Firm-Embedded Productivity and Cross-Country Income Differences

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We measure the contribution of firm-embedded productivity to cross-country income differences. By firm-embedded productivity we refer to firm-specific components of productivity, such as blueprints, management practices, and other intangible capital. Using micro-level data for multinational enterprises (MNEs), we compare market shares of the same MNE in different countries and document that they are systematically larger in less developed countries. This indicates that MNEs face less competition and that firm-embedded productivity is scarce in these countries. We implement a measure of firm-embedded productivity based on this observation. Differences in firm-embedded productivity account for one-third of the cross-country variance in output per worker in our sample.

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I. Introduction

Differences in total factor productivity (TFP) account for about half of the cross-country differences in income per capita.[1] Understanding TFP differences is thus at the center of development economics. A common view is that aggregate productivity is determined partly by knowledge and expertise that are embedded in individual firms in the form of blueprints, management practices, and other intangible capital.[2] This view has motivated a wide array of policies that promote firm-embedded productivity around the world, ranging from tax incentives for R&D to incubator programs for start-ups.[3] More recently, randomized control trials have shown that micro-level interventions fostering different aspects of firm-embedded productivity can improve firm outcomes.[4] Nonetheless, the macro development literature has been mostly silent on the aggregate contribution of firm-embedded productivity to cross-country income differences.[5]

This paper introduces and implements a framework for measuring the contribution of firm-embedded productivity to cross-country income differences. By "firm-embedded productivity" we refer to the components of productivity that are specific to the firm. We contrast these components with "country-embedded factors," which are available to all firms producing in a country, such as natural amenities, infrastructure, and workers' quality. As noted by Burstein and Monge-Naranjo (2009), separating between these two components is challenging, as different combinations of firm-embedded productivity and country-embedded factors can result in the same level of output per worker.

Our approach overcomes this challenge by bringing to bear 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 the same firm should have larger market shares in countries where aggregate firm-embedded productivity is relatively scarce, as they face less

[1] See Hall and Jones (1999) and Caselli (2016).

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

[3] For a review, see the policy report by Atkin et al. (2019).

[4] For example, Giné and Yang (2009) and Atkin et al. (2017) facilitate technology adoption at the firm level; Bloom et al. (2013) and Brooks, Donovan, and Johnson (2018) improve management practices; and Atkin, Khandelwal, and Osman (2017) and Cai and Szeidl (2017) provide intangible capital in the form of business networks and market access.

[5] Burstein and Monge-Naranjo (2009) is a notable exception that we discuss in detail below.

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 data on market shares of the foreign affiliates of MNEs that simultaneously operate in multiple countries. The framework assumes that producers in a country are heterogeneous in their production efficiency and product 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 an MNE in a country is determined by the MNE's productivity relative to the aggregate firm-embedded productivity in the country. 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. We attribute the residual differences in income per capita across countries to differences in country-embedded factors.

Certainly, MNEs may not be able to fully transfer their productivity across countries. We allow for imperfect technology transfers by assuming that MNEs can use only a fraction of their productivity when operating abroad. This is the standard assumption in the literature on multinational production when modeling imperfect technology transfers, home bias in preferences, and other costs and policies that imply a differential treatment of MNEs versus domestic firms. Under this assumption, the market share of an MNE can be relatively low in a country if either aggregate firm-embedded productivity in that country is high or the MNE faces large transfer costs.

We control for these transfer costs in two straightforward ways. First, we focus on the cross-country variation in the market shares of MNE's *foreign* affiliates (not parent firms) and we control for MNE-specific transfer costs that are common across foreign destinations. Second, we control for the country-pair-specific component of the transfer costs using a gravity specification that follows Waugh (2010). This specification assumes that bilateral costs are a function of bilateral distance and other country-pair-specific characteristics, such as taxes to MNEs, and includes country dummies to control for source-country-specific costs.

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, which allows us to build ownership links between affiliates of the same MNE 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 where ORBIS has the most extensive coverage, so that our sample is comprised mainly of Eastern and Western European countries.

We estimate the key structural equation from our model, which states that the log of an MNE market share in a country and sector can be written as the sum of (i) an MNE-sector component, (ii) a destination-sector component, and (iii) the 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.

The ordinary least squares (OLS) estimates of the destination-sector-specific components of the market shares are unbiased if the assignment of MNEs to destination-sector pairs is exogenous with respect to the error term. This is the case if selection of MNEs into destinations is driven by firm characteristics (e.g., productivity) and destination-sector characteristics (e.g., market size), as is the case in workhorse models of multinational production in the tradition of Helpman, Melitz, and Yeaple (2004). This is also the case if selection is driven by firm-destination characteristics uncorrelated to firm revenues, such as firm-destination-specific fixed costs (e.g., Tintelnot 2017; Head and Mayer 2019). Thus, the fact that MNEs are larger and more productive than domestic firms, the fact that MNEs are more likely to enter sectors where domestic firms are relatively unproductive, and the fact that ORBIS may not cover the universe of MNEs does not bias our estimates of the destination-sector fixed effects. These estimates are identified from variation in market shares *within* MNEs across countries, rather than from variation across MNEs. We evaluate violations of the exogeneity assumption in section V.

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. The relative importance of the differences in firm-embedded productivity varies considerably across countries. For example, 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 due to the difference in country-embedded factors between these two countries.

We show that there is a strong positive correlation between firm-embedded productivity and output per worker and that differences in firm-embedded productivity account for about one-third of the cross-country variance in output per worker. The positive correlation with output per worker also holds once we control for country size. We also show a positive correlation between firm-embedded productivity and measures of innovation and management practices across countries and that the foreign output of a country's MNEs is concentrated in sectors where the country's firm-embedded productivity is relatively high.

Finally, we embed our framework in a standard general equilibrium model of MNE location choices and evaluate the gains from eliminating barriers to the mobility of MNEs. We show that the size of these gains depends on whether we calibrate the model assuming that observed differences in output per worker are due to firm- or country-embedded factors. If we assume that all initial differences in income per capita are driven by country-embedded factors, we obtain gains that are roughly the same for all countries. In this scenario, by assumption, all countries start with the same firm-embedded productivity and end up with the same firm-embedded productivity—since with no barriers to MNE mobility the same firms operate in all locations. In contrast, we obtain gains that vary enormously across countries and are much higher on average if we assume that all initial differences in output per worker are driven by differences in firm-embedded productivity. In this case, the gains are larger for poorer countries that integrate with countries that have more productive firms. Our baseline estimates imply gains that are between these two extremes, with the largest gains accruing to the countries with the lowest firm-embedded productivity.

Related literature.—Our paper is closely related to Burstein and Monge-Naranjo (2009), who separate firm-embedded productivity from country-embedded factors using a model of MNE location choices and aggregate data on output per worker, capital stocks, and corporate tax rates. Their framework is based on the Lucas "span of control" model and assumes that each firm (or manager) must choose only one country where to produce. Under these assumptions, they can recover the contribution of firm-embedded productivity to cross-country income differences using aggregate data and the model's equilibrium condition that equates after-tax managerial profits across countries, without using any data on the cross-country operations of MNEs.[6] In contrast, our approach recovers firm-embedded productivity from firm-level data on MNE market shares in multiple countries; hence, it does not rely on specific assumptions on how MNEs make location choices.

The idea behind our approach is similar to that in Hendricks and Schoellman (2018), who use worker-level data on wage gains upon migration to separate the contributions of aggregate human capital from country-embedded factors in explaining cross-country income differences. They exploit the idea that workers can take their human capital with them when moving to a foreign country. In the same spirit, we use firm-level data and exploit the idea that MNEs can use their firm-specific productivity in many

[6] The main goal of Burstein and Monge-Naranjo (2009) is to analyze the aggregate consequences of reallocating firm-embedded productivity across countries. To such end, they need to estimate the autarky allocation of firm-embedded productivity, which does require data on foreign direct investment stocks in addition to the model's equilibrium.

countries to measure cross-country differences in aggregate firm-embedded productivity.

More broadly, our paper is related to the extensive literature on development accounting, which measures the contribution of factors of production to cross-country income differences directly and computes TFP as a residual (for a survey, see Caselli 2005). This literature has focused on improving measures of factor stocks to better account for differences in productivity embodied in physical and human capital (recent examples are Hendricks and Schoellman 2018; Lagakos et al. 2018; Caunedo and Keller 2020). We contribute to this literature by proposing a measure of the productivity that is embodied in firms. In doing so, we provide a direct (not residual) measure of one of the components of TFP—firm-embedded productivity—using data on MNEs.

Finally, our paper is 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 within the MNE (e.g., Cravino and Levchenko 2017; Bilir and Morales 2020). In contrast, our focus is on measuring the contribution of firm-embedded productivity in explaining cross-country income differences. A different branch of the literature parameterizes general equilibrium models of MNE location choices to measure MNEs' contribution to welfare and TFP (see, e.g., Burstein and Monge-Naranjo 2009; McGrattan and Prescott 2009; Irarrazabal, Moxnes, and Opromolla 2013; Ramondo and Rodrìguez-Clare 2013; Ramondo 2014; Arkolakis et al. 2018; Alviarez 2019). 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 II presents the accounting framework. Section III describes the data and our empirical strategy. Section IV presents the quantitative results. Section V collects robustness exercises. Section VI presents the counterfactual exercises. Section VII concludes.

II. Accounting Framework

In this section, we first develop a stylized framework that formalizes our definition of firm-embedded productivity and show how to measure it using firm-level data on the cross-border operations of MNEs. Next, we present a quantitative version of this framework that allows for multiple sectors and factors of production.

