Factor-biased Multinational Production

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Abstract

The standard model of multinational production assumes that firms differ in Hicks-neutral productivities and ignores differences in factor biases. Using a large firm-level dataset, I show that multinational firms differ from local firms in factor biases along two key dimensions. First, multinational firms are on average larger firms and larger firms on average use more capital-intensive technologies. Second, multinational firms from more capital-abundant home countries choose more capital-intensive technologies. I develop a quantitative framework for modeling factor-biased multinational production that incorporates these two features. The model highlights a new channel through which globalization affects the income distribution between capital and labor: liberalizing multinational production reallocates factors across firms with different factor biases and thus changes the aggregate demand for capital relative to labor. Calibrating the model to both firm-level and aggregate moments for 37 countries, I find that in the past decade, the increase in multinational activity explains 60 percent of the average decline in the labor share. Moreover, the model predicts that countries with a larger increase in multinational activity experience a larger decline in their labor share as observed in the data.

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1 Introduction

Multinational firms have been playing an increasingly prominent role in the global economy. The ratio of multinational sales to world GDP increased from 23 percent in 1990 to 54 percent in 2008[1]. Policy makers worldwide, especially those in developing countries, are interested in attracting more multinational production (MP) since multinational firms use more advanced production technologies and might benefit the host countries in various ways (Javorcik (2004), Harrison and Rodríguez-Clare (2010)). Following this line of thinking, the new generation of quantitative models of MP focuses on the transfer of technologies with different Hicks-neutral productivities through multinational activities (e.g., Arkolakis et al. (2013), Tintelnot (2014)). However, as I show in the data, multinational firms use technologies that are also different in terms of their factor bias, which has received little attention in previous works.

To examine the implication of factor-biased multinational production on aggregate outcomes, I document two empirical regularities about the capital-labor ratio of firms in 24 countries, including multinationals and local firms. First, larger firms use more capital-intensive technologies, which I refer to as the "size effect". Second, within the same country of production and same industry, firms originating from capital-abundant countries use more capital-intensive technologies, which I refer to as the "technology origin effect". Multinational firms can bring technologies of different factor biases into the host countries either because they are larger firms that use more capital-intensive production techniques, or because their technologies originate in countries with different capital abundance.

Building on the size and technology origin effects, I develop a quantitative framework for modeling factor biased multinational production that incorporates these two features. To match the size effect, I assume that overall more efficient technologies use relatively more capital, a form of capital-technology complementarity. To match the technology origin effect, I allow the firm to choose the direction of the factor biases of their technologies (capital- v.s. labor-intensive) before they decide to become multinationals. Beyond the micro-structure that generates heterogeneity in firms' capital intensities, the model nests the multinational production model by Arkolakis et al. (2013) as a special case and is rich enough to match aggregate statistics such as bilateral MP and trade shares. Therefore, the model can be disciplined by both firm-level and aggregate moments, and provides a framework to study the aggregate impact of factor-biased MP, especially its impact on

[1] Author's calculation based on numbers in Table I.5, UNCTAD (2011).

factor prices and income shares.

The model has rich implications for understanding the distributional consequences of MP liberalization, both theoretically and quantitatively. After a reduction in inward MP frictions, the size effect reduces the relative demand for labor (thus the equilibrium labor shares), because MP crowds out small and labor-intensive firms and reallocates factors towards large and capital-intensive firms. The technology origin effect leads to a change in the relative demand for capital, because multinational firms originating from countries with a different endowment structure use inherently different technologies in terms of capital intensity. Theoretically, the technology origin effect tends to reduce the labor shares in capital-scarce countries while increase the labor shares in capital-abundant ones. Quantitatively, since most multinational production originates from capital-abundant countries, it has a larger impact on the labor shares in the capital-scarce host countries because of the technology origin effect.

To understand how MP liberalization has impacted the labor shares in recent years, I parameterize a 37-country version of the model to exactly match, among other moments of the data, the size and technology origin effects in the micro data and the bilateral MP and trade shares in 1996-2001. Though the model does not directly target the factor prices in each country, it captures the cross-country variation in these prices well. With the calibrated model, I then perform counterfactual analyses to study the effect of the reduction in MP frictions from 1996-2001 to a later period, 2006-2011. Over the decade, many countries in my sample, especially the less-developed Eastern European countries, saw large increases in inward multinational activities. Associated with the influx of multinational activities, the average country's labor share declined by 1.3 percentage points, which explains about 60 percent of the average decline of labor shares in the data. At the same time, the model captures some of variation of labor share decline across countries. The predicted and realized changes in labor shares are positively correlated and the model replicates a negative correlation between changes in the labor shares and changes in the output shares by foreign affiliates in the data.[2]

My paper contributes to a large literature on international technology diffusion through multinational production. (Burstein and Monge-Naranjo (2009), Ramondo and Rodríguez-Clare (2013), Arkolakis et al. (2013), Tintelnot (2014), Bilir and Morales (2016)) In these papers, technologies are modeled as Hicks-neutral productivities which can be transferred

[2]In the special case of my model with no heterogeneity in firms' factor biases and no factor mobility across countries, liberalizing multinational production has *no* impact on the labor shares in each country.

to production locations beyond the home country. This paper differs from the previous literature by introducing factor biases as an additional dimension of the technology. Since foreign affiliates' technologies have different factor bias than the technologies used by the local firms, MP not only impacts the efficiency of production, but also alters the relative demand for factors, thus the income shares.

The size effect is closely related to the literature on "factor-biased productivities". In a recent paper, Burstein and Vogel (2015) point out that trade liberalization leads to an increase in skill-premium, because more productive firms are more skill intensive (technology-skill complementarity) and trade reallocates factors towards more productive firms within sectors, which they refer to as the "skill-biased productivity" mechanism. Similarly, I introduce technology-capital complementarity to match the size effect on capital intensity. Though it is well known that larger firms are more capital intensive (see Oi and Idson (1999), Bernard et al. (2007)), previous research has not considered its implication in a setting of global firms. I embed this mechanism into a multi-country, general equilibrium MP model and quantify its importance in understanding the distributional consequences of globalization.

The technology origin effect, on the other hand, contributes to both the recent literature on directed technical change (Acemoglu (2003b); Acemoglu (2003a); Acemoglu et al. (2012)) and an earlier empirical literature on "inappropriate technology" (Mason (1973), Morley and Smith (1977)), which tries to test whether multinational firms from advanced countries are using "inappropriately" capital-intensive production technologies in the developing countries. The key insight from the two strands of literature is that technologies cater to the factor prices in the country where they are most likely to be applied. As a theoretical contribution, I embed the idea of endogenous technology choice in a quantitative model of multinational production and prove the existence of technology origin effect in a two-region special case. On the empirical front, comparing to the case studies in the 1970s, I use comprehensive micro data and modern econometric techniques to quantify the technology origin effect.[3]

The counterfactual analyses show MP liberalization is crucial in understanding the global decline of labor shares. The literature has documented a global decline in labor shares in the past three decades and various mechanisms have been proposed to explain

[3]A notable exception is Li (2010). The author shows that in China, multinational affiliates that come from developed countries are more skill-biased than affiliates from Hong Kong, Taiwan and Macau.

the trend.[4] The two main candidate explanations are the decline in the prices of investment goods (Karabarbounis and Neiman (2014)) and capital-biased technical change. As Oberfield and Raval (2014) point out, mechanisms that work solely through factor prices cannot account for the labor share's decline if the elasticity of substitution between capital and labor is below one, as they estimate using plant-level data. According to their analysis for US manufacturing sector since 1970, the bias of technical change within industries has increased and accounts for most of the decline in the labor share. The direction of technology change in their analysis, however, is treated as a residual term that captures whatever cannot be explained by the factor prices and industry compositions. In contrast, my paper focuses on how globalization leads to capital-biased technical change. The quantitative analysis reveals that the increase in factor-biased multinational production is important in understanding the direction of technical change in the host countries.

The predictions from the quantitative model are quite different from an old literature on capital flows and income distribution (see Caves (2007) for a summary). That literature views MP as a reallocation of capital: a net outflow of capital can cause a relative increase of capital rewards in the country of study, and vice versa for net inflows. In contrast, I view MP as a technology transfer that is not necessarily associated with capital flows. When heterogeneity in factor bias is incorporated, MP can lead to changes in the labor shares without net flows of capital. This also shows the importance of using information on bilateral MP sales rather than the net flow of capital to predict the effect of MP on income distribution.

My paper also contributes to a small but growing literature on firm's heterogeneity in input usage. Following the seminal work of Melitz (2003), the literature has focused mostly on firms' heterogeneity in their Hicks-neutral productivities. The recent literature has acknowledged firms' heterogeneity in other dimensions such as input usage.[5] I show that a firm's capital intensity is systematically correlated with its own size and its home country's capital abundance. The quantitative model rationalizes both empirical regularities and can be used to understand the distributional consequences of MP. Of course, multinational firms may differ from domestic firms in their relative usage of other inputs, such as skilled labor, which my data unfortunately cannot speak to. However, my quantitative framework can

[4]See Karabarbounis and Neiman (2014), Piketty (2014) and Elsby et al. (2013).

[5]See, for example, Crozet and Trionfetti (2013), Blaum et al. (2015) and Burstein and Vogel (2015). Meanwhile, a different but related literature tries to empirically estimate factor-augmenting productivities using techniques developed by Olley and Pakes (1996). See Doraszelski and Jaumandreu (2015) and Hongsong Zhang (2015) for example.

be used to analyze the impact of MP on the skill premium when data permits.

The remainder of the paper is organized as follows. In Section 2, I document two empirical regularities. I develop the quantitative framework for modelling factor-biased MP in the next section. I then calibrate the model and perform counterfactual analysis in sections 4 and 5. I conclude in Section 6. Proofs and additional results are relegated to the online appendix.

2 Empirical Regularities

In this section, I explore the determinants of firms' capital intensities using the Orbis database which covers firms, including multinationals, from many countries. I document two empirical regularities focusing on firms within a narrowly-defined industry. First, larger firms are more capital intensive, which I refer to as the "size effects". Second, firms' capital intensities are positively correlated with their home countries' capital abundance, which I refer to as the "technology origin effect".

2.1 Firm-level Data

To explore the determinants of firm's capital intensity, I use Orbis, the global firm level database maintained by Bureau van Dijk (BvD). The database covers balance sheet and income statement information for millions of firms all around the world. Moreover, it provides a unique opportunity to examine multinational firms' capital intensity since BvD records ownership links between firms and identifies the "Global Ultimate Owner" (GUO) of a firm when there is sufficient information to construct the "ownership tree" of the firm. The database provides ownership linkages that are updated in 2013. In the analysis, I focus on balance sheet data in 2012, the most recent year of data at the time of study, to minimize measurement errors in ownership linkages.

Before any statistical analysis, I clean the data in several steps to (1) exclude firms with missing or abnormal values in total assets, employment and wage bill (2) exclude multinational affiliates located in or originating from tax havens (3) drop host-country-industry cells and home countries with too few observations. The detailed steps are described in the appendix.

The data cleaning procedures leave me with more than 2.6 million firms from 23 host and 24 home countries. I identify a multinational foreign affiliate if the nationality of the firm's GUO is different from where the firm operates.[6] Among the 2.6 million firms, about 40,000 are multinational foreign affiliates while approximately 20,000 are multinational firms' subsidiaries in their home countries. As expected, large and developed countries such as the United States and Germany are home to a large number of multinational affiliates. Nevertheless, the data also includes multinationals from less-developed countries such as Romania, Bulgaria and the Czech Republic. Detailed industry codes (440 four-digit industries) allow me to focus on variation within narrowly-defined industries. Together with firms operating only domestically, the dataset provides a good opportunity to explore the heterogeneity in capital intensity, especially that of multinational firms.

2.2 Size Effect

In this subsection, I document a positive correlation between firm's size and its capital-labor ratio, which is consistent with the consensus in the literature (Oi and Idson (1999); Bernard et al. (2007)). In Table 1, I estimate the elasticity of firm's capital-labor ratio with respect to its size, measured by revenue. To construct the capital-labor ratio, I use the firm's wage bill instead of the number of employees, to control for worker skill differences across firms. [7] I use revenue as a measure of firm size because measures such as assets and wage bills are used to calculate the left-hand variable and measurement errors can cause mechanical correlations if either is used on the right hand side. In all regressions I control for technological differences across industries and factor price differences across producing countries using fixed effects. Columns 1-3 show that the elasticity is positive for non-multinational firms, multinational firms and all firms, respectively. Despite different definitions of the samples, all three regressions give similar estimates, typically between 0.05 and 0.07.

There might be two reasons why large firms are more capital-intensive. First, capital may be complementary with more advanced technologies, therefore large firms demand relatively more capital when facing the same factor prices. Second, large firms may have better access to the capital markets and thus can finance larger investments. Since columns 1-3 already control for country fixed effects, the size effect cannot be explained by differences in financial development across producing countries. In columns 4-6, I further control for

[6]I define the "home" country of a multinational affiliate to be the country of its GUO and the home country of a firm not belonging to any multinational group to simply be where it operates.

[7]For the practice of using the wage bill to measure the efficiency units of labor, see, for example, Hsieh and Klenow (2009).

Table 1: Estimate the size effect for different samples

	Dependent Var: log(total assets/wage bill)					
	Local	MNE	All	Local	MNE	All
	(1)	(2)	(3)	(4)	(5)	(6)
log(Revenue)	0.0706*	0.0529***	0.0698**	0.0421+	0.0434***	0.0429*
	(0.0276)	(0.00957)	(0.0262)	(0.0222)	(0.0105)	(0.0209)
debt-equity ratio				0.00382**	0.00364***	0.00383**
				(0.00123)	(0.000594)	(0.00120)
N	2,746,000	60,000	2,807,000	1,967,000	46,000	2,014,000
R-squared	0.374	0.464	0.374	0.396	0.476	0.396

Dependent variable is log of total asset divided by wage bill. Sample "All" refers to all firms, "Local" refers to firms with no foreign affiliates or parents, while "MNE" refers to firms with at least one foreign affiliate or a foreign parent. All regressions control host-country-industry fixed effects. Standard errors are clustered at host country * industry and home country levels. + 0.10 * 0.05 ** 0.01 *** 0.001. Number of observations is rounded to thousands of firms.

firms' leverage ratios so that I can compare firms with similar access to the financial markets even within a producing country. The coefficients before firms' revenue become slightly smaller but still significantly positive. This leaves capital-technology complementarity as a good candidate to explain the correlation between firm size and capital intensity.

2.3 Technology Origin Effect

The second empirical regularity reveals that firms originating from capital-abundant countries use more capital-intensive production technologies than firms from capital-scarce countries, which I refer to as the "technology origin effect". Somewhat less known, the idea dates back to an old literature on "inappropriate technology". Since Eckaus (1955), development economists are concerned that technologies developed in the capital-abundant countries are "inappropriate" in the capital-scarce developing world and can cause "underemployment problems". A few studies in the 1970s tried to uncover evidence using data on multinational firms and local firms. They aimed to test whether multinational affiliates from rich countries can completely adjust their production to be as labor-intensive as the local firms in the developing countries or their production is still more capital-intensive than that of local firms. As long as multinational affiliates and comparable local firms on average face the same factor prices and the production function is homothetic, the discrepancy in their capital-labor ratios points to technological differences. However, due to a lack of large firm-level datasets, the literature turned to case studies with a few dozens of firms, and no consensus emerged whether multinational firms use different technologies than the local firms (Mason (1973), Morley and Smith (1977)).

