector pairs for which we cannot compute an estimate of $\Delta\phi_n^j$ for our baseline regression.

Table A7: Number of foreign affiliates, by country and sector.

Country	Sales			Employment			Value Added		
	All	Mfg.	Services	All	Mfg.	Services	All	Mfg.	Services
Austria	1,510	293	1,141	1,219	271	895	956	242	661
Belgium	2,743	536	1,973	2,555	526	1,866	1,863	434	1,304
Bulgaria	737	119	536	711	119	522	596	108	437
Czech Rep.	2,507	656	1,602	2,389	652	1,555	1,492	499	866
Germany	3,680	1,046	2,378	3,620	1,040	2,337	2,795	921	1,673
Denmark	819	151	581	703	151	502	635	138	454
Estonia	659	99	502	612	94	476	-	-	-
Spain	4,099	819	2,933	3,909	817	2,825	3,995	809	2,855
Finland	1,417	258	1,045	1,143	219	848	655	139	471
France	4,659	1,075	3,267	3,638	950	2,528	3,469	969	2,337
UK	5,072	1,259	3,402	4,690	1,231	3,144	2,744	881	1,689
Greece	512	74	398	502	74	393	-	-	-
Croatia	829	102	634	776	99	609	-	-	-
Hungary	1,272	306	827	1,172	302	774	568	196	310
Italy	4,545	1,176	2,997	4,279	1,166	2,883	3,654	1,098	2,359
Japan	192	48	141	180	47	130	12	4	8
Korea	899	291	592	694	256	426	384	171	208
Lithuania	445	69	324	439	69	318	-	-	-
Latvia	679	60	543	658	60	533	28	2	24
Mexico	137	51	72	52	24	20	-	-	-
Netherlands	1,130	260	805	1,003	249	710	-	-	-
Poland	3,399	833	2,238	992	293	617	1,871	541	1,189
Portugal	1,759	278	1,304	1,651	275	1,249	1,712	275	1,268
Romania	2,040	424	1,365	1,934	416	1,329	1,266	348	788
Sweden	2,694	419	2,064	2,526	411	1,967	1,378	205	1,091
Slovenia	612	108	460	567	106	427	345	64	261
Slovakia	1,603	334	1,102	1,537	332	1,070	996	279	621

Notes: A foreign 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.

Table A8: Number of parents, by country and sector.

Country	Sales			Employment			Value Added		
	All	Mfg.	Services	All	Mfg.	Services	All	Mfg.	Services
Austria	246	55	149	226	54	135	212	53	125
Belgium	218	67	125	204	66	118	185	62	104
Bulgaria	2	-	2	2	-	2	2	-	2
Czech Rep.	54	5	45	53	5	45	44	4	37
Germany	629	192	379	627	192	378	508	174	288
Denmark	156	42	101	143	42	92	136	40	87
Estonia	50	5	36	45	5	33	-	-	-
Spain	248	54	156	246	54	156	243	53	154
Finland	161	45	99	145	44	89	119	34	74
France	715	170	446	639	163	398	647	167	401
UK	459	91	328	425	89	304	308	68	220
Greece	18	3	12	18	3	12	-	-	-
Croatia	8	3	4	8	3	4	-	-	-
Hungary	34	2	28	33	2	27	23	1	20
Italy	387	118	241	376	118	234	361	116	223
Japan	418	180	225	418	180	225	208	137	65
Korea	32	13	18	29	12	17	23	9	14
Lithuania	18	1	15	18	1	15	-	-	-
Latvia	10	2	5	10	2	5	2	-	-
Mexico	8	5	1	6	4	1	-	-	-
Netherlands	109	10	87	92	9	76	-	-	-
Poland	40	7	29	30	6	20	21	1	17
Portugal	36	7	20	36	7	20	35	7	19
Romania	2	-	2	2	-	2	2	-	2
Sweden	365	99	237	348	95	232	188	39	138
Slovenia	13	-	11	13	-	11	10	-	8
Slovakia	10	2	7	9	2	6	8	2	5

Notes: A parent is defined as a corporate group-country-sector triplet located in the source country of the MNE.