A. 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 an MNE. Factor markets are competitive and integrated within countries, and markups are constant across firms. 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

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

where $Y_{in}(\omega)$ represents the output of firm ω from country i operating in country n, Ω_{in} denotes the set of firms from country i that are active in country n, and $Q_{in}(\omega)$ is a shifter for firm ω, which we interpret as product quality and can differ across production locations. The parameter $\rho \geq 1$ represents the elasticity of substitution across intermediate goods.

The production function for intermediate goods is

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

where $L_{in}(\omega)$ represents the number of workers 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 affect all firms in a country, such as infrastructure, institutions, 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 refer to $A_{in}(\omega)$ as "firm-embedded productivity." This variable captures production, managerial, and marketing know-how specific to the firm.

We assume that firm-embedded productivity can be transferred imperfectly across countries, so that the productivity of an MNE from country i when it produces in country n is

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

with $\kappa_{ii}(\omega) = 0$. Here $A_i(\omega)$ represents the productivity embedded in firm ω in its home country i and $\kappa_{in}(\omega)$ represents a technology transfer cost that captures the degree to which firm-embedded productivity can be moved from i to n. If $\kappa_{in}(\omega) = 0$, the MNE can use the same $A_i(\omega)$ in all the countries where it produces.

Aggregate output and TFP.—Using equations (1) and (2), we can write aggregate output as

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

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 all 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 micro-level data on the cross-border operations of MNEs to separate ϕ_n from z_n.

B. Decomposing Cross-Country Differences in Output per Worker

We now show how cross-country differences in 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 firm ω from country i producing in country n, relative to the sum of the revenues of all firms producing in n, as

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

An 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.

We build on this intuition to identify cross-country differences in Φ_n. Substituting equation (3) in (7), the log market share 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 of affiliates of the same MNE pin down differences in ϕ_n. In this case, one could regress affiliate-level market shares on MNE- and destination-level dummies to recover 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) (given a value for the elasticity ρ). This two-way fixed effect approach constitutes the basis of our estimation strategy described in section III.B.

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 the costs to transfer technology are large (high $\kappa_{in}(\omega)$). Section III.B shows how, if we observe market shares for MNEs 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 standard in the international trade and multinational production literature.

Two remarks are in order. First, the firm-level market shares in equation (7) vary only across destinations due to competition in the destination, captured by ϕ_n, and the technology transfer cost, $\kappa_{in}(\omega)$. In contrast, aggregate market shares, $S_{in} = \int_{\omega \in \Omega_{in}} S_{in}(\omega)\, d\omega$, also vary across destinations if MNEs with different $a_i(\omega)$'s select into different n's. This comparison highlights the importance of including firm-level dummies to recover ϕ_n from destination-level dummies. We show the biases of an estimation based on aggregate market shares in appendix D.1.

Second, country-embedded productivity, Z_n, does not affect the MNE market share $S_{in}(\omega)$ in equation (7), since it proportionally affects all the firms producing in n. This result follows from the assumption that Z_n and $X_{in}(\omega)$ enter log linearly into the production function in equation (2). Together with the assumption on transfer costs in equation (3), the assumption also implies that country-embedded factors that have different effects across domestic and foreign firms—such as regulations that apply only to foreign firms—would be captured by $\kappa_{in}(\omega)$.[7] Section V.B and appendix C show that the log-linear functional form provides a good approximation of the data.

[7] That is, our model is isomorphic to assuming a production function given by $Y_{in}(\omega) = \tilde{Z}_{in}(\omega) X_{ii}(\omega) L_{in}(\omega)$, with $\tilde{Z}_{in}(\omega) \equiv \kappa_{in}(\omega) Z_n$.

C. 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 sectoral output according to

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

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

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

where $Y_{in}^j(\omega)$ represents the output of intermediate-good producer firm ω from country i in sector j and $Q_{in}^j(\omega)$ denotes product quality of firm ω from country i in sector j.

Intermediate goods in each sector are produced with a Cobb-Douglas technology,

$$Y_{in}^j(\omega) = Z_n^j X_{in}^j(\omega) H_{in}^j(\omega)^{1-\alpha^j} K_{in}^j(\omega)^{\alpha^j}, \tag{11}$$

where $\alpha^j \in [0, 1]$. The variables $H_{in}^j(\omega)$ and $K_{in}^j(\omega)$ denote the effective units of labor and capital employed by firm ω in country n and sector j.[8]

As in the previous section, we define $A_{in}^j(\omega) \equiv [Q_{in}^j(\omega) \times X_{in}^j(\omega)]^{\rho^j - 1}$ and assume that

$$A_{in}^j(\omega) = A_i^j(\omega) \times \exp\left(-\kappa_{in}^j(\omega)\right). \tag{12}$$

Aggregate output in each sector satisfies

$$Y_n^j = Z_n^j [\Phi_n^j]^{1/(\rho^j - 1)} [\bar{H}_n^j L_n^j]^{1-\alpha^j} [K_n^j]^{\alpha^j},$$

where $\Phi_n^j \equiv \Sigma_i \int_{\omega \in \Omega_{in}^j} A_{in}^j(\omega) d\omega$ represents the aggregate firm-embedded productivity in sector j and country n, L_n^j denotes the number of workers employed in sector j, $\bar{H}_n^j \equiv [\Sigma_i \int_{\omega \in \Omega_{in}^j} H_{in}^j(\omega) d\omega]/L_n^j$ gives the units of effective labor per worker in sector j, and K_n^j represents the physical capital employed in sector j. Output per worker in sector j can be written as

$$\frac{Y_n^j}{L_n^j} = \tilde{Z}_n^j \tilde{\Phi}_n^j, \tag{13}$$

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

where $\tilde{Z}_n^j \equiv [Z_n^j]^{1/(1-\alpha^j)} \bar{H}_n^j [K_n^j / Y_n^j]^{\alpha^j/(1-\alpha^j)}$, $\tilde{\Phi}_n^j \equiv [\Phi_n^j]^{\beta^j}$, and $\beta^j \equiv [1/(1-\alpha^j)][1/(\rho^j - 1)]$. In what follows, we refer to both $\tilde{\Phi}_n^j$ and Φ_n^j as firm-embedded productivity and refer to $\tilde{Z}_n^j$ as country-embedded factors since physical and human capital are included, in addition to the country-embedded productivity z_n^j.

Aggregate output per worker can be written as

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

Here $\tilde{\Phi}_n \equiv \prod_j [\tilde{\Phi}_n^j]^{\theta_n^j(\beta_n/\beta^j)[(\rho_n - 1)/(\rho^j - 1)]}$, $\beta_n \equiv [1/(1-\alpha_n)][1/(\rho_n - 1)]$, $\alpha_n \equiv \Sigma_j \theta_n^j \alpha^j$, $\rho_n \equiv \Sigma_j \theta_n^j \rho^j$, and $\tilde{Z}_n \equiv \bar{\theta}_n \bar{H}_n [K_n / Y_n]^{\alpha_n/(1-\alpha_n)} \prod_j [Z_n^j]^{\theta_n^j/(1-\alpha_n)}$. The variables L_n and K_n represent the number of workers and capital stock in country n, and $\bar{H}_n \equiv [\Sigma_j \Sigma_i \int_{\omega \in \Omega_{in}^j} H_{in}^j(\omega) d\omega]/L_n$ represents the average human capital in country n.[9]

Applying logs to equation (14), we can thus write

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

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

$$s_{in}^j(\omega) = a_i^j(\omega) - \kappa_{in}^j(\omega) - \phi_n^j. \tag{16}$$

An MNE revenue 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 sectoral market shares across affiliates of the same MNE that are located in different country-sector pairs to pin down differences in ϕ_n^j. These differences can be aggregated to obtain $\tilde{\phi}_n = \Sigma_j \theta_n^j (\beta_n/\beta^j)[(\rho_n - 1)/(\rho^j - 1)]\phi_n^j$. 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 in output per worker. We follow the variance decomposition in Klenow and Rodrìguez-Clare (1997) and compute

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

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

[9] $\bar{\theta}_n \equiv \prod_j [[[\theta_n^j[1-\alpha^j][1-1/\rho^j]]/[\Sigma_j[\theta_n^j[1-\alpha^j][1-1/\rho^j]]]]^{1-\alpha^j}[[\theta_n^j\alpha^j[1-1/\rho^j]]/[\Sigma_j[\theta_n^j\alpha^j[1-1/\rho^j]]]]^{\alpha^j}]^{\theta_n^j/(1-\alpha_n)}$ is a country-specific constant.

III. Data and Empirical Strategy

A. *Data Description*

Our firm-level data come from ORBIS, a worldwide dataset maintained by Bureau van Dijk that includes comprehensive information on firms' revenue and employment. 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 links between affiliates of the same MNE, including cases in which the affiliates and the parent are in different countries.

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 of foreign firms in ORBIS account for at least 20% of the aggregate revenues of foreign firms reported by the Organization for Economic Cooperation and Development (OECD) Activity of Multinational Enterprises database and the Eurostat Foreign Affiliate Statistics database. In contrast, every country in the world is a potential source country of MNEs in ORBIS, so that our sample of source countries is much larger than our sample of destination countries.[10]

The original unit of observation in ORBIS is a tax ID number. Often, affiliates located in different addresses within the same country and belonging to the same corporate group are registered with different tax ID numbers. We aggregate revenues of all firms in ORBIS that belong to the same corporate group and that operate in the same country and two-digit North American Industry Classification System (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 Renault's total revenues in this sector in Germany. Our procedure compares affiliates of Renault in the transportation and equipment sector located in different countries and separately compares affiliates of Renault's in, for example, the retail sector across countries.