Equipped with the Orbis dataset spanning multiple home and host countries, I re-examine this idea and estimate the impact of home country endowment on the firms' capital-labor ratios, conditional on producing in the same country and industry. In particular, I run the following regression

$$\log\left(\frac{K_f}{wL_f}\right) = \delta_{s(f)\times l(f)} + \beta \log\left(\frac{K_{i(f)}}{L_{i(f)}}\right) + X_f + \varepsilon_f,$$

where f refers to an independent local firm or a multinational affiliate, $s(f)$, $l(f)$ and $i(f)$ are the sector, producing country and home country of the firm. For an independent local firm, its home country $i(f)$ is defined to be the same as its producing country $l(f)$. To measure labor input, I again use the total wage bill wL_f for reasons discussed in the previous subsection. The country-by-industry fixed effects $\delta_{s(f)\times l(f)}$ control for technological differences across sectors and potential substitution between capital and labor when facing different factor prices in different producing countries. The key independent variable is the ratio of capital stock to human capital in the home country, $K_{i(f)}/L_{i(f)}$, a measure of capital abundance.[8] My hypothesis is that firms from more capital-abundant countries are more capital-intensive, i.e., β is significantly positive.[9]

Table 2 shows the technology origin effect estimated using a variety of samples and specifications. The baseline specification of column 1 shows that an elasticity of firms' capital intensity with respect to its home country's capital abundance of 0.233, with a standard error of 0.046.[10] To get a sense of the magnitude of the coefficient, one can compare firms from the US with firms from Hungary, a country with only half of the US capital abundance (measured in $K_{i(f)}/L_{i(f)}$). Comparing firms from the two countries produce in the same industry in Hungary, the estimated technology origin effect implies a 16% difference in capital-labor ratio in their production. Suppose factor prices in Hungary are fixed but one makes all Hungarian firms adopt the US technologies, the demand for

[8]Human capital is the product of average human capital and total employment, both obtained from Penn World Table 8.0. A detailed description of the aggregate data used in the paper can be found in the appendix.

[9]The identification of the technology origin effect relies on the inclusion of multinational firms in the regression. Since the "home country" $i(f)$ of a local independent firm is defined to be the same as its producing country $l(f)$, the country-by-industry fixed effects will completely absorb the variation in $\log(K_{i(f)}/L_{i(f)})$ and β is not identified for local firms only.

[10]To address potential correlation of the error term among firms from the same home or host country, I cluster the standard errors at both the home and host country level.

Table 2: Technology Origin Effect on $log(K/wL)$

	Dependent Var: log(total assets/wage bill)					
	All	MNE	All	MNE	All	MNE
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(K_i/L_i)$	0.233***	0.268**	0.164*	0.249*	0.163**	0.289*
	(0.0644)	(0.102)	(0.0806)	(0.113)	(0.0610)	(0.118)
log(Revenue)			0.0696**	0.0523***	0.0427*	0.0429***
			(0.0263)	(0.00934)	(0.0210)	(0.0102)
leverage ratio					0.00383**	0.00374***
					(0.00120)	(0.000604)
# of host * industry	8169	4624	7973	4483	7495	3848
# of home countries	24	24	24	24	24	24
# of foreign links	39,000	39,000	37,000	37,000	28,000	28,000
R-squared	0.312	0.407	0.321	0.414	0.344	0.431
N	2,957,000	63,000	2,807,000	60,000	2,014,000	46,000

All specifications regress log of firms' capital intensity (defined as total assets divided by total wage bill) on home country endowment (log of capital stock divided by efficiency units of labor) and firm level characteristics conditional on host country × NACE 4-digit industry fixed effects. Sample "All" refers to all firms including local firms and multinational subsidiaries sample "MNE" refers to multinational subsidiaries. Standard errors are clustered at both home country and host country * industry levels. + 0.10 * 0.05 ** 0.01 *** 0.001. Number of observations is rounded to thousands of firms.

capital relative to labor will increase by 16%, which is economically significant given the aggregate capita-labor ratio is only 100% larger in the US than in Hungary.

In columns 2-4, I show the results are not simply driven by the interaction between size effects and different sources of selection. Since larger firms are more capital intensive, the technology origin effect in column 1 could be over-estimated if either (1) the barrier to invest in foreign countries are larger for multinational firms from capital-abundant countries so they are a more selected group of firms or (2) Orbis disproportionately covers large firms and the coverage is more biased for firms from capital-abundant countries. Column 2 focuses on multinational affiliates, a more homogeneous group of firms in terms of firm sizes and productivities but only finds a coefficient slightly larger than that in column 1. In columns 3 and 4, I directly control for the revenue of the firm. As expected, the coefficient before firm size is positive and significant. However, controlling for the size effect does not mitigate the technology origin effect, which suggests the latter is not simply driven by the potential selection biases discussed above.

A crucial assumption for the identification is that, conditional on being in the same producing country and industry, the relative prices faced by the firms are not correlated with their home countries' capital abundance. Previous research suggests that multinational affiliates finance their capital using both local and parent firms' funds (Desai et al. (2004), Antràs et al. (2009)). If multinational firms from rich countries have access to better financial markets, their affiliates will have higher capital-labor ratio than firms from poor countries even if they use the same production technology. To address this concern, I report regression results controlling for firms' access to external borrowing using their leverage ratios in columns 5 and 6 of Table 2. Consistent with the findings in Table 1, controlling for the leverage ratios reduces the size effects, but has essentially no effect on the technology origin effects. Therefore, it is unlikely that the technology origin effect is driven by firms' differential access to financial markets. In the appendix, I provide additional robustness checks by directly controlling for firms' relative factor prices r/w. The results are similar (see Table A3 and A4).

The results are also robust to alternative definitions of "technology origins". In the main specifications, I use the Global Ultimate Owner (GUO) to define the home country of a multinational affiliate. In the data, the GUO can be at the very top of the "ownership tree" and may not have direct interaction with the affiliate. Alternatively, I can look at "controlling shareholders"[11] within a certain number of layers and also require the shareholders to be in the same industry as the affiliates. For example, I can define the home country to be a foreign country only when a foreign controlling shareholder is within three layers of the ownership tree and is in the same industry as the affiliate. I experiment with alternative definitions in Table A6 and the results are largely unchanged.[12]

In Table 3, I perform the regression in column 4 of Table 2 separately for each one-digit industry. Clearly, there is heterogeneity across industries but the majority of the coefficients are positive. For the largest two industries, manufacturing and wholesale/retail, the technology origin effects are estimated to be positive and significant. The results for wholesale/retail sector also suggests that the technology origin effect is not only driven by quality specialization (firms from rich countries produce higher quality goods thus are more capital intensive) since Nir Jaimovich et al. (2015) recently show that labor intensity, if anything, is positively correlated with service quality in the retail industry.

[11] A controlling shareholder is a shareholder that has the majority of shares of the affiliate in a particular layer.

[12] Another possibility is that multinational firms choose technologies that cater to the factor prices of the largest host country or the average factor prices of all host countries, weighted by revenue. In Table A7, I also include a measure of the capital abundance of the largest host country or the average capital abundance of all host countries. However, these variables have no impact on firms' capital intensities when home country capital abundance is controlled for.

Table 3: Technology Origin Effect by Industry

Industry	Coef	Std. Err	Obs
Agriculture, Forestry and Fishing	0.981***	0.103	764
Other Services	0.724**	0.259	505
Construction	0.564*	0.279	3219
Professional and Scientific Activities	0.425+	0.218	5662
Manufacturing	0.327***	0.089	13022
Administrative and Support	0.274*	0.130	3435
Health	0.273	0.251	734
Wholesale and Retail; Repair	0.237+	0.140	16325
Transportation and Storage	0.202	0.225	3413
Arts and Entertainment	0.176	0.216	475
Utilities	0.084	0.222	510
Real Estate	0.061	0.174	1583
Accommodation and Food	0.045	0.166	1513
Information and Communication	-0.035	0.217	4465
Utilities	-0.086	0.375	665

Estimate technology origin effect using the same sample and specification as Column 4 in Table 1 by industry. Significance levels + 0.1, * 0.05, ** 0.01, *** 0.001. Industries with fewer than 300 observations are ignored.

To summarize, the size effect and the technology origin effect reveal that multinational firms use technologies with systematically different capital intensities than local firms. These patterns are missing in heterogeneous-firm models with only differences in Hicks-neutral productivities. In the next section, I develop a model of factor-biased multinational production that incorporates these two features and can be taken to the data.

3 Model

The model features N countries, indexed by $i = 1, \ldots, N$. Each country i is endowed with two factors of production, capital K_i and labor L_i. I assume both factors are immobile throughout the paper except for the sensitivity analysis in section 6.3 where I allow capital to be mobile across countries. The economy has a single sector with a continuum of firms, each producing a different variety, engaging in monopolistic competition in the product market and taking the factor prices in the production location as given. Consumers have CES preferences, so demand for a particular variety available in country i is

$$q(\omega) = \frac{X_i}{P_i^{1-\sigma}} p(\omega)^{-\sigma}, \omega \in \Omega_i,$$

where X_i is the total expenditure and Ω_i is the set of varieties available in country i. The price index P_i is

$$P_i = \left(\int_{\omega \in \Omega_i} p_i (\omega)^{1-\sigma} \, d\omega \right)^{1/(1-\sigma)}.$$

While the model can easily incorporate multiple industries, I abstract from such features largely due to limited data availability.[13]

3.1 The firm's problem

Timing and technology Firms' activities can be divided into three stages as shown in Figure 1. First, they pay an entry cost F_{ei} to headquarter in a particular country i and choose a technology (a, b) from a menu containing technologies with different capital intensities. Second, their "core productivity" ϕ is drawn from a Pareto distribution

$$\phi \sim F(\phi) = 1 - (\phi / \phi_{\min})^{-k},$$

which determines their overall efficiency no matter where they produce and the Pareto tail parameter k governs the dispersion of overall efficiency. In this stage, the firms also need to decide which market(s) to serve. They have to pay marketing cost F to access a certain market. This induces selection in the model - only the most productive firms can overcome the marketing costs and serve foreign markets. Third, location-specific productivities $\mathbf{z} = (z_1, z_2, \ldots, z_N)$ are drawn independently from Fréchet distributions

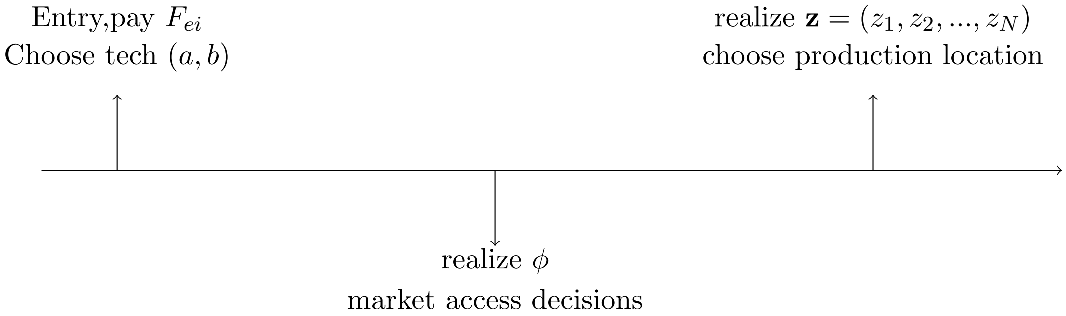
$$z_l \sim \exp\left(-T_{il} z^{-\theta}\right), \; l = 1, \ldots, N,$$

where the location parameter T_{il} determines the average quality of ideas and θ determines the dispersion of productivity draws. Given all the realized shocks, firms choose the minimum-cost location to produce for each market for which they have incurred the fixed marketing cost.

In a potential production location l, firms produce using capital and labor according

[13] The biggest challenge to calibrating a multi-industry model is to obtain high-quality foreign affiliates statistics (FATS) by origin-destination-industry cells in the baseline period (1996-2001). I am currently working on obtaining such data for the more recent period (2001-2013) and trying to incorporate multiple industries into the model.

Figure 1: Timing of the firm's activities



to the CES production function

$$q = z_l \left(\lambda^{1/\varepsilon} \left(a\phi^{1-\xi/2} K \right)^{\frac{\varepsilon-1}{\varepsilon}} + (1-\lambda)^{1/\varepsilon} \left(b\phi^{1+\xi/2} L \right)^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}}, \tag{1}$$

with the following parameter restrictions: $\xi \in (-2, 2)$, $\xi (1 - \varepsilon) \geq 0$.

In this production function, λ is a common shifter for capital shares for all firms in all countries and ε is the elasticity of substitution between capital and labor. The two new mechanisms introduced to generate heterogeneous capital intensity can be seen from the capital- and labor-augmenting productivities $a\phi^{1-\xi/2}$ and $b\phi^{1+\xi/2}$. First, under the parameter restriction $\xi \in (-2, 2)$, the "core productivity" ϕ increases both factor-augmenting productivities, but with different elasticities.[14] Second, firms must choose (a, b) before they make their market access and production decisions, which I refer to as the endogenous technology choice mechanism. Since firms are price takers in the factor market in location l, the demand for capital relative to labor is

$$\frac{K}{L} = \frac{\lambda}{1-\lambda} \phi^{\xi(1-\varepsilon)} \left(\frac{a}{b} \right)^{\varepsilon-1} \left(\frac{r_l}{w_l} \right)^{-\varepsilon}. \tag{2}$$

From this expression, it is clear how the core productivity leads to a positive correlation between firm's capital-labor ratio and its size when $\xi (1 - \varepsilon) > 0$: higher core productivity leads to both higher output and higher capital-labor ratio, holding other variables fixed. This is essentially a form of technology-capital complementarity, since more efficient technology employs more capital relative to labor. The endogenous choice mechanism will

[14]See Burstein and Vogel (2015) with an application to the demand for skilled workers relative to unskilled workers.

help to match the technology origin effect in the data as long as firms from more capital-abundant countries choose technologies with higher $(a/b)^{\varepsilon-1}$.

The menu of all feasible technologies is characterized by the set

$$\Theta \equiv \{(a,b) \,|\theta(a,b) \leq 1\},$$

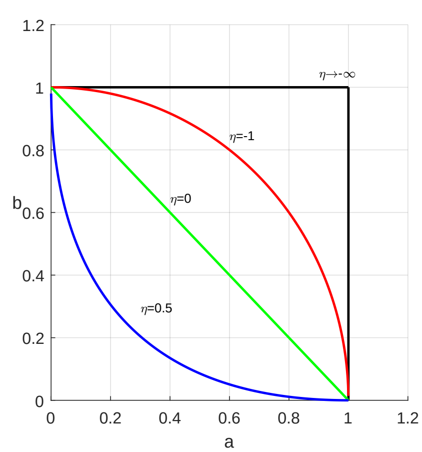
where $\theta(a,b)$ is a function increasing in both a and b. Given (K,L), output increases in both a and b in any production location l. Therefore the firm always chooses a technology on the technology frontier, $\theta(a,b)=1$. However, since $\theta(a,b)$ increases in both a and b, firms face a trade-off between choosing a technology with high capita-augmenting productivity or high labor-augmenting productivity. For quantitative implementation, I assume θ takes the CES form (also see Caselli and Coleman (2006), Oberfield and Raval (2014))

$$\theta(a,b) = \left(a^{1-\eta} + b^{1-\eta}\right)^{1/(1-\eta)},$$

with the additional parameter restriction $\eta + \varepsilon < 2$.

The parameter η governs the shape of the technology frontier, thus the trade-off between capital- and labor-augmenting productivities. The smaller η is, the harder it is to substitute one factor-augmenting productivity for the other. Figure 2 presents the technology frontier for typical values of η. When $\eta \to -\infty$, the function $\theta(a,b)$ becomes $\max(a,b)$ and the trade-off is the strongest. Firms will always choose $(a,b)=(1,1)$ in this limiting case and the mechanism of endogenous technology choice is completely shut down.

Figure 2: Technology Menu under different η



Another way to see the economic meaning of the parameter η is to consider a firm producing in a closed economy l. The firm takes factor prices (r_l, w_l) as given and minimizes its cost by choosing both (a,b) and (K,L). For simplicity, I also normalize the capital share parameter $\lambda = 0.5$ and the core productivity ϕ to be 1 just in this example. Under the parameter restriction $\eta + \varepsilon < 2$, the optimal technology (a,b) is an interior solution[15] and satisfies

$$\frac{a}{b} = \left(\frac{r_l}{w_l}\right)^{\frac{1-\varepsilon}{2-\varepsilon-\eta}}$$

and the capital-labor ratio is

$$\frac{K}{L} = \left(\frac{a}{b}\right)^{\varepsilon-1}\left(\frac{r_l}{w_l}\right)^{-\varepsilon} = \left(\frac{r_l}{w_l}\right)^{-\varepsilon-\frac{(1-\varepsilon)^2}{2-\varepsilon-\eta}}.$$

Oberfield and Raval (2014) define the response of the relative demand to the relative price as the "total elasticity of substitution"

$$\varepsilon^{tot} \equiv \frac{d\ln(K/L)}{d\ln(r_l/w_l)} = \varepsilon + \frac{(1-\varepsilon)^2}{2-\varepsilon-\eta},$$

or equivalently

$$\frac{1}{\varepsilon^{tot}-1} = \frac{1}{\varepsilon-1} + \frac{1}{\eta-1}. \tag{3}$$

Therefore, the total response can be decomposed into the *extensive* margin (optimal choice of (a,b)) and the *intensive* margin (adjusting K/L after (a,b) has been chosen). Under the assumption $\eta + \varepsilon < 2$, one can further show that ε^{tot} is always larger than ε.

