Multinational Production with Non-neutral Technologies

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Abstract

This paper develops a quantitative model of multinational production (MP) with non-neutral technologies incorporating two stylized facts observed in a global firm-level data: first, larger firms on average use more capital-intensive technologies; second, among firms producing in the same industry and country, those from more capital-abundant home countries use more capital-intensive technologies. I quantify the model using both firm-level and aggregate moments for 37 countries. I found that the reduction in MP costs accounts for 56% of the average decline in labor shares from 1996 to 2011, and the model also replicates a negative relationship between the change in a country's labor share and the change in the foreign affiliates' output share as observed in the data.

JEL code: F1, F4

Key words: multinational production, non-neutral technologies, labor shares

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1 Introduction

Multinational firms have played an increasingly prominent role in the global economy. Policymakers, especially those in developing countries, are interested in attracting 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 thought, the new generation of quantitative models of MP focuses on the transfer of technologies with different Hicks-neutral productivities through multinational activities.[1] However, as I show in the data, multinational firms use technologies that also differ in terms of factor intensities, which has received little attention in previous works.

In this paper, I document two empirical regularities about the capital-labor ratio of local and multinational firms from 22 countries. First, larger firms use more capital-intensive technologies, which I refer to as the "size effect." Second, within the same industry and country of production, firms originating from capital-abundant countries use more capital-intensive technologies, which I call the "technology origin effect." Multinational firms can bring technologies of different capital intensities into 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.

Based on the empirical facts, I develop a quantitative framework for modeling multinational production with non-neutral technologies. To match the size effect, I assume a form of technology-capital complementarity, i.e., overall more efficient technologies require relatively more capital. To match the technology origin effect, I allow firms to endogenously choose their technologies from a menu of capital- and labor-intensive technologies before they become multinationals. Beyond the micro-structure that generates heterogeneity in firms' capital intensities, the trade and MP structure of the model resembles that of Arko-

[1]See, for example, Burstein and Monge-Naranjo (2009), Ramondo and Rodríguez-Clare (2013), Arkolakis et al. (2018), Tintelnot (2017), and Bilir and Morales (2016).

lakis et al. (2018). Therefore, the model is rich enough to match aggregate statistics such as bilateral MP and trade shares. Overall, the model provides a quantitative framework for understanding the impact of MP with non-neutral technologies on aggregate outcomes such as MP patterns, factor prices and income shares.

The model has rich implications on MP patterns as well as the distributional consequences of MP liberalization. First, I show analytically that firms from capital-abundant countries tend to adopt more capital-intensive technologies because of endogenous technology choices. This, in turn, creates larger endogenous MP costs for firms investing in countries with relative factor prices more different from their home countries. This mechanism can help to explain the negative relationship between the bilateral MP sales and the difference in capital abundance between home and host countries in the data (also see Fajgelbaum et al. (2015)). Second, because firms differ in their capital intensities, MP liberalization reallocates factors across firms and affects the relative demand for capital and labor and thus the equilibrium labor shares.

To understand the quantitative implications of the model, I parameterize the model to match the size and technology origin effects estimated from the micro data as well as aggregate bilateral trade and MP shares in 37 countries 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 perform a model-based decomposition and show that the endogenous technology choice mechanism can explain most of the negative relationship between bilateral MP sales and the difference in capital abundance between the home and host countries.

I then use the calibrated model to understand the distributional consequences of MP. In particular, I estimate the change in MP frictions from 1996-2001 to a later period, 2006-2011 and find that the reduction in MP frictions leads to an overall decline in labor shares. On average, the model predicts a 1.2-percentage-point average decline in the labor shares across my sample countries, which is around 56% of what is observed in the data. The model also replicates a negative relationship between the change in a country's labor share and the change in the foreign affiliates' output share observed in the data. This is because of two reasons. First, inward MP brings in productive firms from foreign countries which are also capital-intensive (technology-capital complementarity). They crowd out less productive labor-intensive domestic firms and raise the relative demand for capital. Second, because MP mostly originates from capital-abundant countries, new foreign affiliates in capital-scarce countries tend to use more capital-intensive technologies than the local firms due to endogenous technology choices. A model-based decomposition shows that the technology-capital complementarity explains around 75% of the predicted average labor share decline, while the endogenous technology choice mechanism is particularly important for understanding the decline in the emerging economies.