[10] Figure A.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. Our sample of source countries includes the United States, China, and Canada, among others. As destinations, these countries have very low (or nonexistent) coverage in ORBIS, and thus they are not included in our sample of destination countries. In addition, we exclude Ireland, Luxembourg, and Switzerland from our sample, as MNE revenues in those countries are particularly sensitive to profit-shifting strategies.

Finally, to compute market shares, we divide the revenues of each corporate group-country-sector by the aggregate revenues in each country-sector. Since ORBIS does not always cover the population of firms in each country-sector pair, we use data on aggregate revenues from the European Union–level analysis of capital, labor, energy, materials, and service inputs (EU KLEMS) database and OECD.

We obtain aggregate output per worker from the Penn World Tables (ver. 9.1) and compute output per worker in international dollars at the sector level using data on output per worker from EU KLEMS and the purchasing power parity conversion factor from the Penn World Tables (ver. 9.1). We refer the reader to appendix B for further details on the data construction.

B. *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 an MNE-destination-sector-specific component, $\varepsilon_{in}^j(\omega)$. We proxy for the bilateral component B_{in}^j with a log-linear function of bilateral distance and a dummy for common language, which we obtain from Centre d'Etudes Prospectives et d'Informations Internationales. Section V.F shows that our results are unchanged if we add country-pair-specific taxes for MNEs, bilateral tax treaties, and other gravity variables as additional controls for B_{in}^j.

Substituting equation (18) into (16), we obtain our estimating equation:

$$s_{in}^{j}(\omega) = \delta_{i}^{j}(\omega) + \mathbb{A}_{n}^{j} + B_{in}^{j} + \epsilon_{in}^{j}(\omega). \tag{19}$$

Here $\delta_i^j(\omega)$ represents MNE-sector fixed effects and $\mathbb{A}_n^j$ denotes a set of dummies that take a value of one if the destination country is n and the sector is j. We estimate equation (19) by OLS using the sample of foreign affiliates of MNEs in the ORBIS data—MNEs in their home country are not included. The regression identifies $\delta_i^j(\omega)$ 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 $\mathbb{A}_n^j$ 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 $\epsilon_{in}^j(\omega)$ is (the negative of) $\varepsilon_{in}^j(\omega)$ in equation (19).

The OLS estimates of the destination-sector-specific components of the market shares, $\mathbb{A}_n^j$, are unbiased if $\mathbb{E}[\mathbb{A}_n^j \epsilon_{in}^j(\omega) \mid \delta_i^j(\omega), B_{in}^j] = 0$. This requires the assignment of MNEs to destination countries to be exogenous with respect to the error term, $\varepsilon_{in}^j(\omega)$. This restriction is satisfied if selection is driven by firm characteristics (e.g., productivity), by destination-country characteristics (e.g., market size), or by firm-destination characteristics uncorrelated with firm revenues (e.g., firm-destination-specific fixed costs). In contrast, the OLS estimates would be biased if the assignment of MNEs to destination countries were driven by $\varepsilon_{in}^j(\omega)$. Appendix D formalizes this intuition in the context of a general equilibrium model of MNE location choices.

For the remainder of this section, we assume that MNEs do not select into countries based on $\varepsilon_{in}^j(\omega)$. In section V.B, we show that our main results are robust to reestimating equation (19) using subsamples of MNEs that are more likely to satisfy the exogeneity assumption.

C. *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 sectoral expenditure shares in each country, θ_n^j, and our OLS estimates of $\Delta\mathbb{A}_n^j$, we compute the aggregate destination-specific 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 average MNE market share in each destination relative to France after controlling for the MNE-sector fixed effects and the bilateral variables.

Figure 1 reports $\exp(\Delta\mathbb{A}_n)$ against output per worker.[11] On average, MNE market shares are larger in less developed countries. Differences

[11] The country-sector dummies $\Delta\mathbb{A}_n^j$ and the MNE-sector dummies $\delta_i^j(\omega)$ respectively account for 0.27 and 0.45 of the total variance of $s_{in}^j(\omega)$ in eq. (19), while the R^2 value of the regression is 0.72. Table A.1 reports the OLS coefficients on bilateral distance and common language, ψ_d^j and ψ_l^j, for each sector, while app. C presents additional statistics on our two-way fixed effect estimator. Figure A.2 reports standard errors for our estimates of $\Delta\mathbb{A}_n$ and shows that these dummies are tightly estimated and exhibit substantial variation across countries.

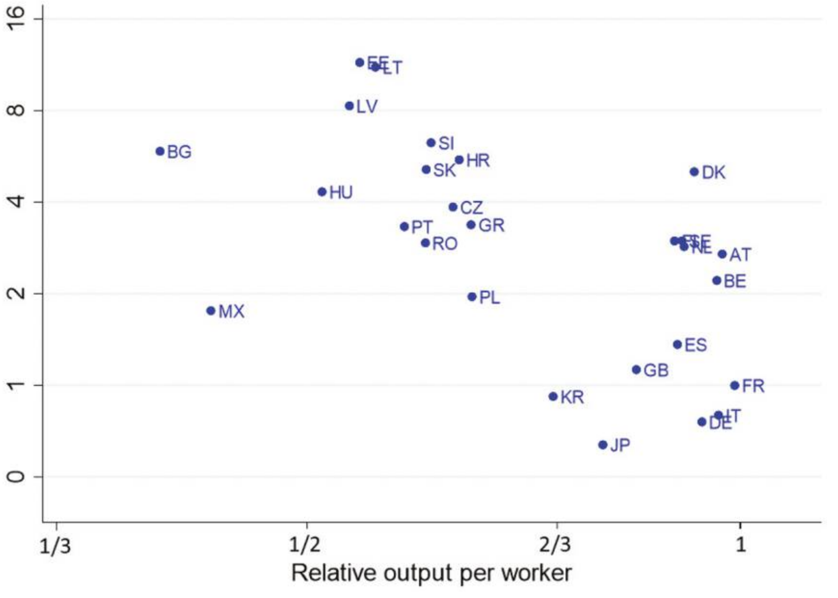

FIG. 1.—Market shares of foreign MNE affiliates, relative to France. This figure shows $\exp(\Delta \mathbb{A}_n)$, calculated using equation (20) and the OLS estimates of equation (19). The x-axis reports the output per worker of each country, relative to France, from Penn World Tables (ver. 9.1).

between developed and developing countries are enormous: MNE market shares are about 3.5 times larger in Greece and Portugal and about 12 times larger in Estonia and Lithuania compared with their market shares in France. In contrast, MNEs have similar market shares in the United Kingdom, Germany, and France.

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 estimation. Figure A.2 shows that we obtain very similar estimates if we use data on employment shares or data on value-added shares as the dependent variables in equation (19).[12]

D. *Interpreting Differences in MNE Market Shares*

We calculate the differences in $\Delta\phi_n^j$ using our estimated country-sector effects, $\Delta\mathbb{A}_n^j$. Using equations (16) and (18), these effects correspond to

[12] We use revenue shares for our baseline estimates since ORBIS has more complete coverage of revenues than of employment and value added. Using employment data, however, alleviates concerns about profit-shifting strategies by MNEs.

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

which conflates firm-embedded productivity, $\Delta\phi_n^j$, and the destination-specific component 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 ($\Delta O_i^j \neq 0$) but not destination-specific ($\Delta D_n^j = 0$) component. In that case, the country dummies can be interpreted as $\Delta\mathbb{A}_n^j = -\Delta\phi_n^j$, and the MNE-level dummies, $\delta_i^j(\omega)$, would absorb the origin-specific component of the technology transfer cost, ΔO_i^j. But what if this identification assumption is not satisfied and $\Delta D_n^j \neq 0$? If ΔD_n^j is high for low-income countries (i.e., it is harder to transfer technology into less developed countries), then $\mathrm{cov}(\Delta y_n, \Delta D_n^j) \leq 0$. This inequality implies that our baseline estimates of $\Delta\phi_n^j$ based on equation (21) would understate the contribution of aggregate firm-embedded productivity to the cross-country variance in output per worker,

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

Section V presents a robustness exercise that allows for $\Delta D_n^j > 0$ but assumes that $\Delta O_i^j = 0$. Those results are remarkably similar to our baseline results.

Parameterization.—As shown in section II.C, 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 in equation (13) and using our baseline identification assumption on technology transfer costs so that $\Delta\mathbb{A}_n^j = -\Delta\phi_n^j$ yields

$$\Delta y_n^j = -\beta^j \Delta\mathbb{A}_n^j + \Delta\tilde{z}_n^j. \tag{23}$$

The composite elasticity $\beta^j \equiv [[\rho^j - 1][1 - \alpha^j]]^{-1}$ 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, the quality of institutions, and the infrastructure in country n. In particular, we estimate

$$\Delta y_n^j = b_0^j + b_1^j \Delta\mathbb{A}_n^j + b_2^j \Delta C_n + u_n^j, \tag{24}$$

where C_n is a vector of country-specific controls.