This decomposition is useful for understanding how the observed technology origin effect can help discipline the model. I assume that, when a firm opens plants abroad, I assume the foreign affiliates have the same (a,b) as the parent firm. This is different from assuming they have to adopt the same capital-labor ratio - the intensive margin still allows the firm to substitute capital for labor. The two margins of substitution allow both the possibility that multinational affiliates have different capital-labor ratios when they produce in different countries and the possibility that multinational affiliates with different origins have different capital-labor ratios even when they face the same factor prices. The

[15] When $\varepsilon + \eta \geq 2$, one can show that the marginal cost is monotonic in a/b. Thus the optimal technology would be either $(0,1)$ or $(1,0)$. This is the case when the substitution between capital and labor through ex-ante technology choice is so strong that the firm tends to use only capital or labor.

extent of these differences will depend on the parameter values of ε and η.

Firm Optimization Since the firm's activities can be divided into three stages (see Figure 1), I solve for the firm's problem backwards. After all shocks are realized, the unit cost of a country i firm producing in country l is

$$C_l(\phi, z_l, a, b) = \frac{1}{z_l}\left(\lambda\left(\frac{r_l}{a\phi^{1-\xi/2}}\right)^{1-\varepsilon} + (1-\lambda)\left(\frac{w_l}{b\phi^{1+\xi/2}}\right)^{1-\varepsilon}\right)^{1/(1-\varepsilon)},$$

which can be derived from cost-minimizing using the CES production function (1). The marginal cost to serve market n from country l for a firm headquartered in country i is

$$C_{iln}(\phi, \mathbf{z}, a, b) = \gamma_{il} C_l(\phi, z_l, a, b)\,\tau_{ln},$$

where τ_{ln} is the iceberg trade cost between the producing country l and final destination n, while γ_{il} is the efficiency loss when country i firms produce in a foreign country l. I refer to γ_{il} as the "MP costs" which captures various impediments in multinational production.[16]

In stage 3 (the last stage), the firm knows both its core productivity and its country-specific productivities and has chosen its technology (a, b). For each destination market n to which it has obtained access, it finds the production location that minimizes the cost to serve n, namely,

$$l = \arg\min_m C_{imn}(\phi, \mathbf{z}, a, b).$$

Using the property of the Fréchet distribution, one can integrate over the distribution of z and obtain the the expected operating profit associated with market n at the second stage, which I denote as $\pi_{i\cdot n}(\phi, a, b)$ and its exact expression can be found in the online appendix. Note that this expression can be calculated for any market, including ones that the firm decides not to enter in stage 2.

In stage 2, the firm chooses the markets that it will serve. Given the expected operating profit $\pi_{i\cdot n}(\phi, a, b)$, a firm enters market n if and only if the expected profit from that market is larger than the F units of marketing costs, which I assume is paid using the composite good available in the destination market n

$$\pi_{i\cdot n}(\phi, a, b) \geq P_n F.$$

[16] Most of the recent quantitative MP models assume the iceburg MP costs. See Arkolakis et al. (2013), Ramondo and Rodríguez-Clare (2013) and Tintelnot (2014).

Under the assumption that both capital- and labor-augmenting productivities increase with the core productivity ϕ (i.e., $-2 < \xi < 2$), a higher ϕ implies both higher capital- and labor-augmenting productivity thus lower marginal costs in all countries. Thus, I obtain the following lemma

Lemma 1 *For a firm from country i and for each potential destination market n, there exists a unique cutoff ϕ_{in}^* such that the firm enters market n for $\phi \geq \phi_{in}^*$ and does not for $\phi < \phi_{in}^*$.*

Unlike Arkolakis et al. (2013), there is no closed-form expression for ϕ_{in}^* since ϕ affects the marginal cost not only through the overall efficiency but also through the factor bias. When I shut down technology-capital complementarity, i.e., set $\xi = 0$, I recover closed-form expression for ϕ_{in}^* and gravity-type expressions for aggregate trade and MP shares.

In the first stage, the firm chooses the optimal technology (a, b) by maximizing the expected global profit

$$E_\phi \left[\pi_i \left(\phi, a, b\right)\right] \equiv E_\phi \left[\sum_n S_{in}\left(\phi\right)\left(\pi_{i \cdot n}\left(\phi, a, b\right) - P_n F\right)\right] \tag{4}$$

where $S_{in}(\phi)$ indicates whether the firm decides to serve market n in the second stage

$$S_{in}\left(\phi\right) \equiv \mathbf{1}\left[\pi_{i \cdot n}\left(\phi, a, b\right) \geq P_n F\right].$$

Implications for firms' capital-labor ratios

According to the objective function (4), all firms from the same home country will face the same technology choice problem in the first stage. As long as the optimal technology choices are unique, they must be the same for firms from the same country. These country-specific technology choices will determine the "technology origin effect". To see this, consider a firm from country i producing in country l with core productivity ϕ. I can rewrite its capital-labor ratio (2) with the full set of subscripts

$$\frac{K_{il}\left(\phi\right)}{L_{il}\left(\phi\right)} = \frac{\lambda}{1-\lambda} \phi^{\xi(1-\varepsilon)} \left(\frac{a_i}{b_i}\right)^{\varepsilon - 1} \left(\frac{r_l}{w_l}\right)^{-\varepsilon}.$$

The endogenous choice of (a_i, b_i) allows firms from different countries to have different capital intensity even when they face the same set of factor prices (r_l, w_l). Beyond the technology origin effect, country i firms producing in country l still different in their capital-labor ratios because of the technology-capital complementarity term $\phi^{\xi(1-\varepsilon)}$.

It is also clear from this equation that multinational firm data is crucial for the identification of the technology origin effect (extensive margin of substitution) and the usual CES elasticity (intensive margin). If the dataset only covers local firms in multiple countries, the home and production countries are always identical for each firm. It is thus impossible to separately identify the two margins of substitution. In this situation, the differences in factor prices (r_i, w_i) leads firms to choose different capital-labor ratio both because of the intensive substitution term and its impact on the ex-ante technology choice (a_i, b_i). However, when we have data on multinational firms, it is possible to separate the two margins because the dataset contains firms with $i \neq l$.

3.2 Aggregation and equilibrium

In this subsection, I derive expressions for aggregate variables and define the general equilibrium of the model. The expressions are useful both for the calibration and for deriving analytical results in section 3.3.

Aggregate variables are expressed in integrals of firm level variables over the distribution of core productivity ϕ. Conditional on ϕ and the firm entering market n, the probability that country l becomes the lowest cost production location is (see Online Appendix A for derivation)

$$\psi_{iln}(\phi, a, b) \equiv \frac{T_{il}\left(\gamma_{il} C_l(\phi, 1, a, b)\, \tau_{ln}\right)^{-\theta}}{\sum_m T_{im}\left(\gamma_{im} C_m(\phi, 1, a, b)\, \tau_{mn}\right)^{-\theta}},$$

and the expected sales from country l to n by affiliates owned by country i firms are

$$X_{iln}(\phi) = \sigma \psi_{iln}(\phi)\, \pi_{i \cdot n}(\phi).$$

To obtain aggregate sales by affiliates in country l from country i to destination n, I integrate over all country i firms

$$X_{iln} = M_i \int S_{in}(\phi)\, X_{iln}(\phi)\, dF(\phi),$$

where M_i is the mass of firms headquartered in country i. Similar to Burstein and Vogel (2015), X_{iln} does not have closed-form expression due to technology-capital complementarity. Consumers in market n can purchase goods produced by firms from all different origins thus the price index is

$$P_n = \left(E_\phi \left[\sum_i M_i S_{in} (\phi) \frac{\sigma}{\sigma - 1} E_{\mathbf{z}} \left(\min_l C_{iln} (\phi, \mathbf{z}, a, b) \right) \right] \right)^{1/(1-\sigma)}, \tag{5}$$

where I have applied the constant markup rule under the CES demand.

For quantitative implementation, I define trade and MP shares as follows. The "trade shares" are the ratio of goods produced in country l and sold to market n by firms headquartered all around the world to the total absorption in market n

$$\lambda^T_{ln} = \frac{\sum_i X_{iln}}{\sum_{i,l} X_{iln}}. \tag{6}$$

Similarly, the "MP shares" are the share of output produced by country i firms in the total output of country l

$$\lambda^M_{il} = \frac{\sum_n X_{iln}}{\sum_{i,n} X_{iln}}. \tag{7}$$

General Equilibrium An equilibrium of the model is a vector of $\{(a_i, b_i), r_i, w_i, P_i, X_i, M_i\}$ such that

1. Firms choose optimal technologies to maximize global expected profit

$$(a_i, b_i) = \arg \max_{(a,b)\in\Theta} E_\phi [\pi_i (\phi, a, b)]$$

2. Net profit is non-positive due to free entry $E_\phi [\pi_i (\phi, a, b)] - P_i F_{ei} \leq 0$, and $E_\phi [\pi_i (\phi, a, b)] - P_i F_{ei} = 0$ when $M_i > 0$.

3. Capital and labor markets clear

$$K_i = \frac{1}{\tilde{\sigma}} \sum_{j,n} M_j \int S_{jn} (\phi) X_{jin} (\phi) \frac{\kappa_{ji} (\phi)}{r_i} dF_j (\phi)$$
$$L_i = \frac{1}{\tilde{\sigma}} \sum_{j,n} M_j \int S_{jn} (\phi) X_{jin} (\phi) \frac{1 - \kappa_{ji} (\phi)}{w_i} dF_j (\phi)$$

where $\kappa_{ji}(\phi)$ is the capital share of firms producing in i from country j

$$\kappa_{ji}(\phi) = \left(\frac{1-\lambda}{\lambda} \phi^{\xi(\varepsilon-1)} \left(\frac{a_i}{b_i} \right)^{1-\varepsilon} \left(\frac{r_l}{w_l} \right)^{\varepsilon-1} + 1 \right)^{-1}.$$

4. Goods market clear

$$X_i + \Delta_i = r_i K_i + w_i L_i + P_i \sum_j M_j F_{ji} E_\phi \left[S_{ji}(\phi) \right] + M_i P_i F_{ei}$$

   where Δ_i is the current account surplus that I treat as exogenous in the quantitative implementation.

5. The price index satisfies equation (5).

Due to the complication introduced by the heterogeneity in factor biases and the options firms have to produce in foreign countries, I cannot directly apply the existence and uniqueness results of Allen et al. (2015). However, I do not find any indication of multiple equilibria in my quantitative exercises.[17]

3.3 Analytical Results

In this subsection, I derive three analytical results from the model. The first proposition considers a benchmark case without the size effect and the technology origin effect. In this case, globalization has no effect on relative factor prices, which stands in sharp contrast to the results for the full model with both effects. The second and third propositions consider only the technology origin effect. The second proposition shows that, under some simplifying assumptions, the model predicts that firms from more capital-abundant countries choose more capita-intensive technologies. The third proposition illustrates how relative factor prices change after MP liberalization.

As discussed earlier, when $\xi = 0$ and $\eta \to -\infty$, both mechanisms are shut down and we have the following proposition

Proposition 1 *If $\xi = 0$ and $\eta \to -\infty$, there is no heterogeneity in the capital intensities used by firms producing in a given country, regardless of their origins. Moreover, the*

[17] After I solve the calibrated model, I start from different initial guesses and resolve the model. All solutions are the same up to the convergence criteria, 10^{-4}.

relative factor price in country l satisfies

$$\frac{r_l}{w_l} = \left(\frac{1-\lambda}{\lambda}\frac{K_l}{L_l}\right)^{-1/\varepsilon},$$

and is unaffected by changes in trade and MP costs.

Proof. See the online appendix. ■

When $\eta \to -\infty$, all firms adopt the same technology $(a,b) = (1,1)$. Moreover, when $\xi = 0$, firms' capital-labor ratios are not systematically affected by the core productivities ϕ. This means that firms producing in country l have the same capital-labor ratio, which must match the aggregate capital-labor ratio by the market clearing conditions. Therefore, the intensive margin of substitution dictates the relationship between capital-labor ratios and relative factor prices according to the above equation, which is not affected by the levels of trade and MP costs. This result breaks down when either the size effect $(\xi(1-\varepsilon) > 0)$ or the technology origin effect $(\eta > -\infty)$ is present.

So far, I have conjectured that when $\eta > -\infty$, firms from more capital-abundant countries choose technologies that are more capital intensive, i.e., with higher $(a/b)^{\varepsilon-1}$. To obtain sharp analytical results to support this conjecture, I consider a special case of the model with no size effect $\xi = 0$ and with two regions, North and South. Each region consists of multiple symmetric countries. For the next two results, I make the following assumptions

Assumption 1 *[Symmetry]*

1. *Each Northern country is endowed with (K_N, L_N) and each Southern country is endowed with (K_S, L_S). The North is more capital abundant; $K_N/L_N > K_S/L_S$.*

2. *Entry costs F_{ei} are common within a region and so are the exogenous current account surpluses Δ_i.*

3. *MP and trade costs are the same for all country pairs:*

$$\gamma_{ii} = 1, \gamma_{il} = \gamma > 1 \text{ for } i \neq l,$$
$$\tau_{ll} = 1, \tau_{ln} = \tau > 1 \text{ for } l \neq n.$$

Under these additional assumptions, the model predicts a technology origin effect - firms from the North choose a technology (a_N, b_N) that is more capital intensive than the Southern technology (a_S, b_S).

Proposition 2 *[Technology Origin Effect] Assume foreign trade and MP costs satisfy* $\gamma \geq \tau > 1$ *or* $\tau = \infty, \gamma > 1$*, and assume that in equilibrium, the entrants with the lowest core productivity* $\phi_{\min}$ *do not sell in any markets. Then in a symmetric equilibrium*

1. *the North has relatively cheap capital* $r_N/w_N < r_S/w_S$*;*
2. *an optimal technology chosen by a Northern firm* (a_N, b_N) *is more capital-intensive than one chosen by a Southern firm* (a_S, b_S)

$$\left(\frac{a_N}{b_N}\right)^{\varepsilon-1} \geq \left(\frac{a_S}{b_S}\right)^{\varepsilon-1};$$

3. *Northern firms enjoy a cost advantage in the North while Southern firms enjoy a cost advantage in the South*

$$C_l\left(a_i, b_i\right) \leq C_i\left(a_i, b_i\right) \text{ for } i, l \in \{N, S\}, \ i \neq l,$$

where $C_l\left(a_i, b_i\right) \equiv \left(\lambda\left(r_l/a_i\right)^{1-\varepsilon} + (1-\lambda)\left(w_l/b_i\right)^{1-\varepsilon}\right)^{1/(1-\varepsilon)}$.

Proof. See the online appendix. ■

The intuition for these results comes from the fact that bilateral MP costs γ are greater than one. This implies that production in other countries is less efficient than that in the home country. Therefore, when choosing optimal technology, firms give more weight to the expected profit obtained from producing in the home market. Firms choose technologies that rely more intensively on the factor that is abundant at home. The result resonates with the market size effect in Acemoglu (2003b), but is derived in a model of multinational production where the barriers to MP play the central role.