Besides introducing non-neutral technologies to the quantitative MP models, my paper contributes to several other strands of literature. First, the size effect is closely related to the literature on "factor-biased productivities." In a recent paper, Burstein and Vogel (2017) point out that trade liberalization leads to an increase in the 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. 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 the setting of global firms. I embed this mechanism into a multi-country, general-equilibrium MP and trade model and quantify its importance in understanding the distributional consequences of globalization.

The technology origin effect connects with the literature on directed technical change (Acemoglu (2003b); Acemoglu (2003a); Acemoglu et al. (2015)). The key insight from this literature is that the direction of technical change caters to the factor prices in countries where they are most likely to be applied. I embed a similar idea in a quantitative MP model, where I show that multinational firms endogenously choose technologies that cater to their home countries' factor prices. This prediction is consistent with firm-level evidence, while the strength of the mechanism can be calibrated using firm-level data together with aggregate data.

The technology origin effect is also related to an earlier literature on "inappropriate technology." Since Eckaus (1955), development economists have been concerned that technologies developed in the capital-abundant countries are "inappropriate" in the capital-scarce developing world, which can lead to "underemployment problems." A few studies in the 1970s tried to test the hypothesis that multinational firms from advanced countries used more capital-intensive technologies than local firms in the developing countries. However, due to a lack of large firm-level datasets, the literature turned to case studies involving a few dozens of firms, with no consensus on the validity of this hypothesis.[2] I use comprehensive micro data and modern econometric techniques and provide support for the hypothesis. Though the quantitative model does not feature underemployment, it predicts that FDI liberalization can potentially lower workers' wages in the host countries, which resonates with the "underemployment problem".

My quantitative analyses show that MP liberalization is crucial for understanding the global decline of labor shares. Karabarbounis and Neiman (2014) first document this trend and they argue that the main explanation for this phenomenon is the decline in prices of investment goods.[3] As Oberfield and Raval (2014) point out, mechanisms that work solely through factor prices cannot account for the decline of labor shares if the elasticity of substitution between capital and labor is below one, as they estimate using plant-level data. When calibrating my model, I provide a model-consistent estimate of the elasticity of substitution, which is also smaller than one and confirms the findings in Oberfield and Raval (2014).

[2] A notable contribution to this old literature 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.

[3] Other prominent explanations include Elsby et al. (2013), Rognlie (2016), Koh et al. (2016), Autor et al. (2017), Grossman et al. (2017) and Barkai (2017).

Though Oberfield and Raval (2014) emphasized the role of technological change in the decline of labor shares, they are silent on the drivers of such changes. In contrast, I show that globalization can lead to reallocation of factors across firms, which leads to "biased technological change" at the aggregate level. Using panel data on establishments and firms, Autor et al. (2017) decompose the change in aggregate labor shares into within-firm and between-firm components. They show that the between-firm component is crucial for explaining the labor share decline. The quantitative model I develop captures the between-firm reallocation effects and provides a multi-country framework for quantifying the impact of policies and technologies on the labor shares through this mechanism.

My paper also contributes to the literature on firms' 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 more recent literature has acknowledged firms' heterogeneity in other dimensions such as input usage.[4] I show that a firm's capital intensity is systematically correlated with its 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, to which my data unfortunately do not speak. However, my model can be used to analyze the impact of MP on the skill premium where data permit.

The remainder of the paper is organized as follows. In Section 2, I document the two empirical regularities. I develop the quantitative framework for modelling MP with non-neutral technologies in the Section 3. I then calibrate the model and perform counterfactual analysis in Sections 4 and 5 and conclude in Section 7. I discuss sensitivity of the calibration and counterfactuals with respect to model parameters in the appendix and relegate details about the data, proofs, and additional empirical and quantitative results to the online appendix.

[4]See, for example, Crozet and Trionfetti (2013), Blaum et al. (2015) and Burstein and Vogel (2017). Meanwhile, a related literature tries to empirically estimate factor-augmenting productivities using techniques developed by Olley and Pakes (1996). See Doraszelski and Jaumandreu (2015) and Zhang (2015) for example.

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 effect." Second, firms' capital intensities are positively correlated with their home countries' capital abundance, which I name the "technology origin effect."