Table 1 reports these estimates. Columns 1, 4, and 7 show the results for the pooled sample of sectors, for manufacturing sectors, and for service

TABLE 1
ESTIMATING THE COMPOSITE ELASTICITY β

	All Sectors			Manufacturing Sectors			Service Sectors		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\Delta\,\mathbb{A}_n^j$	−.194***	−.199***	−.197***	−.189***	−.203***	−.196***	−.193***	−.194***	−.193***
	(.0267)	(.0261)	(.0282)	(.0338)	(.0372)	(.0340)	(.0342)	(.0342)	(.0386)
$\Delta[k_n - y_n]$		.381***	.275*		.496**	.297		.195	.121
		(.115)	(.157)		(.165)	(.167)		(.122)	(.128)
Δh_n		.244	−.168		.774	.144		−.0915	−.456
		(.385)	(.522)		(.494)	(.751)		(.301)	(.423)
$\Delta\text{Governance}_n$			.479			.780			.348
			(.350)			(.432)			(.219)
$\Delta\text{Infrastructure}_n$			.117			.00421			.197
			(.390)			(.385)			(.380)
Observations	445	445	445	158	158	158	161	161	161
R^2	.334	.393	.422	.397	.513	.581	.420	.447	.482

NOTE.—This table reports the OLS estimates from eq. (24). $\Delta[k_n - y_n]$ denotes the capital-output ratio. Δh_n denotes human capital from the Penn World Tables (ver. 9.1). $\Delta\text{Governance}_n$ is an aggregate indicator of governance averaging the six World Governance Indicators: (1) rule of law, (2) voice and accountability, (3) political stability and absence of violence, (4) government effectiveness, (5) regulatory quality, and (6) control of corruption. $\Delta\text{Infrastructure}_n$ is measured by the number of mobile cellular subscriptions per capita (from World Development Indicators). Sector fixed effects are included, and standard errors are clustered by country and sector (shown in parentheses).

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

sectors, estimated under the restriction that b_1 is the same in all (sub)sectors (see table A.2 for results on estimating b_1^j for each subsector in manufacturing and services). The coefficient b_1 is precisely estimated around -0.20 in the three samples. As shown in columns 2, 5, and 8, 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, as well as in columns 3, 6, and 9 when controlling for measures of a country's governance and infrastructure.[13] Overall, we cannot reject the null hypothesis that $\beta = 0.2$ in any of these samples.

Using $\beta = 0.2$ for all j 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).[14] We calculate $\Delta\tilde{z}_n$ as a residual using data on output per worker.

IV. Quantitative Results

This section combines the estimates from equation (20) with our elasticity estimates from "Parameterization" in section III.D to decompose differences in output per worker across countries into aggregate firm-embedded productivity and country-embedded factors. Figure 2 plots the result of this decomposition (see table A.5 for the exact numbers). The x-axis shows the log difference in output per worker in each country relative to France, Δy_n. On the y-axis, the circles show the difference in firm-embedded productivity in each country relative to France, $\Delta\tilde{\phi}_n$, while the 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. However, there is 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.

[13] Our measure of infrastructure is the number of mobile cellular subscriptions per capita, from the World Development Indicators. Our estimates are unchanged if we use alternative measures of infrastructure, such as the number of fixed broadband subscriptions per capita or the electric power consumption per capita.

[14] In a one-sector model, estimating eq. (24) without controlling for ΔC_n would yield $\beta = -(\mathrm{cov}(\Delta\mathbb{A}_n, \Delta y_n)/\mathrm{var}(\Delta\mathbb{A}_n))$. Using this expression to calculate $\Delta\tilde{\phi}_n = -\beta\,\Delta\mathbb{A}_n$, the second term of the variance decomposition in eq. (17) would boil down to $\mathrm{cov}(\Delta y_n, \Delta\tilde{\phi}_n)/\mathrm{var}(\Delta y_n) = -\beta(\mathrm{cov}(\Delta y_n, \Delta\mathbb{A}_n)\,/\,\mathrm{var}(\Delta y_n)) = (\mathrm{cov}(\Delta\mathbb{A}_n, \Delta y_n)\mathrm{cov}(\Delta y_n, \Delta\mathbb{A}_n))\,/\,(\mathrm{var}(\Delta\mathbb{A}_n)\mathrm{var}(\Delta y_n))$, which corresponds to the R^2 value of a regression of Δy_n on $\Delta\mathbb{A}_n$ and does not depend on the model parameters. Rather than focusing exclusively on this R^2 value, we parameterize β to evaluate the decomposition for each individual country in our sample.

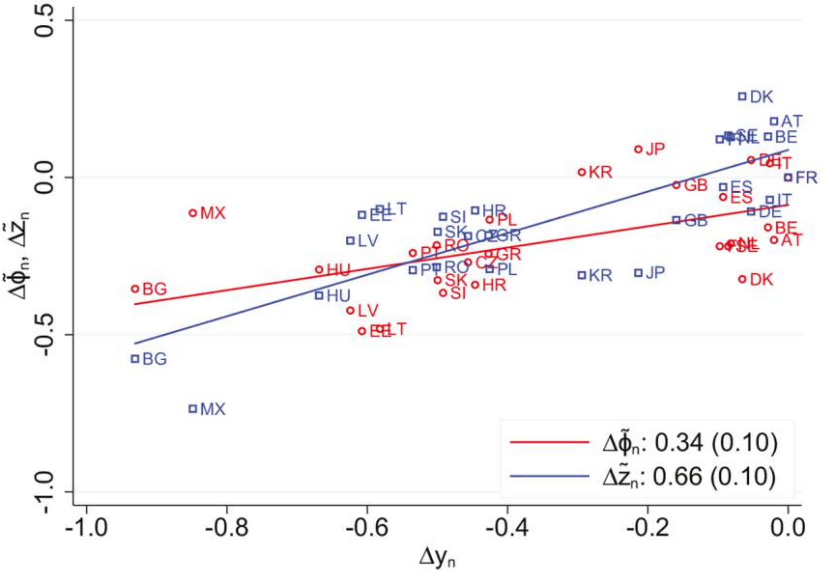

Fig. 2.—Development accounting: firm-embedded productivity versus country-embedded factors. Each circle (square) represents a country's firm-embedded productivity (country-embedded factors) relative to France. This figure plots the decomposition in equation (15), where Δy_n is plotted on the x-axis and $\Delta \tilde{z}_n$ and $\Delta \tilde{\phi}_n$ are plotted on the y-axis. The key reports the slopes of a bivariate OLS regression of $\Delta \tilde{\phi}_n$ $(\Delta \tilde{z}_n)$ on Δy_n.

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 European Union 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 the Netherlands firm-embedded productivity is 0.15 log points 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. 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.

For our development accounting exercise, we compute the share of the cross-country variance in output per worker accounted for by aggregate firm-embedded productivity and country-embedded factors, in the spirit of Klenow and Rodrìguez-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 2. Differences in $\Delta\tilde{\phi}_n$ account for roughly one-third of the cross-country variance in output per worker; differences in country-embedded factors account for the remaining two-thirds.

Correlation with country characteristics.—Table 2 evaluates how our measures of firm-embedded productivity and country-embedded factors correlate with country characteristics. In particular, we regress output per worker, firm-embedded productivity, and country-embedded factors on a country's capital-output ratio, human capital, measures of governance

TABLE 2
CORRELATIONS WITH COUNTRY CHARACTERISTICS

	Dependent Variable					
	Δy_n		$\Delta\tilde{\phi}_n$		$\Delta\tilde{z}_n$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta[k_n - y_n]$	.379**	.183	−.045	−.0496	.428***	.232**
	(.179)	(.187)	(.094)	(.103)	(.127)	(.103)
Δh_n	.772*	−.157	−.019	−.331	.792**	.174
	(.424)	(.630)	(.274)	(.213)	(.350)	(.525)
$\Delta\text{Governance}_n$		.689*		−.134		.823***
		(.385)		(.205)		(.235)
$\Delta\text{Infrastructure}_n$		−.0643		−.101		.0365
		(.597)		(.338)		(.319)
$\Delta\text{Patents(pc)}_n$		.0841**		.110***		−.0264
		(.0366)		(.0211)		(.0262)
Observations	27	27	27	27	27	27
R^2	.201	.525	.007	.610	.358	.637

NOTE.—This table reports the OLS estimates from eq. (24). $\Delta[k_n - y_n]$ denotes the capital-output ratio. Δh_n denotes human capital from the Penn World Tables (ver. 9.1). $\Delta\text{Governance}_n$ is an aggregate indicator of governance averaging the six Worldwide Governance Indicators: (1) rule of law, (2) voice and accountability, (3) political stability and absence of violence, (4) government effectiveness, (5) regulatory quality, and (6) control of corruption. $\Delta\text{Infrastructure}_n$ is measured by the number of mobile cellular subscriptions per capita. $\Delta\text{Patents(pc)}_n$ denotes the total number of patent applications per capita from the World Development Indicators. Sector fixed effects are included, and standard errors are clustered by country and sector (shown in parentheses).

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

and infrastructure, and the number of patent applications per capita. Table 2 shows that differences in firm-embedded productivity are uncorrelated with physical and human capital (col. 3) and with governance and infrastructure (col. 4) but are strongly correlated with the number of patent applications per capita (col. 4). In contrast, differences in country-embedded factors are significantly correlated with physical and human capital (col. 5) and governance (col. 6) but are uncorrelated with the number of patent applications per capita (col. 6). These results are reassuring since, as explained in section II.C, cross-country differences in factors should be captured by our measure of country-embedded factors and not by our measure of firm-embedded productivity.[15]

Correlation with country size.—A recurring theme in the international trade and growth development literatures is that aggregate scale or variety effects may be important for TFP (e.g., Krugman 1980; Jones 1995; Hsieh and Klenow 2009). We next evaluate whether differences in firm-embedded productivity are driven by country size. With this in mind, we fit the regression given by $\Delta\tilde{\phi}_n = b \times \Delta\text{pop}_n + u_n$, where country size is proxied by population. We evaluate the relation between the residual u_n and output per worker also residualized by population.[16] Figure 3 shows that the cross-country variation in firm-embedded productivity, after controlling for population, accounts for 16% of the cross-country variance in output per worker, almost half of the variation accounted for our aggregate measure of firm-embedded productivity.