Part (3) of Proposition 2 provides a supply-side explanation for the observation that firms invest relatively more in countries with income levels similar to their home country (Fajgelbaum et al. (2014)). When $\xi = 0$, consider the marginal cost of a country i firm with $\phi = 1$, producing in l and selling to n

$$\zeta_{iln}\left(a_i, b_i\right) \equiv \gamma_{il} C_l\left(a_i, b_i\right) \tau_{ln}.$$

Like the iceberg MP cost γ_{il}, the middle term $C_l(a_i, b_i)$ is also home-host country specific. Though the exogenous MP costs γ_{il} are symmetric i.e., same for within-region MP (South-to-South or North-to-North) and cross-region MP (South-to-North or North-to-South), the endogenous choice of (a_i, b_i) leads to differences in $C_l(a_i, b_i)$ for within-region MP and cross-region MP. This creates an endogenous barrier to MP between the North and the South, which can generate more MP within regions than across regions.

Though the above proposition is derived from a framework in which frictions to multinational production take the iceberg form, the intuition of the technology origin effect applies to other approaches to modelling the investment frictions. In the online appendix, I prove similar results in a model where the barrier to multinational production is a fixed cost of setting up a plant abroad. As long as the firms are choosing optimal technology to maximize expected global profit and the ex-ante probability of entering a foreign country is smaller than one, I show that technologies adopted by a Northern firm must be more capital intensive than technologies adopted by a Southern firm.

What is the impact of MP in a world where firms develop technologies that cater to domestic prices as in the previous proposition? The following proposition states that relative prices across countries diverge after MP liberalization.

Proposition 3 *Under the assumptions of symmetry, suppose trade is frictionless $\tau = 1$ and $\varepsilon < \theta + 1$, after multinational production liberalization, i.e., reducing γ from above 1 to 1, relative factor prices r/w in the two regions will diverge.*

Proof. See the online appendix. ■

The intuition for the proposition comes from the fact that the "total elasticity" of substitution is a combination of the extensive and the intensive elasticities of substitution. The complete liberalization of MP eliminates the origin effect in technology choice, and all firms become "footloose" and adopt the same technology. The extensive substitution no longer adjusts factor prices. When the "total" elasticity of substitution drops, the relative factor prices must diverge to allow the factor markets to clear in both regions.

This result contrasts with the Helpman (1984) model which predicts that multinational activities lead to an expansion of the factor price equalization (FPE) set and thus become a force of convergence in relative factor prices. The Helpman (1984) model focuses on vertical FDI. The separation of production and headquarter services adds another "sector" to the economy. This causes the expansion of the FPE set since now the country rich in capital can substitute into the most capital-intensive sector - headquarter services. In contrast, my model focuses on technology transfer through FDI. The possibility that firms tailor their technology to their global investment opportunities leads technology to diverge when there are barriers to MP. Thus, compared to the case where MP is frictionless, the "total elasticity" is larger in the frictional world and the factor prices required to clear the factor markets are less different across regions.

4 Calibration

To understand the quantitative importance of technology-capital complementarity and endogenous technology choice, I calibrate the model to match both firm-level and aggregate data between 1996 and 2001 for 37 countries including both developed and developing nations. The sample of countries represent 91% of world GDP, 95% of world inward FDI stocks and 99% of world outward FDI stocks.

The micro data help to discipline three important parameters in the model. The size effect and technology origin effect discipline the strength of the technology-capital complementarity ξ and the extensive elasticity of substitution η when firms choose technologies. Using variation across affiliates of the same parent firm, I can also directly estimate the intensive elasticity of substitution, ε. I target the other parameters of the model to aggregate moments such as trade and MP shares. After calibration, I discuss the model's fit in terms of additional aggregate and firm-level moments that I do not target and the model's implications for MP patterns across countries.

4.1 Parameters calibrated without solving the model

Two of the parameters are calibrated without solving the model. For the demand elasticity σ, I choose a value of 4, which is common in the literature (Bernard et al. (2003)). For the elasticity of substitution in the CES production function, I directly estimate it using firm's relative demand for capital and labor. Recall that an affiliate f's relative demand for capital can be written as

$$\frac{r_{l(f)}K_f}{w_{l(f)}L_f} = \phi^{(1-\varepsilon)\xi}\left(\frac{a_{i(f)}}{b_{i(f)}}\right)^{\varepsilon-1}\left(\frac{r_{l(f)}}{w_{l(f)}}\right)^{1-\varepsilon},$$

where $i(f)$ and $l(f)$ denote the home and host countries as before. According to the model, both the core productivity ϕ and the endogenous choice of technology $\left(a_{i(f)}, b_{i(f)}\right)$

are specific to a parent firm. Therefore I can control these unobservables with a parent-firm fixed effect. The extent to which the affiliates adjust their capital-labor ratios across production locations l is informative about the elasticity of intensive substitution, ε.

In practice, I run the following regression for multinational affiliates:

$$\log\left(\frac{r_{l(f)}K_f}{wL_f}\right) = (1-\varepsilon)\log\left(\frac{r_{l(f)}}{w_{l(f)}}\right) + \delta_{g(f)\times s(f)} + u_f,$$

where $g(f)$ and $s(f)$ denote the parent firm and industry of an affiliate, respectively. I add industry fixed effects to absorb differences in capital intensities across industries. To account for worker skill differences across firms, I again use the wage bill wL_f as the denominator on the left hand side. Finally, since the host-country rental rate (backed out using the labor share data from Karabarbounis and Neiman (2014)) appears both on the left- and right-hand side of the equation, I instrument $\log\left(r_{l(f)}/w_{l(f)}\right)$ with the endowment, $\log\left(K_{l(f)}/L_{l(f)}\right)$, to avoid mechanical correlation caused by measurement error in $r_{l(f)}$.

The cross-sectional data lack a measure of firms' real capital stock, K_f. I construct a host-country-specific asset deflator and then deflate firms' total assets using the deflator. The asset deflator assumes the firm's capital stock has been growing at a constant rate (same rate as that of the national aggregate capital stock) for a decade. Together with a constant, country-specific growth rate of investment prices and inflation rate, I derive an expression for the asset deflator and deflate the total assets of the firm to obtain K_f.[18]

My preferred IV estimate is

$$\log\widehat{\left(\frac{r_{l(f)}K_f}{wL_f}\right)} = \underset{\substack{0.455 \\ (0.108)}}{\left(\widehat{1-\varepsilon}\right)}\log\left(\frac{r_{l(f)}}{w_{l(f)}}\right) + \delta_{g(f)\times s(f)},$$

which implies that the elasticity of intensive substitution is 0.545 with a standard error 0.108. The instrument is strongly correlated with the relative factor prices, with an F statistic of 80.1 in the first-stage regression. This estimate is in line with those in Oberfield and Raval (2014) who use a similar cross-sectional approach to identify ε. Other studies using micro data but different identification strategies have also found similar estimates (e.g., 0.45 as in Hongsong Zhang (2015) and 0.56 as in Klump et al. (2007)).

[18] See the appendix for detailed derivation of the asset deflator and data used for each component. I experiment with different assumptions on the time period that firms have been accumulating capital when constructing the asset deflator and the estimated elasticity are not sensitive to the assumption (Table A8).

4.2 Parameters calibrated to match endogenous outcomes from the model

All of the other parameters of the model, γ_{il}, τ_{ln}, k, θ, η, ξ, λ are calibrated to match endogenous outcomes of the model. The location parameter of the Fréchet distribution T_{il} cannot be separately identified from the iceberg MP costs γ_{il}, so I normalize T_{il} to 1 for all i and l. I also normalize the lower bound of the core productivity, $\phi_{\min}$, and the marketing costs F to 1. I normalize the entry costs F_{ei} such that the fraction of firms serving their domestic markets is 0.7 in all countries.[19]

Trade and MP shares: I target the trade and MP costs $\{\tau_{ln}, \gamma_{il}\}$ to match the trade and MP shares $\left\{\lambda_{ln}^T, \lambda_{il}^M\right\}$ (see equations (6) and (7)), normalizing the domestic costs τ_{ii} and γ_{ii} to 1. I obtain the trade flows $\sum_i X_{iln}$ from BACI and the MP sales $\sum_n X_{iln}$ from Ramondo et al. (2015). For countries with missing nonfinancial total output Y_l, I use their GDP to predict Y_l under a log-linear equation specification. All country pairs in my sample have positive bilateral trade flows, although some of them have zero MP sales. I simply assign bilateral MP costs to be infinity for these country pairs. Detailed data sources and the extrapolation procedures can be found in the appendix.

Average labor share: The parameter λ is common across countries and determines the average labor share. A higher λ implies lower labor shares in all countries. Among the sample countries, the average labor share is 0.52, and I target λ to match this value. The calibrated λ is 0.316.

Restricted and Unrestricted Trade Elasticities: As is shown in Arkolakis et al. (2013) (ARRY henceforth), the Pareto shape parameter k and the Fréchet shape parameter θ are well disciplined by the "unrestricted" and "restricted" trade elasticities, respectively. The "restricted" trade elasticity is estimated conditional on trade flows generated by firms originating in a given country, therefore reflects the sensitivity of the three-way sales X_{iln} to the trade costs τ_{ln}. In particular, the restricted elasticity β^r is estimated from the regression

$$\log X_{iln} = \delta_{il} + \delta_{in} - \beta^r \tau_{ln} + u_{iln}.$$

In ARRY, β^r equals the Fréchet shape parameter θ regardless of the other model parameters and thus can be estimated without solving the model. In my model, because of technology-

[19] Given other parameters, the entry costs F_{ei} affect the mass of firms in each country and the fraction of firms serving each the domestic market. However, I do not have data on these variables. Targeting lower values of the probability to serve domestic markets (0.1 instead of 0.7), I find the normalization barely affects the calibration of the other parameters and the counterfactuals. These results are available upon requests.

capital complementarity, there is no analytical gravity and β^r can differ from θ. However, the calibration reveals the trade costs τ_{ln} and three-way sales X_{iln} therefore I can estimate the above equation in the model and target θ to match an estimate $\hat{\beta}^r = 10.9$ as in ARRY. The calibrated θ is 10.933, very close to $\hat{\beta}^r$, which suggests that β^r still pins down θ tightly despite the complication introduced by the technology-capital complementarity.

Similarly, I discipline k using the "unrestricted" trade elasticity, which measures the responsiveness of the usual two-way trade flows to trade costs. The two-way trade flows $X_{\cdot ln}$ aggregates the three-way trade flows over firms originating in any country i, i.e., $X_{\cdot ln} = \sum_i X_{iln}$. Specifically, I can estimate the unrestricted trade elasticity using the following regression

$$\log X_{\cdot ln} = \delta_l + \delta_n - \beta^u \tau_{ln} + u_{ln}.$$

I adjust k to match an estimate $\hat{\beta}^u$ of 4.3 as in ARRY. The calibrated k is 4.201, slightly larger than that in ARRY (4.0).

Technology origin effect and size effect: As discussed before, the parameter ξ governs how the core productivity ϕ affects the capital- and labor-augmenting productivities differently, thereby determining the size effect; the parameter η governs the extensive margin of substitution, thus the strength of the technology origin effect. In section 2, I run different specifications to check the robustness of the two effects. The size effect is typically between 0.04 and 0.07 and the technology origin effect ranges from 0.16 to 0.29. In the quantitative implementation, I pick one set of estimates and provide sensitivity analysis in section 6.

Specifically, I use the estimates for the multinational subsample (column 4 in Table 2):

$$\log\left(\frac{K_f}{wL_f}\right) = \delta_{s(f)\times l(f)} + \underset{(0.109)}{0.249} \log\left(\frac{K_{i(f)}}{L_{i(f)}}\right) + \underset{(0.0130)}{0.0523} \log\left(X_f\right) + \varepsilon_f, \tag{8}$$

where $K_{i(f)}/L_{i(f)}$ is the home country capital abundance and X_f is the affiliate's revenue. Different from previous moments, the size and technology origin effects are regression coefficients from an affiliate level dataset. Therefore, for each guess of model parameters, I solve for the general equilibrium and then simulate a panel of multinational affiliates (see details in section 4.3). I then run the above regression in the simulated data and adjust parameters to match the two regression coefficients. The calibrated value of η is 0.604 and that of ξ is 0.613 as shown in Table 4.

Table 4: Baseline calibration - targets and parameters

Parameters	Values/Normalization	Targets
τ_{il}	$\tau_{ii} \equiv 1$	trade shares
γ_{il}	$\gamma_{ii} \equiv 1$	MP shares
F_{ei}		Prob serving home market 0.7
η	0.604	Technology origin effect 0.249
ξ	0.613	coefficient of revenue 0.052
k	4.201	unrestricted trade elasticity 4.3
θ	10.928	restricted trade elasticity 10.9
λ_k	0.316	average labor share 0.520

4.3 Algorithm

As shown in Table 4, I need to calibrate two N-by-N matrices of trade and MP costs $\{\gamma_{il}, \tau_{il}\}$, N parameters of entry costs F_{ei} and five additional parameters $(\eta, \xi, k, \rho, \lambda)$ by solving the model. I calibrate the model using a two-loop procedure by grouping the country and country-pair specific variables and parameters into the inner loop and the five additional parameters into the outer loop.

Given a set of outer loop parameters $(\eta, \xi, k, \theta, \lambda)$, I iterate over guesses of $(a_i, b_i, r_i, w_i, P_i, X_i, M_i, F_{ei})$ and the trade and MP costs $\{\tau_{ln}, \gamma_{il}\}$ such that (1) all equilibrium conditions are satisfied and (2) trade and MP shares are exactly the same as those in the data and (3) the probability of a firm serving its domestic country is 0.7 in all countries (normalization). Note that to solve this inner loop, I must perform numerical integrations to obtain aggregate variables such as sales and factor demand. I use a 20-node Gauss–Legendre quadrature to obtain high precision. Given the large number of parameters, I use an adjustment approach to reduce the computational burden (also see Burstein and Vogel (2015)). Intuitively, I increase prices if there are excess demands, increase trade and MP costs if the corresponding trade and MP shares are higher than those in the data, and increase F_{ei} if the probability of a firm serving its domestic country is higher than 0.7. The details of the algorithm can be found in the online appendix.

The outer loop iterates over guesses of $(\eta, \xi, k, \theta, \lambda)$ until the five corresponding moments are matched exactly. The restricted and unrestricted trade elasticities are estimated using $X_{iln}, X_{\cdot ln}$ and calibrated τ_{ln} obtained from the inner loop. To obtain the size effect and technology origin effect from the model, I simulate 20,000 entrants in each country. Each entrant is characterized by its home country i, its core productivity ϕ and a vector of productivity shocks $\mathbf{z}$. Firms choose which markets to serve and from which country to serve a particular market according to the model. Thus, for each firm, I can determine the size of their affiliate in each country l. Similar to the data, some of the firms are multinationals while some only operate in their domestic countries. I run the firm-level regression (8) and estimate the two coefficients using the simulated data for the same set of home and host countries. The outer loop again uses an intuitive adjustment approach as the inner loop. The entire calibration typically takes from one hour to ten hours on a 20-core cluster machine, depending on the choice of the initial guesses.

4.4 Model Fit

In this section, I discuss the fit of the model from several perspectives. First, for the targeted moments, the calibration exactly matches the data. Second, the calibration produces thousands of iceberg trade and MP costs γ_{il} and τ_{ln} which, I find, are highly correlated with gravity variables. I then discuss the fit of the factor prices, which are the main focus in the counterfactual analysis. Finally, I discuss the fit of other untargeted moments, such as firm-level operation statistics and the firm size distribution.

Trade and MP costs

The calibration produces thousands of iceberg trade and MP costs, τ_{ln} and γ_{il}. In Table 5 I project the calibrated costs on standard gravity variables, controlling for origin and destination fixed effects. In general, these calibrated costs are positively correlated with distance and the impact of distance are similar for trade and MP costs. Trade and MP costs are lower for countries that share borders and a common official language and for those that have former colonial relationships. These results are reassuring that the model can be used to back out meaningful bilateral trade and MP costs even though it is more complicated than standard models with analytical gravity equations.