2.1 Firm-Level Data

To explore the determinants of firms' capital intensity, I use Orbis, the global firm-level database maintained by Bureau van Dijk (BvD). This database provides balance sheet and income statement information on millions of companies around the world. Moreover, it offers a unique opportunity to examine multinational firms' capital intensity, since BvD records ownership links between companies and identifies the "Global Ultimate Owner" (GUO) of a company when there is sufficient information to construct its ownership structure. In my analysis, I use data for the year 2012, the most recent year of data at the time of study. I also choose the definition of GUO to be companies owning at least 50.01% of the subsidiary, so structures such as joint ventures are excluded. I only use the unconsolidated accounts to make sure that key variables of multinational affiliates are measured properly.

After dropping companies in the financial industries, those in and from tax havens, and those with abnormal wages or capital intensities, along with country-industry cells with too few observations, I obtain a cross-section of more than 2.6 million companies. These companies come from 22 home countries and operate in 21 host countries. About 40,000 of the observations are multinational foreign affiliates while approximately 20,000 are multinational firms' subsidiaries in their home countries.[5] As expected, large and developed countries such

[5]I identify a multinational foreign affiliate if the nationality of the company's GUO is different from where the company operates. I define the "home" country of a multinational affiliate to be the country of its GUO

as the United States and Germany are home to a large number of multinational affiliates. Nevertheless, the dataset also covers multinationals from emerging economies such as Romania, Bulgaria and the Czech Republic. Compared with aggregate statistics from OECD and Eurostat, my data on average covers 42% of the total employment and 21% of the employment by foreign affiliates in the sample countries. In Online Appendix OA.1.3, I provide more details about data cleaning procedures and sample coverage. I also perform various robustness checks and show that the results are similar when different criteria are used to drop outliers and that the main empirical facts are unlikely to be driven by the differential coverage across countries.

2.2 Technology Origin and Size Effects

In this subsection, I document two stylized facts regarding firm heterogeneity in capital-labor ratios. Since each observation in my data is either a non-MNE company or a multinational affiliate, and multiple multinational affiliates can have the same parent firm, the word "firm" may be confusing in this context. Throughout the paper, I refer to non-MNE companies or multinational affiliates as "affiliates" (denoted by a), and refer to the entire group of multinational affiliates owned by the same ultimate owner as "firms" (denoted by f).[6] For each affiliate, I construct its capital-labor ratio by dividing its total assets by its wage bill. I use wage bill instead of the number of employees as the denominator to account for worker skill differences across affiliates.

I then project this ratio on affiliate revenue and home country capital abundance (see footnote 5 for the definition of home country), controlling for host-country-industry fixed

and the home country of a non-MNE company (a company not belonging to any multinational group) to simply be where it operates.

[6]This is a slight abuse of terminologies since a non-MNE company may or may not be an affiliate of another domestic company. Whether or not they belong to another domestic company does not affect the analysis here since the non-MNE company's home country is always the one where it operates.

effects. In particular, I run the following regression

$$\log\left(\frac{K_a}{w_a L_a}\right) = \delta_{s\times l} + \beta_1 \log\left(\frac{K_i}{L_i}\right) + \beta_2 \log(R_a) + \epsilon_a, \tag{1}$$

where a refers to an affiliate (possibly a local independent firm), and s, l and i are the industry, country of production (host country), and home country of the affiliate, respectively. The key variables in this regression are the ratio of aggregate capital stock to human capital in the home country[7], K_i/L_i, and the affiliate's revenue R_a. The country-by-industry fixed effects $\delta_{s\times l}$ control for technological differences across sectors and substitution between capital and labor when firms face different factor prices in different countries of production. Therefore, the effects of home country capital abundance and affiliate revenue are identified using variation within production countries and narrowly defined industries.[8]

Two points are worth some discussion here. First, the country of production and home country are different only for multinational affiliates located in a foreign country. Therefore, the coefficient β_1 is only identified when multinational foreign affiliates are present, given that I have controlled for host-country-by-industry fixed effects. Second, I use revenue as a measure of firm size because variables such as assets and total wage bill are used to calculate the left-hand variable. Any measurement error in these variables can cause mechanical correlations if they are also used on the right hand side.