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. Firm-embedded productivity for the average country (relative to France) is similar for manufacturing and services (-0.18 vs. -0.20 log points), as well as its contribution to cross-country income differences, which is roughly one-third for both sectors. There is substantial variation across countries. For example, Japan, Korea, and Germany have relatively 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 Germany, Mexico, and Hungary.[17]

[15] Our measure of firm-embedded productivity is also strongly correlated (0.52) with the index of management practices from the World Management Survey, while the correlation with our measure of $\Delta\tilde{z}_n$ is not significant (see fig. A.6). Unfortunately, this index is available for only 12 countries in our sample, and thus we cannot include it in the regressions in table 2.

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

[17] Figures A.3 and A.4 show that for each subsector in manufacturing and in services, the correlation between our sectoral measures of firm-embedded productivity and output per

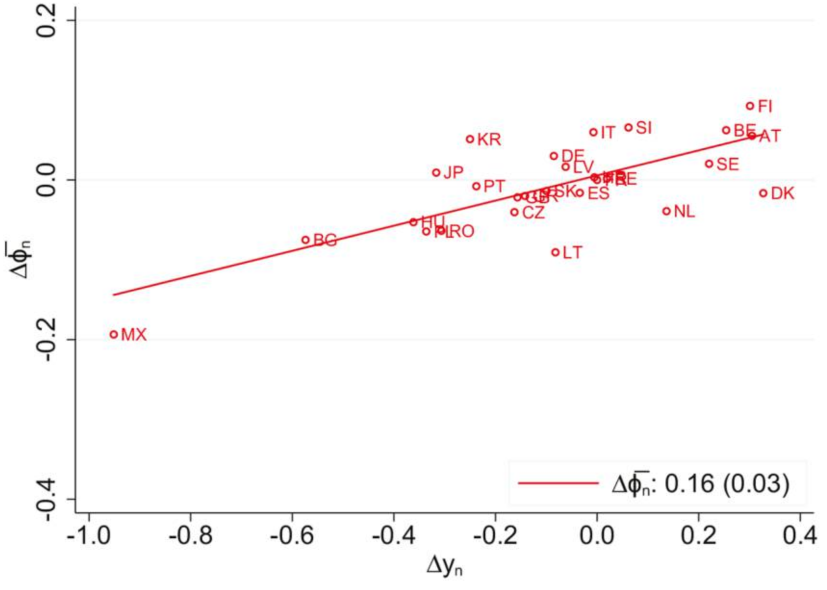

FIG. 3.—Development accounting: firm-embedded productivity residualized by population. Each circle represents a country. The y-axis plots the residual of a regression of firm-embedded productivity, $\Delta\tilde{\phi}_n$, on the log of population. The x-axis plots the residual of a regression of the log of output per worker, y_n, on the log of population.

Firm-embedded productivity and comparative advantage.—We now evaluate how sectoral differences in firm-embedded productivity and in country-embedded factors shape the sectoral concentration of the foreign output of a country's MNEs. The notion that MNEs can use their firm-specific 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, defined as

$$\Delta \mathrm{RCA}_n^j \equiv \ln\left(\frac{R_{n,\mathrm{row}}^j / \sum_{j'} R_{n,\mathrm{row}}^{j'}}{R_{r,\mathrm{row}}^j / \sum_{j'} R_{r,\mathrm{row}}^{j'}}\right), \tag{25}$$

worker at the sector level is very strong. Figure A.5 further shows 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.

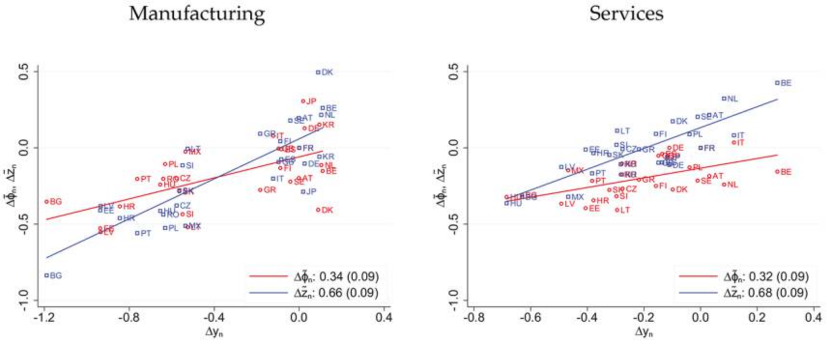

FIG. 4.—Development accounting: manufacturing and services. Each circle (square) represents a country's firm-embedded productivity (country-embedded factors). The panels plot the decomposition in equation (15) at the sectoral level; Δy_n^j is plotted on the *x*-axis and $\Delta \tilde{z}_n^j$ and $\Delta \tilde{\phi}_n^j$ are plotted on the *y*-axis for j = manufacturing (*left*) and j = services (*right*).

where $R_{n,\mathrm{row}}^j$ ($R_{r,\mathrm{row}}^j$) denotes the total revenues of MNEs from country n (reference country r) in the rest of the world.[18] When the share of sector j in outward MNE sales is larger for MNEs from country n than for MNEs from France, $\Delta\mathrm{RCA}_n^j > 0$.[19]

Using disaggregated two-digit sectors, table 3 shows the results of regressing $\Delta\mathrm{RCA}_n^j$ on $\Delta\tilde{\phi}_n^j$ and $\Delta\tilde{z}_n^j$. Columns 1, 4, and 7 show a strong correlation between a country's sectoral firm-embedded productivity and its comparative advantage in outward MNE sales.[20] In contrast, columns 2, 5, and 8 show no correlation between sector-level country-embedded factors and a country's comparative advantage. Columns 3, 6, and 9 report similar results when country-embedded factors and firm-embedded productivity are simultaneously included in the regression.[21]

These results are in line with the notion that firm-embedded productivity is a source of advantage for MNEs operating abroad. Country-embedded factors do not appear to shape the sectoral concentration of a country's MNEs.

Contribution of domestic and foreign firms.—We now decompose the sources of the cross-country differences in firm-embedded productivity

[18] Using the notation from sec. II, $R_{n,\mathrm{row}}^j \equiv \Sigma_{n' \neq n} \int_{\omega \in \Omega_{nn'}^j} P_{nn'}^j(\omega) Y_{nn'}^j(\omega) d\omega$.

[19] Note that, while $\Delta\tilde{\phi}_n^j$ is measured with data on market shares of foreign MNEs in country n, $\Delta\mathrm{RCA}_n^j$ 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.

[20] This result is in line with the findings in Alviarez (2019), who uses sectoral-level data to show a positive correlation between the bilateral sales of affiliates of foreign MNEs in a sector and the RCA index for sectoral TFP in the source country of the MNE.

[21] Figure A.7 complements these results and shows a strong positive correlation between differences in firm-embedded productivity in manufacturing vs. services, $\Delta\tilde{\phi}_n^{\mathrm{man}} - \Delta\tilde{\phi}_n^{\mathrm{serv}}$, and differences in RCA in those sectors for outward MNE sales, $\Delta\mathrm{RCA}_n^{\mathrm{man}} - \Delta\mathrm{RCA}_n^{\mathrm{serv}}$.

TABLE 3
Sectoral Firm-Embedded Productivity and Comparative Advantage

	Dependent Variable: $\Delta \mathrm{RCA}_n^j$								
	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**
	(.663)		(.836)	(1.326)		(1.075)	(.906)		(.812)
$\Delta\tilde{z}_n^j$		.17	.83		1.51	2.49**		−.76	−.19
		(.469)	(.501)		(.927)	(.823)		(.527)	(.645)
Observations	313	313	313	121	121	121	132	132	132
R^2	.072	.001	.094	.138	.056	.274	.063	.023	.064

Note.—Each j corresponds to an NAICS two-digit sector. "All Sectors" includes sectors in manufacturing, services, and others. The dependent variable $\Delta \mathrm{RCA}_n^j$ is defined in eq. (25). Standard errors are clustered by country and sector (shown in parentheses).
** Significant at the 5% level.
*** Significant at the 1% level.

into differences in the productivity embedded in domestic firms versus affiliates of foreign MNEs operating in each country. The market share of domestic firms in country n and in sector j is

$$S_{nn}^j \equiv \int_{\Omega_{nn}^j} S_{nn}^j(\omega) d\omega = \frac{\Phi_{nn}^j}{\Phi_n^j}, \tag{26}$$

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

$$S_{Fn}^j \equiv \sum_{i \neq n} \int_{\Omega_{in}^j} S_{in}^j(\omega) d\omega = \frac{\Phi_{Fn}^j}{\Phi_n^j}, \tag{27}$$

where $\Phi_{Fn}^j \equiv \Sigma_{i \neq n} \int_{\Omega_{in}^j} A_{in}^j(\omega) d\omega$ denotes the productivity embedded in foreign firms operating in country n. Log approximating the definition of Φ_n^j and aggregating across sectors, we can calculate 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 ($\Delta\tilde{\phi}_n$),

$$\Delta\tilde{\phi}_n = \underbrace{\sum_j \theta_n^j S_{rr}^j \Delta\tilde{\phi}_{nn}^j}_{\Delta\tilde{\phi}_{nn}} + \underbrace{\sum_j \theta_n^j [1 - S_{rr}^j] \Delta\tilde{\phi}_{Fn}^j}_{\Delta\tilde{\phi}_{Fn}}. \tag{28}$$

Here S_{rr}^j refers to the market share of domestic firms in France (and sector j), $\Delta\tilde{\phi}_{nn}^j \equiv \beta^j \Delta\phi_{nn}^j$, and $\Delta\tilde{\phi}_{Fn}^j \equiv \beta^j \Delta\phi_{Fn}^j$.[22]