Factor Prices

The model fits the relative factor prices in each country well. Figure 3 plots the predicted values of $\log(r/w)$ against the data. Since I do not target factor prices in each country, the match between the model and the data is not perfect. However, the calibrated model captures the broad variation in factor prices across countries - less developed countries such as India and China have higher r/w than developed economies. The correlation

Table 5: Gravity in τ and γ

	(1) $log(\tau_{ln})$	(2) $log(\tau_{ln})$	(3) $log(\gamma_{il})$	(4) $log(\gamma_{il})$
log(distance)	0.280***	0.253***	0.268***	0.236***
	(0.0153)	(0.0157)	(0.0151)	(0.0144)
contiguity		-0.0837**		-0.0784*
		(0.0269)		(0.0309)
common language		-0.0712		-0.0917*
		(0.0358)		(0.0375)
colony		-0.0824*		-0.141***
		(0.0307)		(0.0389)
N	1332	1332	1052	1052
R^2	0.988	0.989	0.935	0.939
mean of Y	1.544		1.515	
sd of Y	1.420		0.703	

Dependent variables are either iceberg trade costs τ or MP costs γ. All regressions control host and home country fixed effects. Standard errors clustered at host-country level. * 0.05, ** 0.01, *** 0.001. γ_{il} is set at infinity for country pairs with zero MP. They are automatically excluded from the regressions.

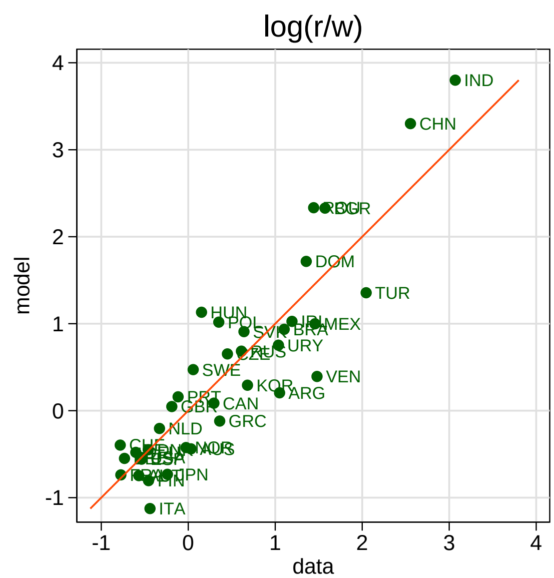
between the model and the data is 0.9.[20]

The good fit of factor prices results from two features of the calibration. First, the calibration matches the average labor share across countries, which helps to match the average r/w in the data. Second, as I have discussed in section 3, in a world economy with no MP ($\gamma_{il} = \infty$ for all $i \neq l$), the total elasticity (equation (3)) dictates the relationship between r/w and K/L. The calibrated value of η (0.60) together with the intensive elasticity $\varepsilon = 0.55$ implies a total elasticity of 0.79. Since the extent of multinational production is limited in most countries, the factor prices across countries are well disciplined by countries' endowments and the total elasticity.

When the technology origin effect is shut down ($\eta \to -\infty$), the total elasticity converges to the intensive elasticity $\varepsilon = 0.55$. A lower total elasticity implies that factor prices respond more to the factor endowments to make the factor markets clear. This intuition is confirmed by the regressions in Table 6. In the data, the elasticity of countries relative factor prices with respect to capital abundance is 1.33 (column 1), while the baseline calibration with technology origin effect predicts a coefficient of 1.27 (column 2), within the 95% confidence interval of the coefficient estimated off the data. I then set $\eta \to -\infty$, recalibrate the model by targeting all the other moments except the technology origin effect, and run the same

[20]To be consistent, in the counterfactual exercises below, I always compare the counterfactual factor prices with the factor prices in the calibrated baseline.

Figure 3: Model Fit - Factor Prices



Note: $log(r/w)$ in the model and in the data. Wage in the US is normalized to 1.

regression using the predicted factor prices from this alternative model. The elasticity in column 3 becomes much larger and moves beyond the 95% confidence interval of the coefficient in column 1. Therefore, the technology origin effect is important to match the relationship between the relative factor prices and capital abundance across countries.

Firm-level moments

The simulated panel of firms allow me to compare the untargeted firm-level moments in the data and in the model. Bernard et al. (2007) report the fraction of exporting firms in the US as 4 percent in 2000, whereas in my calibration the corresponding number is 1.1 percent. The smaller share of exporters likely results from the lack of fixed costs of setting up a plant abroad. The same reason also leads to a higher number of production locations of multinational firms in the model compared to the data. For example, the model predicts that the average German multinational firm produces in 2.64 foreign countries, while in the data it is 1.57 (Tintelnot (2014)).

Although the calibration does not directly target the firm-size distribution, it is able to match firm size heterogeneity as observed in the data. Using the panel of firms, I estimate the power law exponent for firms operating in each country. For US firms, the estimated

Table 6: Relationship between relative price and endowment

	Data	Model	
		ETC	No ETC
	(1)	(2)	(3)
$\log(K/L)$	-1.326	-1.266	-1.710
	(0.0701)	(0.0170)	(0.0102)
N	37	37	37

The dependent variable is $log(r/w)$ of the country, either predicted by the model or observed in the data. The independent variable is $log(K/L)$ of the country, where labor is measured in efficiency units using the average human capital and total employment in Penn World Table 8.0. Factor prices in column 1 are those backed out from the labor share data provided by Karabarbounis and Neiman (2014), while column 2 and 3 use the equilibrium prices in the calibrated models, with and without endogenous technology choice (ETC), respectively. Standard errors are heteroskedasticity-robust.

exponent is 1.04, very close to the values presented in Axtell (2001). The country at the 25th percentile has a power law exponent of 1.07 while that of the 75th percentile has a power law exponent of 1.17, slightly larger than those estimated in di Giovanni and Levchenko (2013).

4.5 Endogenous technology choice and MP patterns

Besides explaining the technology origin effect as observed in the data, the endogenous choice of technology can also help to explain MP patterns. As is documented in Fajgelbaum et al. (2014), countries tend to produce in other countries with similar income levels as their income. They provide a demand-side explanation: firms from the North develop high quality products that have higher demand domestically and also in other Northern countries, and vice versa for firms from the South. Due to the proximity-concentration trade-off, firms are more likely to set up affiliates in countries of the same income level, which have relatively similar demand composition to their home market. The technology origin effect provides a complementary, supply-side explanation: firms from the North develop more capital-intensive technologies and they tend to invest in countries with similar factor prices. Part (3) of Proposition 2 states this argument formally: the marginal cost of production is smaller for within-region MP (North-to-North or South-to-South) than cross-region MP (North-to-South or South-to-North). The mismatch between technology and factor prices generates endogenous barriers to MP between country pairs with different endowment structures.

To see the quantitative importance of the mechanism in explaining MP patterns, I deviate from the baseline calibration and assume that firms are given the "average world technology" exogenously. The counterfactual setup still incorporates technology-capital complementarity (TCC) but not endogenous technology choice. The average world technology is kept at $\bar{\delta} \equiv \sum_i \delta_i / N$ where $\delta_i \equiv (\varepsilon - 1) \log (a_i / b_i)$ is one of the equilibrium objects solved in the baseline calibration. Under this restriction, I solve the general equilibrium ignoring the optimality condition for δ_i's and predict counterfactual MP shares $\lambda_{il}^{M,TCC}$. I can then compare these MP shares with the MP shares in the baseline model $\lambda_{il}^{M,base}$, which by construction equal those in the data.

In columns 1 and 2 of Table 7, I regress $\lambda_{il}^{M,base}$ and $\lambda_{il}^{M,TCC}$ on differences in income per capita[21] between the home country i and host country l, controlling for home and host country fixed effects. Since $\lambda_{il}^{M,base}$ perfectly matches the MP shares in the data, column 1 simply replicates the findings in Fajgelbaum et al. (2014) in my sample countries: 1% differences in income per capita between i and l reduces MP sales from i to l by 0.76%. However, when I assume away the endogenous technology choice (column 2), this effect becomes much weaker - about 60% smaller than that in the data. The effect is still negative, which reflects the fact that the calibrated MP costs γ_{il}^{base} are larger between countries with different income levels (column 3). Based on the difference between column 1 and 2, the endogenous technology choice explains about 60% of the effect of income differences on bilateral MP sales, while the remaining 40% might be due to other mechanisms such as dissimilarity in demand. Adding additional gravity controls (columns 4-6) slightly reduces the explanatory power of the endogenous choice mechanism to 56%.

5 Counterfactuals

I use the calibrated model to conduct two counterfactuals in which I vary the MP costs to illustrate the impact of MP liberalization on the host countries. The first counterfactual considers the increase in multinational activities of the past decade. I calibrate the change in MP costs to match the change in MP shares observed in the data and examine the impact implied by the model. The second counterfactual considers unilateral MP liberalizations

[21] The theory highlights the miss-match between technology and factor prices that leads to less cross-region MP than within-region MP. It is natural to use the differences in capital abundance as an explanatory variable. I use income per capital instead since it is more comparable to the exercises in Fajgelbaum et al. (2014). Table A9 reports the same regressions using differences in capital abundance and the results are similar.

Table 7: MP shares, MP costs and country differences

	(1) $log(\lambda_{il}^{M,base})$	(2) $log(\lambda_{il}^{M,TCC})$	(3) $log(\gamma_{il}^{base})$	(4) $log(\lambda_{il}^{M,base})$	(5) $log(\lambda_{il}^{M,TCC})$	(6) $log(\gamma_{il}^{base})$
diff in income	-0.763***	-0.309*	0.118***	-0.805***	-0.352*	0.124***
	(0.151)	(0.148)	(0.0290)	(0.149)	(0.144)	(0.0281)
log(dist)	-1.697***	-1.728***	0.364***	-1.809***	-1.850***	0.382***
	(0.0980)	(0.102)	(0.0184)	(0.116)	(0.121)	(0.0212)
contiguity				-1.105***	-1.192***	0.174***
				(0.240)	(0.241)	(0.0368)
common language				0.112	0.177	-0.0326
				(0.236)	(0.229)	(0.0426)
colony				1.054**	1.015**	-0.161**
				(0.331)	(0.326)	(0.0591)
N	1089	1089	1089	1089	1089	1089
R^2	0.785	0.782	0.904	0.793	0.791	0.907
T-stat		2.145			2.186	

[a] Dependent variables are real/counterfactual MP shares or calibrated MP costs. $\lambda_{il}^{M,base}$ is the MP share from home country i in host country l in the data and in the baseline calibration). $\lambda^{M,TCC}$ is the counterfactual MP share when I assume all firms adopt the world average technology. γ_{il}^{base} refers to the calibrated MP costs.

[b] All regressions control host and home country fixed effects. Standard errors clustered at host-country level. + 0.1, * 0.05, ** 0.01, *** 0.001.

[c] Differences in country characteristics are absolute differences in log values.

[d] The T-stat is calculated based on a T-test for whether the coefficients in columns 1 and 2 (or 4 and 5) are the same. It assumes that the observations in the two regressions are independent.

in which the MP costs to produce in a particular host country are reduced by 10 log points for all its partners.

5.1 MP liberalization up to 2011

Over the past two decades, multinational production has become more prevalent in global production. To obtain the increase in multinational production in each country, I combine data from OECD and Eurostat and calculate the "total inward MP share" for each country and year after 2000.[22] The "total inward MP share" is the share of foreign affiliates' output in domestic production. Using the notation of the model, it is defined as

$$\text{total inward MP share}_l \equiv \sum_{i \neq l} \lambda_{il}^M,$$

where λ_{il}^M is the production share of country i firms in country l. I then average them over a six-year period, 2006-2011, and compare it to the total inward MP share in the baseline period (1996-2001). The new MP shares do not cover all the sample countries. In this counterfactual, I focus on the 23 countries with data for both periods.

Columns 1 and 2 in Table 8 report the statistics for both periods. 19 out of the

[22] For China, I calculate the share using the Chinese industrial enterprises database. See the appendix for more details.

23 countries see an increase in the total inward MP share. The average increase is 9.6 percentage points. Less-developed countries such as Romania, Bulgaria and China had small shares of multinational production in the baseline period, but the shares increased dramatically over the decade. Other countries such as Slovakia, Ireland, the Czech Republic and Hungary had sizable total inward MP shares at the beginning and saw further increases in MP during this period.

To understand the impact of the influx of multinational activities, I recalibrate the model by choosing different values of MP costs γ'_{il} to match the new total inward MP shares, holding all other model primitives and parameters fixed. Since the MP costs are bilateral, the number of parameters exceeds the number of data points[23], I make the following two assumptions to solve the under-identification problem. First, for a particular host country l, I assume the change in the MP costs are the same for all of its partner countries,

$$\frac{\gamma_{il}^{'}}{\gamma_{il}} = \hat{\gamma}_l \text{ for all } i \neq l.$$

For country pairs with zero bilateral MP sales in the baseline period, I keep the restrictions that their bilateral MP costs are prohibitively high, i.e., $\gamma'_{il} = \gamma_{il} = \infty$. Second, for countries that do not have data for the later period, I assume the decline in their MP costs $\log \hat{\gamma}_l$ is simply equal to the global average.[24] As in the baseline calibration, domestic production costs γ'_{ll} are normalized to 1.

Column 3 in Table 8 presents the calibrated change in MP costs for the 23 countries I consider. The average decline in MP costs is estimated to be 8.0 log points. As expected, countries with the largest increase in MP shares are estimated to have experienced the largest declines in their MP costs. Developed countries such as Germany, Japan and the US have little changes in their inward MP shares and correspondingly, the calibration shows their MP costs barely changed over this period.

As discussed earlier, in my model, changes in MP reallocate production across firms with different factor biases. This leads to changes in relative demand for capital and labor, therefore to changes in relative prices and labor shares. As can be seen in column 4 of

[23] It would be ideal to obtain a complete matrix of MP shares in the later period. However, more than half of the bilateral MP shares λ_{il}^M are missing in the OECD and Eurostat database. Since the countries in my sample represents the majority of the MP sales, I use the total inward MP shares instead of the bilateral MP shares.

[24] An alternative is to assume the MP costs do not change for these "background" countries, i.e., $\hat{\gamma}_l = 1$. This alternative assumption affects the results for these countries but barely affects the predictions on the 23 countries studied here.

Table 8: Counterfactual of the baseline calibration

ISO3	(1) inward MP share 96-01	(2) inward MP share 06-11	(3) Δ log MP costs (calibrated)	(4) Δ labor share (model)	(5) Δ labor share (data)	(6) $\Delta log(r/P)$	(7) $\Delta log(w/P)$	(8) Δ log real income
AUT	25.6	31.8	-1.7	-0.1	-2.5	0.2	-0.2	-0.0
BEL	40.8	47.3	-2.5	-0.2	-2.1	2.6	2.0	2.3
BGR	3.5	31.8	-33.8	-6.7	-7.5	11.8	-15.6	0.1
CHN	2.4	15.6	-27.2	-2.4	-4.6	3.3	-6.4	-0.8
CZE	30.3	45.7	-6.2	-1.8	-0.8	4.2	-3.0	0.7
DEU	23.7	22.4	-0.1	0.7	-5.1	1.0	4.0	2.7
DNK	11.7	23.8	-10.8	-1.0	2.1	2.4	-1.7	0.1
ESP	15.2	20.9	-3.9	-0.2	-0.3	0.1	-0.8	-0.4
FIN	17.1	20.0	-5.4	0.7	3.3	3.0	5.9	4.8
FRA	16.1	21.5	-4.1	0.1	1.2	-0.0	0.6	0.3
GBR	26.6	35.3	-4.3	-0.5	0.0	1.0	-1.1	-0.1
HUN	39.6	50.5	-3.7	-1.7	-4.6	4.3	-2.4	1.3
IRL	36.0	51.4	-8.8	-3.4	5.8	8.9	-4.9	3.1
ITA	11.0	16.5	-6.1	0.2	3.1	-0.5	0.5	0.1
JPN	3.9	4.1	0.1	0.3	-2.1	-0.1	1.3	0.7
NLD	34.6	31.6	0.8	0.8	-1.3	1.7	5.1	3.5
NOR	11.6	25.1	-13.3	-1.3	-6.4	3.1	-2.1	0.2
POL	19.9	35.3	-8.4	-1.9	-13.3	3.0	-4.4	-0.6
PRT	33.8	20.1	9.1	1.8	1.2	-2.3	4.9	1.5
ROU	5.6	42.4	-33.8	-7.7	-4.1	13.3	-18.5	-0.0
SVK	20.0	49.9	-15.9	-5.1	-4.6	10.1	-10.4	0.6
SWE	24.8	32.4	-4.5	-0.7	-1.1	3.2	0.3	1.7
USA	12.0	11.2	0.1	0.4	-4.4	0.3	2.0	1.3
Avg	20.3	29.9	-8.0	-1.3	-2.1	3.2	-2.0	1.0

Counterfactual experiment of changing inward MP costs such that inward MP shares match those in 2006-2011. All numbers are in percentage points or 100× change in log points

Table 8, the model predicts a decline in labor shares in 15 out of the 23 sample countries in response to the estimated changes in MP costs. The average country sees a 1.3-percentage-point decline, while the average decline in the data was 2.1 percentage points (column 5). Therefore, the change in MP activity can explain about 60 percent of the average decline in the labor shares. The changes predicted by the model also capture some of the variation in the changes of the labor shares across countries. For example, when I regress the changes in the data on the predicted changes in the model, the coefficient is positive and significant (coef = 0.58 and standard error = 0.25), while the R-squared of the regression is 0.11.