Table A9: Countries with less than 3 affiliates, by NAICS2.

Sector	Country
Other goods	
Agriculture and Mining	KR, MX
Construction	JP
Electricity	KR, MX
Manufacturing	
Food and Beverages	JP, MX
Textiles, Apparel and Wood	JP
Transport Equipment and Other Manufacturing	GR
Services	
Information	MX
Others	
Real Estate	JP
Health	DK, EE, GR, JP, LV, SI
Education	AT, CZ, DK, HU, KR, NL, PT, RO, SI, SK

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

Aggregate data:

In addition to the ORBIS data, to construct 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 maximize the number of countries-sectors in our sample, we combine some ISIC sectors 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 use the real GDP at chained PPPs in 2016 US dollars over total employment to measure output per-worker in each country from Penn World Tables (PWT, 9.1). 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 (9.1).

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: two-way fixed-effect estimation

To identify the country-sector fixed effects in Equation (19), the MNEs in our sample need to connect the countries in our sample. We perform our estimation 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.[1] Nonetheless, it is possible that countries are poorly connected, even within the LCS, if only few MNEs 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 MNE 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). We note that all countries in our sample stay connected regardless of which MNE is dropped from the set. The second 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 MNEs, this restriction is always satisfied in our sample. The third 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, but is not useful for our purposes of estimating firm-embedded productivity in each country-sector.

Log-linearity assumption: In Section 5.2 we showed that the standardized residuals are mostly flat across the MNE-sector fixed effects and country-embedded factors decile-bins. We also showed that our results are robust to excluding deciles at the top and bottom of the MNE fixed effect distribution. 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 MNE-sector fixed effects with an interaction between country-group and MNE-sector 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 A10 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 MNE and country effects to overall affil-

[1] By definition all MNEs 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. In that literature, identification is achieved by workers who switch employers over their careers Abowd et al. (1999).

Table A10: 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 fixed-effect (K = 5).

iates' shares variance remain almost unchanged in the additive model using individual countries (baseline) or country groups.

C Extension: Intermediate inputs

This section shows how to extend our framework to allow for intermediate inputs in production. We again focus on the one sector case to facilitate the exposition. We assume that the final good can be used as an input, and that the production function for intermediate goods is

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

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

$$\mathcal{Y}_n = \gamma^{\frac{1}{\gamma}} Z_n^{\frac{1}{\gamma}} \Phi_n^{\frac{1}{\gamma}\frac{1}{\rho-1}} [H_n L_n]^{1-\alpha} [K_n]^{\alpha}.$$

We can write cross-country differences in the log of value added per-worker as

$$\Delta y_n = \frac{1}{\gamma}\Delta\tilde{z}_n + \frac{1}{\gamma}\Delta\tilde{\phi}_n. \tag{C.1}$$

We show next how to obtain the contribution of aggregate firm-embedded productivity to cross country differences in value added per-worker, $\frac{1}{\gamma}\Delta\tilde{\phi}_n$. Note that in this economy, the revenue, employment, and the value-added shares coincide and are given by Equation (16). We can thus use Equation (19) 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 $\Delta\mathbb{A}_n = -\Delta\phi_n$.

The last step is to reestimate $\beta \equiv [1-\alpha][\rho-1]$ in a way that is consistent with Equation

(C.1). With intermediate inputs equation (23) is

$$\Delta y_n = b_0 + \frac{b_1^{inp}}{\gamma}\Delta\mathbb{A}_n + b_2 C_n + u_n,$$

so that the coefficients in Table 1 should be interpreted as $b_1 = \frac{b_1^{inp}}{\gamma}$. The contribution of firm-embedded productivity to cross-country income differences is $\frac{1}{\gamma}\Delta\tilde{\phi}_n = \frac{b_1^{inp}}{\gamma}\Delta\mathbb{A}_n = b_1\Delta\mathbb{A}_n$, which coincides with the estimate used in our baseline analysis.