[22] To measure these contributions, we use domestic shares S_{nn}^j from the data, our estimates of Φ_n^j, and eq. (26) to compute Φ_{nn}^j. Similarly, we use the revenue share of foreign

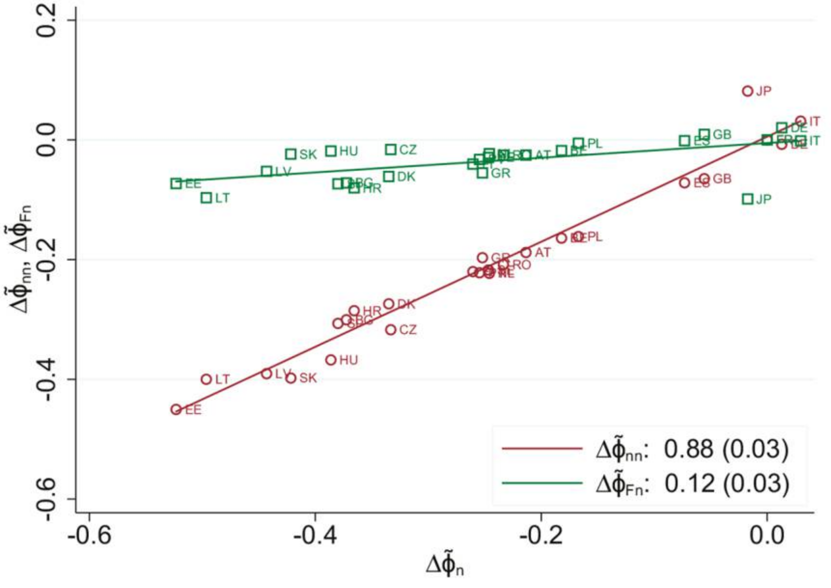

Fig. 5.—Aggregate firm-embedded productivity: domestic versus foreign firms. Circles and squares respectively report $\Delta\tilde{\phi}_{nn}$ and $\Delta\tilde{\phi}_{Fn}$ defined in equation (28).

Figure 5 shows the two terms on the right-hand side of equation (28). The average country has a 0.21 log point difference relative to France for domestic firm-embedded productivity, while the gap for foreign firms is only 0.04. Differences in firm-embedded productivity for domestic firms account for 88% 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.

V. Sensitivity Analysis

This section presents a sensitivity analysis for our baseline estimates of country-embedded productivity. First, we show how to estimate firm-embedded productivity under alternative assumptions on the technology transfer costs. Second, we evaluate potential selection concerns. Third, we

firms in country n, S^j_{Fn}, together with the estimates of Φ^j_n and eq. (27) to compute Φ^j_{Fn}. We aggregate across sectors using sectoral shares θ^j_n and the sectoral revenue share for French firms, S^j_{rr}.

evaluate the log-linearity assumption on the production function. Fourth, we evaluate the potential bias created by abstracting from trade in intermediate goods. Fifth, we show how to interpret our results when there are output distortions, such as markups, that vary across firms. Finally, we repeat our empirical analysis using alternative samples, finer sectoral disaggregations, and other gravity controls.

A. *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. As explained in section III.B, 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 ($\Delta D_n^j \neq 0$) but not origin-specific ($\Delta O_n^j = 0$) component, as in Eaton and Kortum (2002). In particular, we estimate

$$s_{in}^j(\omega) = \delta_i^j(\omega) + \mathbb{A}_n^j + \mathbb{P}_n^j + B_{in}^j + \epsilon_{in}^j(\omega). \tag{29}$$

Here $\mathbb{A}_n^j$ is a set of dummies that take a value of one 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 a value of one if the destination country is n and the firm is a parent, $i = n$, in sector j. In this specification, the dummies $\mathbb{A}_n^j$ are given by equation (21), while the dummies $\mathbb{P}_n^j$ are

$$\Delta\mathbb{P}_n^j = -[\Delta\phi_n^j - \Delta O_n^j]. \tag{30}$$

If $\Delta O_n^j = 0$, $\Delta\mathbb{P}_n^j$ can be interpreted as (the negative 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, $\text{cov}(\Delta y_n^j, \Delta O_n^j) \leq 0$, estimates based on equation (30) would overstate the contribution of firm-embedded productivity to the cross-country variance of output per worker,

$$\text{cov}(\Delta y_n, -\Delta\mathbb{P}_n^j) = \text{cov}(\Delta y_n, \Delta\phi_n^j - \Delta O_n^j) \geq \text{cov}(\Delta y_n, \Delta\phi_n^j). \tag{31}$$

Hence, 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 6 compares our baseline estimates with those based on equations (29) and (30) and the restriction that $\Delta O_n^j = 0$. The two alternative identification assumptions on transfer costs yield similar estimates for aggregate firm-embedded productivity (relative to France) for each country. Figure A.8 shows that the OLS estimates from equation (29) are less precise than our baseline estimates, as the number of MNE parent firms in our data is far lower than the number of MNE foreign affiliates. 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 to be -0.42 when we assume that $\Delta O_n^j = 0$ and -0.11 when we alternately assume that $\Delta D_n^j = 0$.

B. *Selection Based on MNE-Destination-Specific Characteristics*

The OLS estimates of the destination-sector-specific components of the market shares, $\mathbb{A}_n^j$, are unbiased if the assignment of MNEs to destination

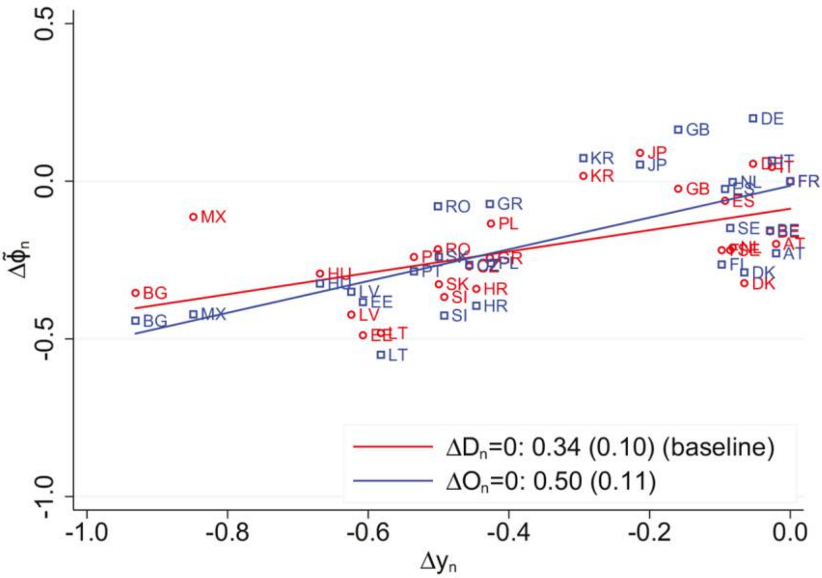

FIG. 6.—Alternative assumptions on the technology transfer costs. Each circle (square) represents a country. This figure plots the decomposition in equation (15), where Δy_n is plotted on the x-axis and $\Delta\tilde{\phi}_n$ is plotted on the y-axis. The key reports the slopes of a bivariate OLS regression 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 shown in parentheses.

countries is exogenous with respect to the error term in equation (19). This is the case if selection is driven by firm characteristics and by destination-country characteristics. In contrast, the estimates 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 $\varepsilon_{in}^{j}(\omega)$ is low, the average of $\varepsilon_{in}^{j}(\omega)$ across the MNEs that choose to enter each destination would vary across n, and thus it would be captured by the country fixed effect $\mathbb{A}_{n}^{j}$.

To assess the severity of this potential bias, we follow the literature on two-way matching (Abowd, Kramarz, and Margolis 1999) and analyze the residuals from estimating our baseline specification in equation (19) by OLS (e.g., Card, Heining, and Kline 2013). 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 (see also app. D for a formal argument).

We evaluate this implication in figure 7*A*, which plots the mean standardized residuals, $\hat{\epsilon}_{in}^{j}(\omega) = (s_{in}^{j}(\omega) - \hat{s}_{in}^{j}(\omega))/\sigma_s$, 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

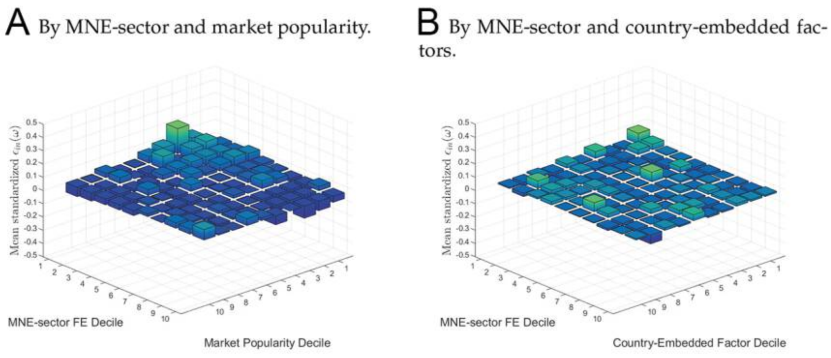

FIG. 7.—OLS residuals. Deciles are calculated within sectors. "Market popularity" refers to the number of foreign MNEs in a country-sector pair, from OECD/Eurostat. "Country-embedded factors" refers to estimates of $\tilde{Z}_{n}^{j}$.

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, indicating that technology transfer costs do not vary systematically across MNEs and locations in those bins.

With this concern in mind, we proceed to reestimate equation (19) using alternative subsamples, restricted to exclude the MNEs at the extremes of the market-share distribution. Concretely, we restrict the sample to subsets of MNEs that lie within the second to ninth, third to eighth, fourth to seventh, or fifth and sixth deciles of the MNE-sector fixed effect distribution for each sector. Alternatively, we also apply our estimation procedure to subsamples of MNEs that operate in at least three, five, 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.