The predicted changes in the labor shares vary across countries. The labor share declines as much as 7.7, 6.7 and 5.1 percentage points in Romania, Bulgaria and Slovakia, respectively, while it increases slightly in countries such as Germany, Finland and the US. To understand the variation across countries, I relate the changes in the labor shares to the changes in the total inward MP shares. Column 1 of Table 9 shows that a one-percentage-point increase in the total inward MP shares is on average associated with 0.2-percentage-point decline in the labor shares. This single variable captures 91 percentage of the variation in the predicted changes. The effect of the increase in the total inward MP shares also depends on the capital abundance of the host country. In column 2, I interact the change in the total inward MP shares with the capital abundance of the host country (in the baseline period). The interaction term is significantly positive, meaning that, in the model, more capital-scarce countries experienced a larger decline in their labor shares for a given increase in their total inward MP shares.

Table 9: Labor shares and MP shares

Δ Labor Share	Model		Data	
	(1)	(2)	(3)	(4)
Δ inward MP share	-0.204***	-0.870***	-0.125*	-1.025
	(0.0212)	(0.119)	(0.0489)	(0.706)
$\times$ $log(K/H)$		0.0673***		0.0909
		(0.0120)		(0.0715)
N	23	23	23	23
R^2	0.908	0.970	0.115	0.154

Dependent variable is percentage point change in labor shares. Robust standard errors in parentheses. + 0.10 * 0.05 ** 0.01 *** 0.001.

These results are intuitive given the two mechanisms that affect the relative demand for capital and labor in my model. First, the technology-capital complementarity mechanism operates essentially through selection. MP liberalization leads to more competition in the host economy, which drives out small and labor-intensive firms, both domestic and foreign. This mechanism should operate in all countries that receive more MP, regardless of their capital abundance. Second, the technology origin effect only affects the labor share when the host country is hosting multinational production from home countries with different endowment structures. Since the majority of the multinational production is performed by firms from capital-abundant countries, it is the capital-scarce countries that are affected the most by the technology transfer of capital-intensive production technologies. Therefore, the technology origin effect contributes further to the decline of the labor shares in these countries.

Are these results consistent with the data? Columns 3 and 4 of Table 9 replicates the regressions in columns 1 and 2 with observed changes in the labor shares. On average, a larger increase in total inward MP share is associated with a larger decline in the labor shares in the data (column 3) as predicted by the model (column 1). Column 4 suggests that the relationship is stronger for less capital-abundant countries. The observed relationship between the change in the labor shares and the change in the total inward MP shares is much less tight than that in the model, which generates imprecise estimates in column 4. However, the coefficients predicted by the model (column 2) have similar magnitudes to those in the data.

In terms of welfare, the model also predicts heterogeneous experiences after the MP liberalization over the period. Columns 7-8 in Table 8 report the simulated changes in real rental rates, real wages and real income per capita in each country. In 13 out of the 23 countries, capital owners gain and labor loses in real terms. Therefore, even though more multinational production can potentially reduce the price of the aggregate final goods, I find that it does not fully compensate for the loss of workers' income due to biased demand towards capital. However, in six developed countries (Belgium, Germany, Finland, Netherlands, Sweden and the United States), both capital owners and labor gain in real terms. These countries are among the top net exporters of multinational activities and the analysis suggests they gained the most from reduction in MP costs all around the world.

In summary, the decade after 1996-2001 saw great progress in MP liberalization in many countries. Such liberalization tends to benefit capital rather than labor in the majority of the sample countries, and can explain about 60 percent of the average decline in labor shares across countries. The model also replicates a negative relationship between changes in the labor shares and changes in the inward MP activities, and predicts that the impact of MP is larger for less capital-abundant countries.

5.2 Unilateral MP Liberalization

Many countries revised their FDI policies over the years to create more favorable business environment for multinational firms. (UNCTAD (2012)) Though I do not model these policies directly, I can approximate such unilateral MP liberalization by reducing the MP costs uniformly for a particular host country. Here I consider a 10-log-points decline in the MP costs for each country. In particular, I assume

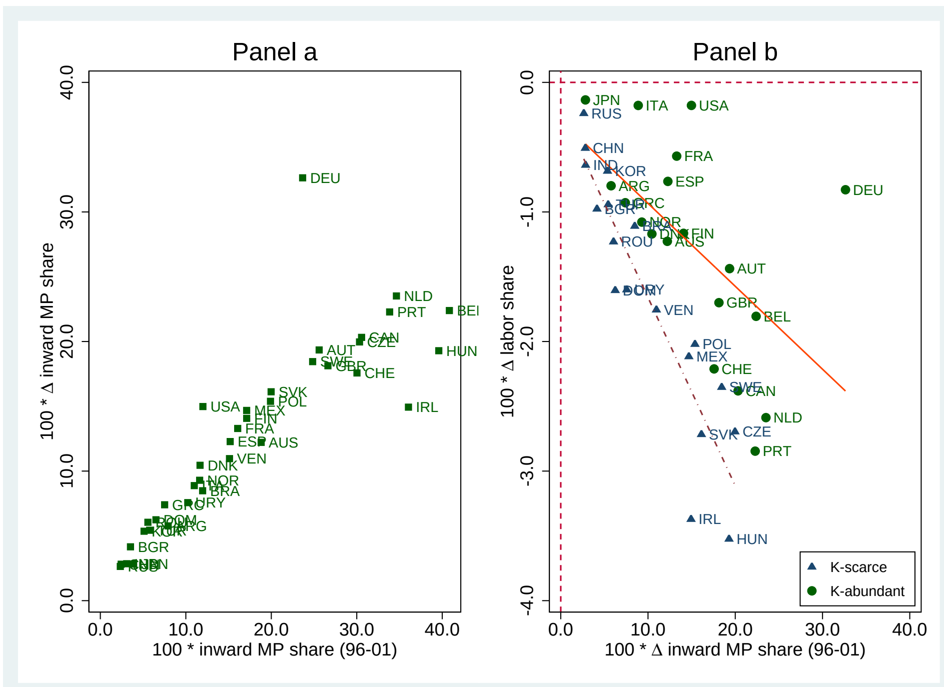
$$\log \gamma'_{il} = \log \gamma_{il} - 0.1 \text{ for all } l \neq i,$$

and solve the new equilibrium for each country l. The procedure produces 37 new equilibria, one for the unilateral MP liberalization in each country. In the following analysis, I focus on the outcome of the country that is assumed to liberalize MP in each counterfactual scenario.

Figure 4 illustrates the effect of unilateral MP liberalizations. Panel a plots the changes in total inward MP shares against the levels in the baseline period. All countries experience an increase in total inward MP shares after unilateral liberalization. The effect of the same 10-log-point decline in γ_{il} on total inward MP shares is non-linear in the sense that countries with higher initial inward MP shares (thus lower γ_{il}) see an even larger increase in inward multinational activities for a given decline in γ_{il}.

Panel b of Figure 4 plots changes in the labor shares against the changes in the total inward MP shares for each country's liberalization. The model implies that all countries would experience declines in the labor shares after MP liberalization and the average decline would be 1.5 percentage points. On average, the larger the increase in the total inward MP share, the larger the predicted decline in the labor share. The impact of the increase in MP shares is stronger for the relatively capital-scarce countries in my sample. For example, when I divide my sample into capital-abundant countries (K/L above median) and capital-scarce countries (K/L below median), and regress changes in the labor shares on changes in the MP shares for each subsample, I find the slope of the capital-scarce subsample (0.145 with a standard error of 0.017) to be significantly larger than that of the capital-abundant subsample (0.064 with a standard error of 0.033). This is because the technology origin effect further increases the demand for capital relative to labor for the capital-scarce countries beyond what is predicted by the size effect.

Figure 4: Unilateral MP liberalization



Note: Each dot represents the results of the country that unilaterally liberalizes its MP. Panel a plots the change in MP shares against the total inward MP shares in the baseline period. Panel b plots the change in labor shares against the change in total inward MP share. The dotted line is the linear fit for the capital scarce countries (K/L below median) while the solid line is the linear fit for the capital abundant countries (K/L above median).

5.3 Decomposing different mechanisms

With the calibrated model in hand, I next consider two alternative setups to further illustrate the quantitative importance of different mechanisms in the model. First, I do a horse race between the two mechanisms by shutting down the technology origin effect. Second, I develop an alternative setup in which the technology origin effects are exogenously given to decompose the effects of technology transfer and technology change after multinational production liberalization. I illustrate the decompositions using the first counterfactual experiment in which I mimic the MP liberalization in the 10-year period following 1996-2001.

5.3.1 Technology-capital complementarity v.s. endogenous technology choice

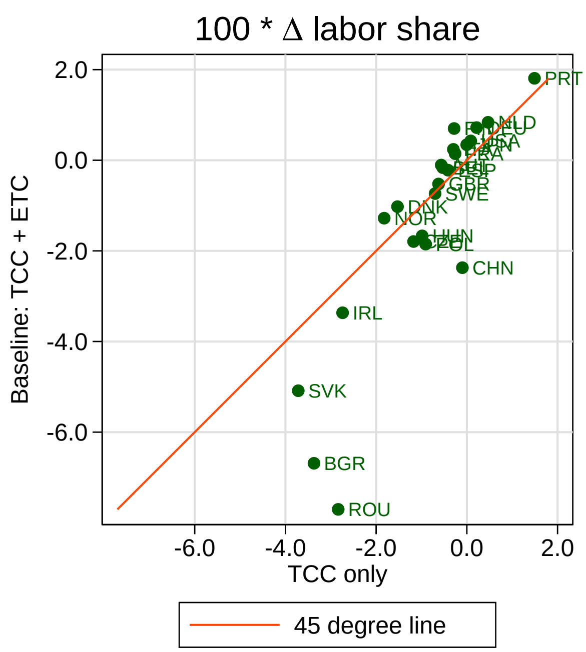
The results from the previous counterfactual experiments suggest that endogenous technology choice has additional implications beyond technology-capital complementarity. In this section, I compare the predictions of the full model to a model without technology origin effect. I recalibrate the model imposing $\eta \to -\infty$, so that all firms from all countries choose the same technology $(a, b) = (1, 1)$. I then perform the first counterfactual experiment as discussed earlier.

The alternative model predicts that labor shares would have declined by 0.9 percentage point on average. This means about 70 percent of the average decline in the model is explained by technology-capital complementarity (TCC) while endogenous technology choice (ETC) explains about 30 percent. However, the latter is relatively more important in less capital-abundant countries. In Figure 5, I plot the predicted changes in the labor shares from the full model (TCC + ETC) against those for the alternative model without ETC; the discrepancies between the two (deviation from the 45 degree line) are the additional impact of ETC. The additional impact of ETC is not large in many countries. However, for countries such as China, Bulgaria and Romania, ETC explains more than 50 percent of the predicted decline in labor shares. Therefore, both mechanisms are important to understand the impact of MP on income distribution, and the relative importance reflects the capital abundance of the country.

5.3.2 Technology transfer v.s. technical change

In the baseline model, technology differences across firms from different countries arise because firms endogenously choose their technologies. In such a setting, reduction in MP costs leads to more technology transfer via MP as well as endogenous adjustments of firms'

Figure 5: Decompose TCC and ETC



Note: I plot the change in labor shares (percentage points) in the first counterfactual for the baseline model (TCC + ETC) against the alternative model with only TCC. TCC stands for technology-capital complementarity, while ETC stands for endogenous technology choice.

technologies (technical change). To separate the contribution of these two mechanisms, I now consider another version of the model, in which technology differences across countries are imposed exogenously instead of being an endogenous result of firms' choices. This alternative model still generates the firm-level technology origin effect but firms no longer adjust their technology after MP liberalization.

In particular, I assume the capital share parameter λ is home-country specific and it increases with the home country's capital abundance in a log linear way

$$\log\left(\frac{\lambda_i}{1-\lambda_i}\right) = \alpha_0^\lambda + \alpha_1^\lambda \log\left(K_i/L_i\right).$$

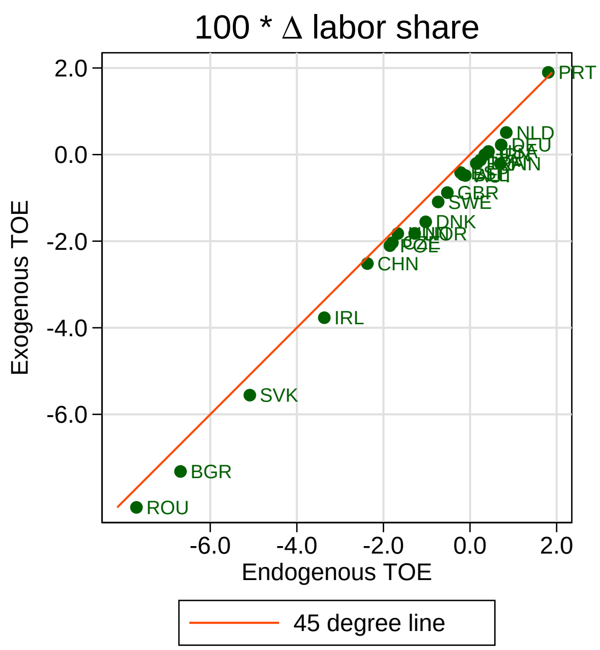
A foreign affiliate from country i inherits λ_i from its parent firm. Therefore, the extensive elasticity η is replaced by a new parameter α_1^λ, which controls the extent to which the factor bias of the technologies correlates with endowments in the home countries. I recalibrate the model targeting exactly the same moments as in the baseline model. The calibration suggests α_1^λ to be 0.236 in order to match the technology origin effect as observed in the micro data. I then conduct the first counterfactual experiment to see the difference between this alternative model and the baseline model.

In Figure 6, I plot the predicted changes in the labor shares in this alternative calibration against the changes in the original model with endogenous choice of (a, b). The differences between the results from the two models are the additional impact of induced technology change by MP liberalization. The predictions in the alternative model and the baseline model are close to one another, which implies that the impact of technical change is limited. The intuition behind this is that even though the inflow of MP activities into the host countries is large, it is still small comparing to the sizes of the home countries (especially the largest home countries such as US and Germany). Thus the potential of foreign production is still too small to alter firms' choices of (a_i, b_i) quantitatively. The importance of technology change relative to technology transfer could become larger when MP costs decline further around the world.

6 Sensitivity

In this section, I conduct a range of sensitivity analyses regarding parameter values and model specifications. I illustrate the sensitivity of results using the first counterfactual and focus on the prediction for the change in labor shares due to the estimated fall in MP costs.

Figure 6: Exogenous vs Endogenous TOE



Note: I plot the change in labor shares (percentage points) in the alternative model with exogenous technology origin effect (TOE) against those in the baseline model (endogenous TOE).

6.1 Intensive elasticity ϵ

I estimated the elasticity of substitution between capital and labor directly using the variation of factor usage and prices within a multinational firm across affiliates in different countries. The estimation strongly supports the hypothesis of an elasticity below unity. However, since the standard error is not negligible (0.11), I consider alternative values of ε. In particular, I choose a lower value (0.3) and a higher value (0.7) than the baseline calibration (0.55). I recalibrate the model keeping all moments unchanged, including the size effect and the technology choice effect. I then predict the change in the labor shares as in the first counterfactual and compare across calibrations with different ε.

Table 10: Sensitivity to the intensive elasticity ϵ

ϵ	0.3	0.55 (baseline)	0.7
Δ labor share	-1.6	-1.3	-1.0

Average change in the labor shares across 23 countries, percentage points. Each column corresponds to calibration with the intensive elasticity ϵ set to 0.3, 0.55 (baseline) and 0.7. All other parameters are recalibrated except for σ, which I set at 4 without calibrating the model.

It is clear from Table 10 that the labor share decline induced by the estimated reduction in MP costs becomes larger when ε is smaller. Intuitively, the two mechanisms, technology-capital complementarity and endogenous technology choice, lead to reallocation of production across firms with different factor bias after liberalizing MP. This can be viewed as capital-biased technical change. Given the increase in the demand of capital relative to labor, higher elasticities imply smaller adjustments in factor prices in order to clear the factor markets, thus smaller changes in the labor shares. However, even when I calibrate the model using a relatively high value of ε, 0.7, the predicted decline can still account for roughly half of the average decline observed in the data.[25]

6.2 Size effect and technology origin effect

In the baseline calibration, I chose to match the size effect and technology origin effect estimated using the multinational subsample. Though the magnitude of the coefficients are similar across specifications and robust to additional controls, there is still some variation

[25]Chirinko (2008) surveys estimates of ε using various identification strategies and conclude that the weight of evidence suggests ε lies in the range between 0.40 and 0.60.

and the standard error on each coefficient is not negligible. I experiment with different values of the two coefficients here. When I target lower values of these two coefficients, I expect both technology-capital complementarity and endogenous choice mechanisms to become weaker. Therefore, the same reduction in MP costs will not bring about as much decline in the labor shares.

Specifically, I pick three values of the size effect, 0.025, 0.05 and 0.075 and three values of the technology origin effect 0.1, 0.2 and 0.3. These moments corresponds to low, medium and high values of ξ and η, respectively. This creates nine combinations of the two moments and I recalibrate the model nine times using each of the combinations. After the calibration, I repeat the first counterfactual experiment and examine the model prediction for the declines of the labor shares in the ten-year period.

Table 11 shows the results of the counterfactuals under alternative calibrations. As expected, the average decline in the labor shares is larger when the two mechanisms are stronger. The predicted change in the baseline calibration, in which I target the technology origin effect to be 0.249 and the size effect to be 0.0523, turns out to be at the high end among all different combinations. However, even when the two effects are reduced to 0.1 and 0.025 in the calibration, the predicted change (-0.7 percentage point) still accounts for one third of the average decline in labor share over this period.

Table 11: Sensitivity to size effect and technology origin effect

ξ	low	medium	high
η			
low	-0.7	-1.0	-1.2
medium	-0.9	-1.1	-1.3
high	-1.0	-1.2	-1.3

Average change in the labor shares across 23 countries, percentage points. Low, medium and high η correspond to calibrations in which the technology origin effect is targeted at 0.1, 0.2 and 0.3, respectively. Low, medium and high ξ correspond to calibrations in which the size effect is targeted at 0.025, 0.05 and 0.075, respectively. All parameters are recalibrated except for σ and ϵ.

6.3 Capital Mobility

In the baseline calibration, I assume that there is no movement of capital across countries. Though there is ample evidence that the international capital market is far from perfect

(Lucas (1990), Prasad et al. (2007), Gourinchas and Jeanne (2013)), one might ask how capital market integration affects the above results. Instead of modeling and quantifying international capital market frictions explicitly, here I simply consider an extreme version of the model where capital markets are perfectly integrated. Because my model features monopolistic competition and increasing return to scale, the reward to the immobile factor (labor) is not necessarily equalized across countries through the mobility of the other factor (capital). The differences in relative factor prices give firms incentives to choose different technologies and the model can still generate the technology origin effect beyond the size effect.

Calibrating the model to the same moments as in the baseline model, I again perform the first counterfactual in which I change the MP costs to match the total inward MP shares in the later period. With cross-country flows of capital, the average decline in the labor shares is reduced to 0.6 percentage point, which, however, still captures 27 percent of the average decline of labor shares in the data. Moreover, the model predicts that countries that have a larger increase in MP activity would see a larger decline in their labor shares as observed in the data. (See online appendix for the full calibration and counterfactual results) Therefore, even when capital is mobile across countries, multinational production is still an important force for the recent decline in labor shares across countries.

7 Conclusion

Multinational firms differ in many dimensions from domestic firms. This paper deviates from standard quantitative multinational production (MP) models by incorporating firm heterogeneity in factor bias. I document two empirical regularities regarding firms' factor bias: (1) larger firms on average use more capital-intensive technologies and (2) firms from capital abundant countries use more capital-intensive technologies. I then build a quantitative model that incorporates these two features by introducing technology-capital complementarity and firms' endogenous choices of the direction of factor bias. In contrast to standard MP models which have no clear prediction regarding income distribution, the model reveals a new mechanism through which MP affects income distribution: liberalizing MP reallocates factors across firms with different factor biases and thus changes the aggregate demand for capital relative to labor.

I calibrate the model to match both firm-level and aggregate moments for 37 countries in 1996-2001. Counterfactual experiments show that, in the 10-year period following 1996-

2001, multinational production liberalization can explain about 60 percent of the average decline of labor shares in my sample of countries. Moreover, the model predicts that countries with a larger increase in multinational activity have experienced a larger decline in their labor shares as has been observed in the data. Both technology-capital complementarity and endogenous choice of technology are important to account for the decline, with the latter relatively more important in less capital abundant countries such as Bulgaria, Slovakia and China.

The quantitative framework I develop highlights the complementarity between technology and a certain factor (capital) and the impact of home country resource scarcity on firms' technologies. The model can be used to study other dimensions of technology heterogeneity among firms, such as the skill bias, and shed light on the impact of multinational production on skill premium. Other aspects of firms' technologies, such as the usage of clean technologies (Wang and Chen (2014)), can also be incorporated into the framework and can be studied quantitatively when data permits.

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A Data

In this section, I provide additional details on the data used in the paper as well as how I infer missing values.

A.1 Aggregate variables

Aggregate variables are used in the firm-level regressions as well as in the quantitative implementation.

Total nonfinancial output: I obtain total nonfinancial output from World KLEMS and OECD STAN for each country. If a country is covered by both databases, I use the one with better coverage in terms of years. For country-years with missing data, I extrapolate using a log-linear relationship between total nonfinancial output and GDP, following Ramondo et al. (2015). In particular, I run the following regression for two different periods separately, the baseline period 1996-2001 and the counterfactual period 2006-2011:

$$\log Y_{lt} = \alpha_0 + \alpha_1 \log GDP_{lt} + u_{lt}.$$

The coefficients before GDP are very close to 1 in both periods. The constant, which reflects the log of output-GDP ratio when $\alpha_1 = 1$, appears to have declined. Among the 37 sample countries, nine of them[26] do not have data on total output and I use extrapolated values.

Endowment: Countries' endowment in capital and labor comes from the Penn World Table 8.0. I use capital stock at constant 2005 national prices (variable "rkna", in mil. 2005US$) to measure capital endowment. For labor endowment, I multiply the number of persons engaged (variable "emp", in mils) by the average human capital (variable "hc") to obtain efficiency units of labor. The Penn World Table 8.0 uses the Barro-Lee dataset and constructs the human capital combining the average years of schooling in each country and assumed return to schooling (see Robert Inklaar and Timmer (2013) for the methodology to develop these variables).

Labor shares: Karabarbounis and Neiman (2014) provides two measures of labor shares: total labor shares and corporate labor shares. The corporate labor share is the labor share within the corporate sector, which is not influenced by the methods to impute labor shares for the non-corporate sectors. It is also more consistent with my micro evidence on multinational firms' technologies. Therefore, I use the corporate labor share wherever possible. For the baseline period in the counterfactuals, all 37 sample countries have data on corporate labor shares. In the later period (2006-2011), seven countries lack information on corporate labor shares thus I use the total labor shares when needed. Factor prices (wages for one efficiency unit of labor and rental rates) are backed out using GDP, labor shares and endowment.

Trade and MP: Bilateral trade data ($\sum_i X_{iln}$) are available from the BACI database (Guillaume and Zignago (2010)). The bilateral trade data is important to derive the total absorption $X_n = \sum_{i,l} X_{iln}$, where the domestic trade volumes are backed out using total output and total export $\sum_i X_{ill} \equiv Y_l - \sum_{i,n \neq l} X_{iln}$. Ramondo et al. (2015) provides bilateral MP sales ($\sum_n X_{iln}$ as in the model) for all countries pairs in my sample for the baseline period (1996-2001). This allows me to calibrate the full MP cost matrix γ_{il} in

[26] These countries are: Argentina, Bulgaria, Brazil, the Dominica Republic, India, Romania, Turkey, Uruguay and Venezuela.

the baseline calibration. For the latter period 2006-2011, I do not have the full matrix of bilateral MP sales. Instead, I have a measure of total inward MP shares for 22 of my sample countries. This measure is obtained from OECD and Eurostat Foreign Affiliates Statistics (FATS) databases and averaged over the period of six years. Some countries may have missing values in certain years, and I extrapolate them using various approaches. The detailed procedures can be found in the online appendix. For China in 2006-2011, I use the industrial enterprises database to compute the total output by foreign owned manufacturing firms (excluding firms owned by Hong Kong, Macau and Taiwan investors) in each year. I then scale the foreign owned manufacturing firms' total output by the share of FDI in manufacturing to obtain an estimate for the total output by all foreign owned firms in China. The total inward MP share can be calculated as the ratio of the total output by all foreign owned firms to the total output reported in the World KLEMS database.

A.1.1 Construction of asset deflators

Since I only use the 2012 firm-level data, I cannot perform a perpetual inventory method to calculate the real stock of capital. Here I provide a way to construct an asset deflator under assumptions about the growth rates of investment prices, firm-level capital stock and the number of years that the firms have been accumulating capital. Consider the perpetual inventory method for a typical firm in country l:

$$\tilde{K}_{lt} = I_{lt} + \frac{P^I_{lt}}{P^I_{lt-1}} (1 - \delta_l) \tilde{K}_{lt-1},$$

where I_{lt} is the **value** of investment in period t at the price of P^I_{lt} and $\tilde{K}_{lt}$ is the **value** of capital stock at the price of P^I_{lt}, at the end of period t. δ_l is the country specific discount rate. Iterate backwards,

$$\begin{aligned}
\tilde{K}_{it} &= I_{lt} + \frac{P^I_{lt}}{P^I_{lt-1}} (1 - \delta_l) \left[I_{lt-1} + \frac{P^I_{lt-1}}{P^I_{lt-2}} (1 - \delta_l) \tilde{K}_{lt-2} \right] \\
&= \sum_{j=0}^{\infty} (1 - \delta_l)^j \frac{P^I_{lt}}{P^I_{lt-j}} I_{lt-j}.
\end{aligned}$$

The real stock of capital equals

$$K_{lt} \equiv \frac{\tilde{K}_{lt}}{P_{lt}^{I}} = \sum_{j=0}^{\infty} (1-\delta_l)^j \, \frac{1}{P_{lt-j}^{I}} I_{lt-j}.$$

However, in practice, the book value of past investment are not adjusted as investment price changes over time. I approximate the book value of total assets as follows

$$\tilde{K}_{lt}^{acct} \equiv I_{lt} + (1-\delta_l)\, \tilde{K}_{lt-1}^{acct} = \sum_{j=0}^{\infty} (1-\delta_l)^j \, I_{lt-j}.$$

Note that in Crozet and Trionfetti (2013), they simply deflate the accounting value of capital stock using the price of investment and get

$$K_{lt}^{CT} \equiv \tilde{K}_{lt}^{acct} / P_{lt}^{I} = \sum_{j=0}^{\infty} (1-\delta)^j \, \frac{1}{P_{lt}^{I}} I_{lt-j},$$

which tends to underestimate the real capital stock if there is constant inflation in investment prices. To properly adjust the real capital stock, I assume that the economies are in steady states and *the real capital stock grows at a constant rate* g_l. This implies

$$\begin{aligned} K_{lt} &= (1+g_l)\, K_{lt-1} = I_{lt}/P_{lt}^{I} + (1-\delta_l)\, K_{lt-1} \\ &\Rightarrow I_{lt}/P_{lt}^{I} = (g_l + \delta_l)\, K_{lt-1}. \end{aligned}$$

Thus real investment grows at the same speed as capital stock. Also assume the investment prices grow at constant rates π_l. I can rewrite the real capital stock as

$$\begin{aligned} K_{lt} &= \sum_{j=0}^{\infty} (1-\delta_l)^j \, \frac{1}{P_{lt-j}^{I}} I_{lt-j} \\ &= \frac{I_{lt}}{P_{lt}^{I}} \sum_{j=0}^{\infty} \left(\frac{1-\delta_l}{1+g_l} \right)^j \\ &= \frac{I_{lt}}{P_{lt}^{I}} \frac{1+g_l}{\delta_l + g_l}, \end{aligned}$$

and

$$
\begin{aligned}
\tilde{K}_{lt}^{acct} &= \sum_{j=0}^{\infty} \left(\frac{1-\delta_l}{1+g_l}\right)^j \frac{I_{lt}}{P_{lt}^I} P_{lt-j}^I \\
&= \frac{I_{lt}}{P_{lt}^I} \sum_{j=0}^{\infty} P_{lt}^I \left(\frac{1-\delta_l}{(1+\pi_l)(1+g_l)}\right)^j \\
&= I_{lt} \frac{(1+\pi_l)(1+g_l)}{(1+\pi_l)(1+g_l)-(1-\delta_l)}.
\end{aligned}
$$

Thus the proper deflator is

$$
\frac{\tilde{K}_{lt}^{acct}}{K_{lt}} = P_{lt}^I \frac{(1+\pi_l)(\delta_l+g_l)}{\pi_l+g_l+\pi_l g_l+\delta_l}.
$$

If the life span of firms is finite, say T, then the deflator should be

$$
\begin{aligned}
\frac{\tilde{K}_{lt}^{acct}}{K_{lt}} &= P_{lt}^I \frac{\sum_{j=0}^{T-1} \left(\frac{1-\delta_l}{(1+\pi_l)(1+g_l)}\right)^j}{\sum_{j=0}^{T-1} \left(\frac{1-\delta_l}{1+g_l}\right)^j} \\
&= P_{lt}^I \frac{(1+\pi_l)(\delta_l+g_l)}{\pi_l+g_l+\pi_l g_l+\delta_l} \frac{1-\left(\frac{1-\delta_l}{(1+\pi_l)(1+g_l)}\right)^T}{1-\left(\frac{1-\delta_l}{1+g_l}\right)^T}.
\end{aligned}
$$

In practice, I calculate g_l and π_l using a log-linear regression of real capital stock and investment prices on time for the sample period 1990-2011, respectively. Then I extrapolate $P_{l,2012}^I$ from 2000-2011 to 2012 using country-specific growth rates. Firm age in all countries is assumed to be 10 years.

In the reduced-form regressions in section 2, it does not matter what deflator I use since it is country specific and will be absorbed by the country-industry fixed effects. However, when it comes to the estimation of the intensive elasticity, the capital-labor ratio has to be comparable across countries. For the estimate used in calibration, I assume firm age to be 10 years in all countries. I experiment with different T and the coefficients are stable as shown in Table A8.

A.2 Firm level data

The firm level data are a cross-section in 2012 downloaded from the Orbis online interface in July 2014. To study firms' capital intensity, I start with firms' unconsolidated accounts with nonmissing key variables for the regressions (host country, industry, total asset, wage bills and number of employees). I next exclude firms using four criteria: (1) firms in the financial sectors (2) multinational affiliates in or from tax havens (3) firms with abnormal capital-labor ratios compare to host-country-industry median (4) countries or industries with too few firms. The details of the procedures and number of firms dropped in each step can be found in Table A1. This results in a sample of more than 2.76 million firms and I present the distribution and coverage of the sample across countries in Table A2.