TABLE 4
Contribution of Firm-Embedded Productivity, Restricted Samples

	$\mathrm{cov}(\Delta y_n,\ \Delta\tilde{\phi}_n)/\mathrm{var}(\Delta y_n)$
Baseline	.34
	(.10)
Keeping MNEs with MNE-sector fixed effects belonging to:	
2nd to 9th decile	.32
	(.10)
3rd to 8th decile	.31
	(.11)
4th to 7th decile	.31
	(.11)
5th to 6th decile	.37
	(.12)
Keeping MNEs operating in:	
At least 3 countries	.32
	(.10)
At least 5 countries	.28
	(.08)
At least 10 countries	.32
	(.08)

Note.—Slopes of a bivariate OLS regression of $\Delta\tilde{\phi}_n$ on Δy_n. MNE-sector fixed effects, for each sector, are estimated using eq. (26) by OLS. Standard errors are shown in parentheses.

C. Assumptions on the Production Function

A related concern with our baseline estimation refers to the separability between firm-embedded productivity and country-embedded factors. Our model assumes a production function that is log linear in firm-embedded productivity and country-embedded factors. This separability is inherited by the aggregate production function, which is linear in $\tilde{z}_n$ and $\tilde{\phi}_n$. But if, for instance, high-productivity MNEs do relatively better in countries with high country-embedded factors, the assumption would no longer hold and our procedure would underestimate market shares for high-productivity MNEs in those markets.

We evaluate this implication in figure 7*B*, which plots the mean standardized residuals, $\hat{\epsilon}^j_{in}(\omega) = (s^j_{in}(\omega) - \hat{s}^j_{in}(\omega))/\sigma_s$, 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, indicating that the log-linearity assumption is not systematically violated in those bins. Table 4 shows that the contribution of firm-embedded productivity to the cross-country variance in output per worker is very similar when estimated in subsamples of MNEs that are not at the extremes of the fixed effect distribution.

An alternative approach to assess the additive separability assumption on the production function is to group destination countries using *k*-means clustering based on the distribution of affiliates' market shares (Bonhomme, Lamadon, and Manresa 2019). Based on this approach, appendix C presents additional tests that support our linearity assumption.

D. Trade in Intermediate Goods and Export Platforms

An important simplifying assumption of our framework is that there is no trade in intermediate goods. This ensures that MNE affiliates sell only in the markets where they produce and that their market shares are given by equation (7). In practice, an MNE market share in a location can be large if the MNE uses that location to serve additional locations through export platforms. In appendix F, we extend our framework to allow for trade in intermediate goods and export platforms. The appendix shows how one could still estimate cross-country differences in firm-embedded productivity by focusing on MNE shares on domestic (nonexport) revenues. Unfortunately, ORBIS reports export data for a very limited number of firms in the manufacturing sector. Despite this limitation, figure F.1 shows that, for the few countries where those data are available, the export-corrected estimates of firm-embedded productivity are close to our baseline estimates.

To understand this result, we note that the difference between an MNE share in total revenues (used for our baseline estimation) and the MNE share in domestic revenues (the appropriate statistic in the model with trade) depends on the MNE export intensity relative to the export intensity of all firms in the economy; if all firms export the same fraction of their revenues, total and domestic revenue shares coincide. The appendix shows that the bias that arises from using total revenue shares is proportional to the difference between the ratio of exports to revenues for the average MNE affiliate in the destination and the ratio of total export to total revenues in that same destination. Table F.1 uses data from the OECD to compare aggregate export shares for foreign MNEs with the economy-wide export shares, for seven countries for which these data are available. The table shows that while the affiliates of foreign MNEs do get a larger share of their revenues from exports than other firms, the difference is quantitatively small relative to the observed differences in MNE market shares across countries. For instance, the fact that foreign MNE affiliates export a relatively large part of their output makes the market share of MNE affiliates located in Estonia 12% larger than the market share of MNE affiliates located in Italy. The appendix shows that this difference is two orders of magnitude too small to account for the fact that foreign MNEs in Estonia have a market share that is 13 times larger than in Italy, as shown in figure 1.

E. Variable Markups and Other Output Distortions

Equation (7) relies on the assumption that the allocation of resources across firms is efficient. Appendix E extends our framework to allow for variable markups and other output distortions across firms. In such case, an MNE would have a relatively low market share in a destination if its productivity is low relative to the aggregate firm-embedded productivity in the destination or if its markup (i.e., the distortion) is high relative to the average markup in the destination. If, as documented by Bento and Restuccia (2017) and Fattal-Jaef (2022), size-dependent distortions are more prevalent in less developed countries—for example, when larger firms are taxed more or have higher markups in developing countries—these distortions would push *down* MNE market shares in those countries. The appendix shows that in this case our procedure would underestimate the contribution of firm-embedded productivity to cross-country income differences.

F. Additional Robustness Exercises

This section briefly describes additional robustness exercises, which are collected in table 5. First, we use additional controls for the bilateral component of MNE costs in equation (18), B_{in}^{j}. In particular, we add bilateral

TABLE 5
Contribution of Firm-Embedded Productivity, Additional Robustness

	$\text{cov}(\Delta y_n, \Delta\tilde{\phi}_n)/\text{var}(\Delta y_n)$
Baseline	.34
	(.10)
Controlling for bilateral MNE-specific tax rates	.34
	(.10)
Controlling for bilateral tax treaties	.35
	(.10)
Controlling for differences in GDP per worker between source and host country	.34
	(.10)
Excluding gravity variables	.29
	(.11)
Aggregation at four-digit NAICS industries	.38
	(.11)
Excluding real estate, health, and education	.32
	(.10)
Excluding MNEs that do not appear in ORBIS every year between 2010 and 2016	.39
	(.09)
Excluding MNE affiliates incorporated after 2006	.33
	(.09)

Note.—Slopes of a bivariate OLS regression of $\Delta\tilde{\phi}_n$ on Δy_n. Bilateral tax treaty data come from the United Nations Conference on Trade and Development International Investment Agreements. Standard errors are shown in parentheses.

MNE-specific taxes, which we compute using data from several sources (for details, see app. B). Alternatively, we include an indicator variable for the existence of a bilateral tax treaty between the source and host country, which allow foreign-owned subsidiaries to avoid or mitigate double taxation. Additionally, we control for the difference between the output per worker of the source and the host country, and finally we repeat our analysis without any gravity control.

In an additional robustness exercise, we consider sectors at the four-digit (rather than two-digit) NAICS classification (336 sectors). Alternatively, we exclude the health, education, and real estate sectors from our sample, as the government has a large participation in these sectors for some countries in our sample. Finally, 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 the highest quality (see table A.4 for results by year). We also repeat our analysis restricting our sample to firms incorporated after 2005—so that they were at least 11 years old by 2016—to mitigate concerns about MNE affiliates having small market shares right after entry.[23] The results of our decomposition for all these alternative specifications are remarkably close to our baseline result.

[23] Existing evidence shows that such dynamics are not quantitatively important in the data: Garetto, Oldenski, and Ramondo (2019) show that affiliate sales relative to parent sales are roughly constant over the affiliate life.

VI. A General Equilibrium Model of MNE Location Decisions

This section closes the model presented in section II by explicitly modeling MNE location choices. We use this model to quantify the output gains from eliminating barriers to the mobility of MNEs and emphasize how our estimates from section IV discipline this quantification. In what follows, we reproduce the main equations of the analysis and relegate details to appendix D.

A. *Modeling MNE Location Decisions*

We close the model by assuming that there is an exogenous measure of firms in each country and sector, M_i^j, and that the productivity embedded in those firms $A(\omega)$ is Pareto distributed with shape $\gamma \geq 1$ and scale $B_i^j \geq 1$.[24] We also assume that all firms must pay a fixed cost of $f^j \theta_n^j H_n$ units of country n's labor to operate in market n and sector j.[25] MNEs operating in a foreign country must also pay a fixed cost of f_{in}^j units of country n's labor, with $f_{nn}^j = 0$. Firms choose to operate in markets where their (gross) profits exceed these fixed costs. This implies a firm-embedded productivity cutoff for operating in country n given by

$$\bar{A}_{in}^j = \frac{W_n}{R_n^j} \tau_{in}^j \left[f^j \theta_n^j H_n + f_{in}^j \right] \rho \Phi_n^j, \tag{32}$$

where W_n and R_n^j respectively denote the wage and aggregate revenues in country n and sector j and $\tau_{in}^j \equiv \exp(\kappa_{in}^j)$.

Let $\Phi_{in}^j \equiv \int_{\omega \in \Omega_{in}} A_{in}^j(\omega)\, d\omega$ denote the aggregate-firm-embedded productivity of the firms from country i that operate in country n and sector j. Using the cutoff rule and the distributional assumption for productivity, we can write

$$\Phi_{in}^j = T_i^j \left[\tau_{in}^j \right]^{-\gamma} \left[1 + \frac{f_{in}^j}{\theta_n^j H_n} \right]^{1-\gamma} \left[\Phi_n^j \right]^{1-\gamma}, \tag{33}$$

where $T_i^j \propto B_i^j \times M_i^j$ is a technology parameter for country i that summarizes the quantity and the quality of its local firms. Equation (33) shows that Φ_{in}^j is large if country i's technology is very productive (high T_i^j) or if firms from country i face a low cost of entering country n (low f_{in}^j and τ_{in}^j).