Table A1: Data cleaning procedures

Steps	# of obs
Firms with nonmissing key variables	3196650
Step1: financial firms	103097
Step2: MNE in tax havens	12823
Step3: firms with abnormal K/wL or K/L	193215
Step4: countries or industries with too few firms	121467
Final sample	2766048

a Key variables refer to : total assets, number of employees, cost of employees, host country, industry and home country K/hL.

b Financial firms refer to firms in the financial sector (NACE Rev2 Sector 64, 65 and 66).

c The major tax haven countries in my original sample are Switzerland, Luxembourg, Ireland and Cyprus.

d An observation is identified with abnormal K/L or K/wl if any of the three variables is non-positive, or the ratio is larger than 200 times of the country-industry median, or smaller than 1/200 of the country-industry median.

e Host and home countries are dropped if fewer than 5000 firms are in the dataset. Industries are dropped if they span fewer than 5 countries with at least 50 observations in each country.

Table A2: Coverage of the firm-level data

Country	(1) # of firms	(2) Employment share	(3) # of inward affiliates	(4) Employment share	(5) # outward affiliates
Belgium	116000	0.52	1812		1223
Bulgaria	143000	0.91	558	0.16	292
Czech	55000	0.45	2348	0.36	143
Germany	44000	0.18	2689	0.19	7488
Denmark	9000	0.15	752	0.23	927
Spain	426000	0.42	3912	0.31	1730
Estonia	32000	0.54	621	0.34	27
Finland	44000	0.35	504	0.15	786
France	207000	0.19	3154	0.22	3810
UK	43000	0.33	5202	0.37	3163
Croatia	55000	0.59	547	0.26	343
Hungary	203000	0.63	361	0.16	823
Italy	418000	0.37	3775	0.24	4206
Japan	208000		73		1775
Korea	66000		411		171
Norway	87000	0.72	1495	0.36	943
Poland	11000	0.07	743	0.07	319
Portugal	212000	0.58	1552	0.37	417
Romania	305000	0.73	5799	0.27	206
Serbia	35000		1139		82
Slovenia	40000	0.53	425	0.25	504
Sweden	180000	0.39	1331	0.15	2302
US	7000		0		7523
Average	128000	0.46	1704	0.25	1704

Total number of firms in column (1) is rounded to 1000. Employment share in column (2) is the share of employment of Orbis firms in the country's total employment. Inward affiliates in column (3) refer to foreign affiliates that produce in the country of study. Employment share in column (4) refers to the share of employment of the Orbis foreign affiliates in column (3) in the corresponding host country' total foreign affiliates' employment, where the aggregate statistics (denominators) come from OECD/Eurostat Foreign Affiliates Statistics database. Outward affiliates in column (5) refer to foreign affiliates that headquartered in the country of study.

B Additional Tables

Table A3: Direct controlling for firm-level log(r/w)

	Dependent Var: log(total assets/employment)			
	All	All	MNE	MNE
	(1)	(2)	(3)	(4)
Home country log(K/L)	0.281***	0.283***	0.355***	0.341***
	(0.0461)	(0.0380)	(0.0790)	(0.0757)
log(Revenue)	0.166***	0.140***	0.113***	0.103***
	(0.0191)	(0.0171)	(0.00903)	(0.0101)
Firm's log(r/w)	-0.132***	-0.134***	-0.118***	-0.124***
	(0.0282)	(0.0261)	(0.0221)	(0.0240)
debt-to-equity ratio		0.00150***		0.00228***
		(0.000342)		(0.000687)
# of host * industry	7311	7215	3844	3583
# of home countries	24	24	24	24
# of foreign links	26,000	22,000	26,000	22,000
R-squared	0.451	0.453	0.492	0.510
N	1,672,000	1,415,000	43,000	36,000

All specifications regress log of firms' capital intensity (defined as total assets divided by employment) on home country endowment (log of capital stock divided by efficiency units of labor) and firm level characteristics conditional on host country × NACE 4-digit industry fixed effects. Firm's cost of capital is defined using the Hall-Jorgenson user cost of capital, while wage is defined by dividing the wage bill by the number of employees. Sample "All" refers to all firms including local firms and multinational subsidiaries sample "MNE" refers to multinational subsidiaries. Standard errors are clustered at both home country and host country * industry levels. + 0.10 * 0.05 ** 0.01 *** 0.001. Number of observations is rounded to thousands of firms.

Table A4: Determinants of capital bias term

	Dependent Var: log of capital bias			
	All	All	MNE	MNE
	(1)	(2)	(3)	(4)
Home country log(K/L)	0.299***	0.319***	0.340***	0.338***
	(0.0442)	(0.0393)	(0.0879)	(0.0852)
log(Revenue)	0.0903***	0.0615***	0.0835***	0.0716***
	(0.0203)	(0.0175)	(0.0103)	(0.0114)
debt-to-equity ratio		0.00173**		0.00227**
		(0.000545)		(0.000739)
# of host * industry	7311	7215	3844	3583
# of home countries	24	24	24	24
# of foreign links	26,000	22,000	26,000	22,000
R-squared	0.398	0.411	0.451	0.476
N	1,672,000	1,415,000	43,000	36,000

Dependent variable is log of firms' capital biases, defined as $log(K/L) + \varepsilon log(r/w)$, where K refers to firms' total assets, L is total employment, r is the user cost of capital and w is the average wage paid by the firm. I pick a value of ε, 0.55, to be consistent with the calibration results in later sections. All regressions control for host country × NACE 4-digit industry fixed effects. Sample "All" refers to all firms including local firms and multinational subsidiaries sample "MNE" refers to multinational subsidiaries. Standard errors are clustered at both home country and host country * industry levels. + 0.10 * 0.05 ** 0.01 *** 0.001. Number of observations is rounded to thousands of firms.

Table A5: Different coverage of Orbis database across home countries does not drive technology origin effect

	Dependent Var: log(total assets/wage bill)			
	All (1)	All (2)	Foreign Aff (3)	Foreign Aff (4)
$\log(K_i/L_i)$	0.242*	0.152+	0.222	0.160
	(0.102)	(0.0876)	(0.157)	(0.159)
log(Revenue)	0.0996***	0.0583**	0.0680***	0.0600***
	(0.0260)	(0.0216)	(0.00689)	(0.00908)
leverage ratio		0.00503***		0.00452***
		(0.000957)		(0.000806)
Emp share (firms)	✓	✓		
Emp share (affiliates)			✓	✓
# of host * industry	6158	5991	3075	2692
# of home countries	15	15	16	16
# of foreign links	22,000	17,000	29,000	23,000
R-squared	0.352	0.410	0.461	0.494
N	1,913,000	1,408,000	28,000	22,000

All specifications regress log of firms' capital intensity (defined as total assets divided by total wage bill) on home country endowment (log of capital stock divided by efficiency units of labor) and firm level characteristics conditional on host country × NACE 4-digit industry fixed effects. Sample "MNE" refers to multinational affiliates including those producing at home. sample "Foreign Aff" refers to multinational foreign affiliates. Coverage in home country i refers to the employment of foreign affiliates from i in Orbis as a share of the corresponding number in the aggregate data (OECD/Eurostat). Standard errors are clustered at both home country and host country * industry levels. + 0.10 * 0.05 ** 0.01 *** 0.001. Number of observations is rounded to thousands of firms.

Table A6: Alternative Definitions of Technology Origin

	Dependent Var: log(total assets/wage bill)					
	Alter Def 1		Alter Def 2		Alter Def 3	
	(1)	(2)	(3)	(4)	(5)	(6)
$log(K_i/L_i)$	0.173**	0.198**	0.227*	0.235*	0.253*	0.262*
	(0.0650)	(0.0700)	(0.109)	(0.113)	(0.105)	(0.108)
log(Revenue)	0.0796***	0.0717***	0.0685***	0.0609***	0.0681***	0.0608***
	(0.0115)	(0.0116)	(0.00839)	(0.00996)	(0.00880)	(0.0102)
leverage ratio		0.00275**		0.00298***		0.00301***
		(0.00103)		(0.000647)		(0.000580)
# of host * industry (Cluster 1)	3071	2792	4010	3639	4012	3642
# of foreign links	10,000	8,000	31,000	25,000	32,000	27,000
N	29,000	24,000	48,000	40,000	48,000	40,000
R-squared	0.481	0.508	0.465	0.488	0.464	0.488

Two-way clustered standard errors in parentheses. + 0.10 * 0.05 ** 0.01 *** 0.001. i indicates the home country of the firm. Each regression controls host country × NACE 4-digit industry fixed effects.
Alternative definition 1: A foreign owner's country is defined as technology origin only if the owner is the closest controlling firm owner and is in the same 2-digit industry as the affiliate.
Alternative definition 2: A foreign owner's country is defined as technology origin only if the owner is an industrial firm and it is within within 3 layers of control of the affiliate.
Alternative definition 3: A foreign owner's country is defined as technology origin only if the owner is the closest foreign owner of the affiliate.

Table A7: Horse race between home country and alternative definitions of technology origin

	Dependent Var: log(total assets/wage bill)			
	(1)	(2)	(3)	(4)
Home country $\log(K/L)$	0.259*	0.274*	0.247*	0.253*
	(0.128)	(0.132)	(0.118)	(0.119)
Largest host $\log(K/L)$	-0.0215	-0.0296		
	(0.0500)	(0.0541)		
Average host $\log(K/L)$			0.0112	0.0254
			(0.0448)	(0.0478)
log(Revenue)	0.0525***	0.0406***	0.0523***	0.0405***
	(0.00930)	(0.0103)	(0.00937)	(0.0103)
debt-to-equity ratio		0.00358***		0.00358***
		(0.000584)		(0.000585)
# of host * industry	4481	4098	4482	4097
# of home countries	24	24	24	24
# of foreign links	37,000	29,000	37,000	29,000
R-squared	0.466	0.494	0.466	0.494
N	60,000	49,000	60,000	49,000

All specifications regress log of firms' capital intensity (defined as total assets divided by total wage bill) on home country endowment (log of capital stock divided by efficiency units of labor) and firm level characteristics conditional on host country $\times$ NACE 4-digit industry fixed effects. Only multinational firms are included in the regression. "Largest host country" refers to the host country that has the largest revenue for a multinational firm. For multinational firms that lack this information, the home country is assumed to be its largest host country. "Average host log(K/L)" refers to the average country level log(K/L) of the host countries, weighted by revenue of affiliates in each host country. Standard errors are clustered at both home country and host country * industry levels. + 0.10 * 0.05 ** 0.01 *** 0.001. Number of observations is rounded to thousands of firms.

Table A8: Estimate ϵ

	(1)	(2)	(3)	(4)
$log(r_{l(f)}/w_{l(f)})$	0.455		0.431	0.486
	(0.108)		(0.105)	(0.113)
$log(r_{l(f)}/w_f)$		0.440		
		(0.0953)		
N	26588	26588	26588	26588
Intensive elasticity	0.545	0.560	0.569	0.514
Assumed Firm Age	10	10	5	20
Fixed Effects	GUO * NACE4	GUO * NACE4	GUO * NACE4	GUO * NACE4
# of groups	7227	7227	7227	7227
# of home countries	23	23	23	23
# of host countries	24	24	24	24
N	26,000	26,000	26,000	26,000
First-stage F	80.093	41.400	80.093	80.093

f indicates the firm, $l(f)$ indicates the host country of the firm. All factor prices are instrumented with host country endowment $log(K/hL)$. The first four columns controls for GUO $\times$ Nace4 fixed effects while the last one controls for Home Country $\times$ Nace4 fixed effects. Columns also differ in the firm age assumed when calculating the asset deflator of each country. (see table)

Table A9: MP shares, MP costs and country differences

	(1) $log(\lambda_{il}^{M,base})$	(2) $log(\lambda_{il}^{M,TCC})$	(3) $log(\gamma_{il}^{base})$	(4) $log(\lambda_{il}^{M,base})$	(5) $log(\lambda_{il}^{M,TCC})$	(6) $log(\gamma_{il}^{base})$
diff in $log(K/L)$	-0.840***	-0.197	0.104***	-0.914***	-0.272*	0.115***
	(0.151)	(0.136)	(0.0251)	(0.146)	(0.133)	(0.0241)
log(dist)	-1.740***	-1.766***	0.375***	-1.851***	-1.884***	0.391***
	(0.0960)	(0.0999)	(0.0182)	(0.113)	(0.119)	(0.0212)
contiguity				-1.148***	-1.191***	0.177***
				(0.239)	(0.243)	(0.0366)
common language				0.238	0.228	-0.0514
				(0.245)	(0.240)	(0.0445)
colony				1.067**	1.008**	-0.160*
				(0.332)	(0.329)	(0.0600)
N	1089	1089	1089	1089	1089	1089
R^2	0.785	0.781	0.902	0.794	0.790	0.906
T-stat		3.160			3.257	

[a] Dependent variables are real/counterfactual MP shares or calibrated MP costs. $\lambda_{il}^{M,base}$ is the MP share from home country i in host country l in the data and in the baseline calibration). $\lambda^{M,TCC}$ is the counterfactual MP share when I assume all firms adopt the world average technology. γ_{il}^{base} refers to the calibrated MP costs.

[b] All regressions control host and home country fixed effects. Standard errors clustered at host-country level. + 0.1, * 0.05, ** 0.01, *** 0.001.

[c] Differences in country characteristics are absolute differences in log values.

[d] The T-stat is calculated based on a T-test for whether the coefficients in columns 1 and 2 (or 4 and 5) are the same. It assumes that the observations in the two regressions are independent.

Table A10: Calibration - targets and parameters - CBP only

Parameters	Values/Normalization	Targets
τ_{il}	$\tau_{ii} \equiv 1$	trade shares
γ_{il}	$\gamma_{ii} \equiv 1$	MP shares
F_{ei}		Prob serving home market 0.7
ξ	0.623	coefficient of revenue 0.052
k	4.268	unrestricted trade elasticity 4.3
θ	10.986	restricted trade elasticity 10.9
λ_k	0.355	average labor share 0.520

Table A11: Counterfactual with CBP only

ISO3	inward MP share 96-01	inward MP share 06-11	Δ log MP costs (calibrated)	$\Delta log(r/P)$	$\Delta log(w/P)$	Δ labor share	Δ log real income
AUT	25.6	31.8	-1.9	1.5	-0.9	-0.6	-0.0
BEL	40.8	47.3	-2.7	3.6	1.4	-0.5	2.3
BGR	3.5	31.8	-30.1	4.0	-11.8	-3.4	-0.9
CHN	2.4	15.6	-26.1	-0.8	-1.3	-0.1	-0.9
CZE	30.3	45.7	-5.9	2.6	-2.2	-1.2	0.3
DEU	23.7	22.4	-0.1	2.2	3.1	0.2	2.7
DNK	11.7	23.8	-11.1	4.0	-2.4	-1.5	0.1
ESP	15.2	20.9	-4.1	0.6	-1.1	-0.4	-0.4
FIN	17.1	20.0	-5.7	5.7	4.5	-0.3	4.9
FRA	16.1	21.5	-4.2	1.0	-0.1	-0.3	0.3
GBR	26.6	35.3	-4.5	1.2	-1.3	-0.6	-0.2
HUN	39.6	50.5	-3.4	2.4	-1.6	-1.0	0.7
IRL	36.0	51.4	-8.2	7.1	-4.1	-2.7	2.4
ITA	11.0	16.5	-6.2	1.0	-0.4	-0.3	0.1
JPN	3.9	4.1	-0.1	0.7	0.7	-0.0	0.7
NLD	34.6	31.6	0.5	2.5	4.4	0.5	3.6
NOR	11.6	25.1	-14.0	5.0	-2.5	-1.8	0.5
POL	19.9	35.3	-8.1	0.8	-2.9	-0.9	-0.9
PRT	33.8	20.1	8.6	-1.7	4.3	1.5	1.5
ROU	5.6	42.4	-29.4	2.5	-10.7	-2.8	-1.7
SVK	20.0	49.9	-14.6	6.3	-8.7	-3.7	-0.3
SWE	24.8	32.4	-4.9	3.2	0.4	-0.7	1.7
USA	12.0	11.2	0.2	1.0	1.4	0.1	1.3
Avg	20.3	29.9	-7.7	2.4	-1.4	-0.9	0.8

Counterfactual experiment of changing inward MP costs such that inward MP shares match those in 2006-2011. All numbers are in percentage points or 100× change in log points