[24] Given that $A(\omega) = [X(\omega) \times Q(\omega)]^{\rho-1}$, this corresponds to assuming that $X(\omega)$ and $Q(\omega)$ are Pareto distributed with scale parameter $\gamma[\rho - 1]$. Thus, the shape parameter γ determines the firm-size distribution.

[25] The assumption that the fixed cost scales with the employment in the country-sector guarantees that MNEs operate in every country when all barriers to the MNE mobility are eliminated.

We can then express the equilibrium level of firm-embedded productivity as a function of the model's parameters:

$$\tilde{\Phi}_n^j = \left[\sum_i \Phi_{in}^j\right]^{\beta} = \left[\sum_i T_i^j \left[\tau_{in}^j\right]^{-\gamma}\left[1 + \frac{f_{in}^j}{\theta_n^j H_n}\right]^{1-\gamma}\right]^{\beta/\gamma}. \tag{34}$$

Finally, using equations (26) and (33), we can relate firm-embedded productivity to the aggregate revenue share of domestic firms in local revenues:

$$\tilde{\Phi}_n^j = \left[\frac{T_n^j}{S_{nn}^j}\right]^{\beta/\gamma}. \tag{35}$$

Equation (35) is standard in the class of models of international trade and MNEs analyzed by Arkolakis, Costinot, and Rodrìguez-Clare (2012). The equation relates aggregate productivity in country n to the primitive technology parameter T_n^j, the observed domestic share S_{nn}^j, and the elasticity β/γ. However, papers in this tradition do not typically distinguish between firm- and country-embedded productivity and interpret the left-hand side of equation (35) as a country's TFP. In contrast, it is clear from our setting that the left-hand side of equation (35) corresponds to only the part of TFP that is firm embedded. As we see below, this distinction has important implications when quantifying the gains from eliminating barriers to the mobility of MNEs.

B. *Gains from Eliminating Barriers to MNE Mobility*

We now evaluate the output gains from eliminating all barriers to MNE mobility across countries. We compare steady-state equilibria in a world economy where human capital and capital-output ratios are independent of productivity.[26] Formally, using the superscript F to denote values in the new equilibrium, we set $\tau_{in}^{jF} = 1$ and $f_{in}^{jF} = 0$ for all n and j. Under these assumptions, we can write the change in output per worker between the two equilibria as

$$\hat{Y}_n \equiv \frac{Y_n^F}{Y_n} = \frac{\tilde{\Phi}_n^F}{\tilde{\Phi}_n} = \prod_j \left[\frac{\left(\sum_i T_i^j\right)^{\beta/\gamma}}{\tilde{\Phi}_n^j}\right]^{\theta_n^j}, \tag{36}$$

where the last equality follows from evaluating equation (33) at the new equilibrium, the definition of $\tilde{\Phi}_n$, and equation (14). The equation shows

[26] These assumptions are common properties of neoclassical growth models and imply that country-embedded factors are constant across steady states.

that the gains from eliminating barriers to MNE mobility are determined by the technology parameter's T_i^j. Using equation (35), we can write these parameters in terms of observables and obtain

$$\hat{Y}_n = \prod_j \left[\sum_i \left[\frac{\tilde{\Phi}_i^j}{\tilde{\Phi}_n^j} \right]^{\gamma/\beta} S_{ii}^j \right]^{\theta_n^j(\beta/\gamma)}. \tag{37}$$

Equation (37) highlights how the gains from eliminating barriers to MNE mobility depend on the inferred differences in firm-embedded productivities, $\tilde{\Phi}_i^j/\tilde{\Phi}_n^j$. If we assume that all differences in output per worker are driven by differences in firm-embedded productivities, then $[Y_i^j/L_i^j]/[Y_n^j/L_n^j] = \tilde{\Phi}_i^j/\tilde{\Phi}_n^j$ and the counterfactual change in output per worker is given by

$$\hat{Y}_n^{\mathrm{FEP}} = \prod_j \left[\sum_i \left[\frac{Y_i^j/L_i^j}{Y_n^j/L_n^j} \right]^{\gamma/\beta} S_{ii}^j \right]^{\theta_n^j(\beta/\gamma)}. \tag{38}$$

In contrast, if we assume that there are no cross-country differences in firm-embedded productivities, $\tilde{\Phi}_i^j = \tilde{\Phi}_n^j$ and we obtain

$$\hat{Y}_n^{\mathrm{CEF}} = \prod_j \left[\sum_i S_{ii}^j \right]^{\theta_n^j(\beta/\gamma)}. \tag{39}$$

Next, we quantify and compare the gains from eliminating barriers to MNE mobility implied by equations (37), (38), and (39).

C. Calibration and Results

This section evaluates equations (37), (38), and (39) by considering a world economy comprising the countries in our sample from section III. Our data sources for sectoral output per worker y_i^j, sectoral domestic revenue shares S_{ii}^j, and sectoral shares θ_n^j are described in section III. We use our estimates of $\Delta\tilde{\phi}_n^j$ and β from section IV to evaluate equation (37). Finally, we set $\gamma = 1.2$ to match the right-tail coefficient of the firm-size distribution, following Atkeson and Burstein (2010).

Figure 8 shows the results. The figure shows that the size of the gains from eliminating barriers to MNE mobility depends on whether we calibrate the model assuming that observed differences in output per worker are due to firm- or country-embedded factors. If we assume that all initial differences in output per worker are driven by country-embedded factors and use equation (39), gains are roughly the same across all countries (0.92; squares). Intuitively, in this scenario, all countries start and also end up with the same firm-embedded productivity—since with no

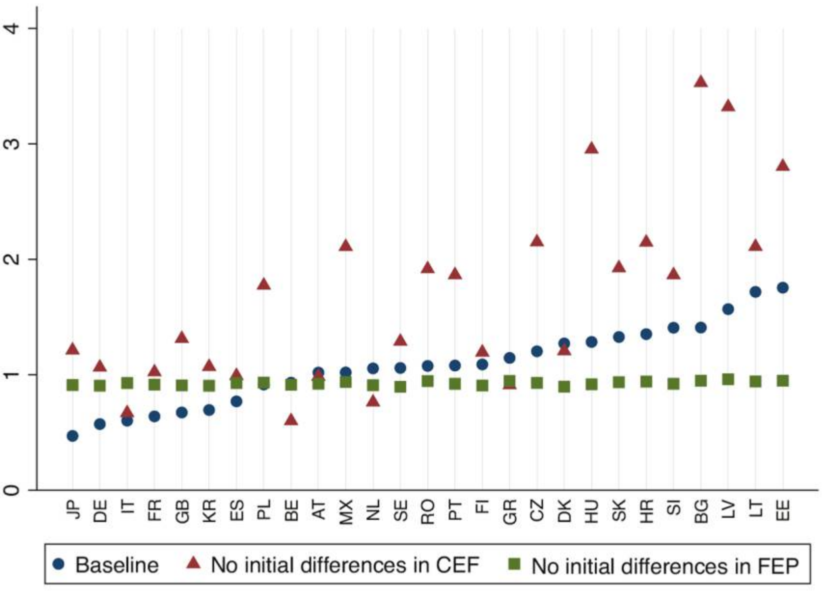

FIG. 8.—Output gains from eliminating barriers to MNE mobility. "Baseline" is calculated from equation (37) and refers to a counterfactual that uses our baseline estimates for cross-country differences in firm-embedded productivity. "No initial differences in CEF" is calculated from equation (38) and refers to a counterfactual that assumes that there are no cross-country differences in country-embedded factors and that all differences in output per worker in the initial equilibrium are due to differences in firm-embedded productivity. "No initial differences in FEP" is calculated from equation (39) and refers to a counterfactual that assumes that there are no cross-country differences in firm-embedded productivity and that all differences in output per worker in the initial equilibrium are due to differences in country-embedded factors.

barriers to MNE mobility the same firms operate in all locations.[27] In contrast, the gains vary enormously across countries and are on average much higher (1.65; triangles) if we use equation (38) and assume that all initial differences in output per worker are driven by differences in firm-embedded productivity. In this case, the gains are larger for poorer countries that integrate with countries that have better firms.[28] Finally, our baseline estimates imply gains that are between these two extremes, with the average country more than doubling output per worker (filled circles) and with the largest gains going to the countries with the lowest firm-embedded productivity.

[27] The gains are not exactly the same for all countries since eq. (39) weights sectors using country-specific weights, θ_n^j.

[28] The gains are also larger on average since the additional term in eq. (38), $[Y_i^j/L_i^j]^{\gamma/\beta}$, is convex.

VII. Conclusion

This paper measures cross-country differences in firm-embedded productivity and their contribution to cross-country income differences. 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, 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 a development accounting framework and measure firm-embedded productivity using firm-level revenue data on MNEs that produce in multiple countries.

Our results indicate that cross-country differences in firm-embedded productivity are large, accounting for roughly one-third of the observed differences in output per worker across the countries in our sample. This suggests that policies that help poor countries catch up in terms of firm-embedded productivity, such as eliminating barriers to firm mobility across countries, can play an important role in eliminating cross-country income differences.

While our sample of developing countries is limited, our new procedure can easily be applied to more countries as new affiliate-parent matched data become available. In addition, if affiliate-parent matched data could be linked to firm-level measures of physical productivity, the logic of our procedure could be applied under more general assumptions on the firm's revenue function. The key insight of our procedure is that by observing the same firm operating in many countries, it is possible to disentangle the firm-embedded from the country-embedded components of productivity.

Data and Code Availability

The code and information about the proprietary data used in this paper as well as the code replicating the tables and figures in this paper can be found in the Harvard Dataverse, https://doi.org/10.7910/DVN/MV1KTF (Alviarez, Cravino, and Ramondo 2023).

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