Column 1 in Table 1 presents estimates of the simplest version of this regression. It shows that the elasticity of the affiliate's capital intensity with respect to its home country's capital abundance is 0.172, with a standard error of 0.084. At the same time, a one percent increase in affiliates' revenue is associated with a 0.08 percent increase in their capital-labor ratios. A back-of-envelope calculation shows that a one-standard-deviation increase in $\log(K_i/L_i)$ and log revenue is associated with a 0.06- and 0.25-standard-deviation increase in firms' capital-

[7]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 Online Appendix OA.1.1.

[8]Orbis provides 4-digit NACE Rev 2 industry codes for each firm. There are around 380 unique industries in my sample.

labor ratios, respectively. In the remainder of the paper, I refer to β_1 as the "technology origin effect" and β_2 the "size effect".

In Column 2, I perform a slight variation of the simplest specification. I replace the home country factor abundance by a MNE affiliate dummy and an interaction term between the dummy and the capital abundance of the home country relative to the host country. The coefficient before the interaction term is very close to the home country effect estimated in column 1. Moreover, the coefficient before the MNE dummy suggests that, after we control for affiliate size, an affiliate from a foreign country of similar capital abundance as the host country does not have a premium in its capital-labor ratio. In Column 3, I further restrict the sample to MNE affiliates. The host-country-industry fixed effects now pick up the average capital-labor ratio of MNE affiliates only. The technology origin and size effects are robust, which suggests that they are not driven only by the differences between non-MNE and MNE affiliates.

There are two main reasons why firms have different capital-labor ratios. First, firms can face heterogeneous factor prices. If large firms and firms from capital-abundant countries have better access to the financial market and lower capital rental rates, they will use more capital instead of labor. Second, firms may differ in their technologies. More advanced technologies make firms more productive and larger, but requires relatively more capital. At the same time, firms from capital-abundant countries may have adopted capital-intensive technologies and they bring these technologies to foreign countries when producing abroad. This paper favors the second explanation. Ideally, to rule out the first mechanism, one would want to control for affiliate-level factor prices, which are not available in standard datasets like Orbis. In columns 4-6, I control for affiliates' debt-to-equity ratios which capture their access to external borrowing. Unsurprisingly, this variable does have a positive impact on firms' capital-labor ratios and reduces the size effects by 22% to 47%, but it does not eliminate the technology origin and size effects. This suggests that heterogeneous factor prices are unlikely to be the only reason for these patterns, and technological differences might be a potential explanation.[9]

Table 1: Size and Technology Origin Effects on $log(K_a/w_aL_a)$

	Dependent Var: log(total assets/wage bill)					
	All Firms		MNE	All Firms		MNE
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(K_i/L_i)$	0.172*		0.277*	0.158**		0.291*
	(0.0841)		(0.141)	(0.0700)		(0.144)
$\mathbb{1}_{MNE}$		-0.0267			0.0309	
		(0.0650)			(0.0576)	
$\mathbb{1}_{MNE} \times (\log(K_i/L_i) - \log(K_l/L_l))$		0.191***			0.138**	
		(0.0604)			(0.0531)	
log(revenue)	0.0803***	0.0807***	0.0543***	0.0428*	0.0423*	0.0422***
	(0.0265)	(0.0272)	(0.00988)	(0.0216)	(0.0223)	(0.0106)
debt-to-equity ratio				0.00390***	0.00390***	0.00379***
				(0.00125)	(0.00125)	(0.000640)
# of firms	2,621,000	2,621,000	55,000	2,009,000	2,009,000	45,000
# of host countries	21	21	21	21	21	21
# of host * industry	7,404	7,404	4,112	7,317	7,317	3,736
# of home countries	22	22	22	22	22	22
# of foreign links	34,000	34,000	33,000	26,000	26,000	26,000
R-squared	0.356	0.356	0.436	0.395	0.395	0.459

All specifications regress log of affiliates' 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 affiliate-level characteristics conditional on host country × NACE 4-digit industry fixed effects. MNE refers to the sample of multinational affiliates. Standard errors are clustered at both home country and host country × industry levels. Significance levels: * 0.10 ** 0.05 *** 0.01. Number of observations is rounded to thousands of affiliates.

The technology origin effect suggests that a firm may choose technologies based on some weighted average factor prices, with a specially large weight on the prices in its home country. When modelling such dependence, there are two plausible timing assumptions on firms' technology choices: (1) firms choose technologies before they know their own profitability in each potential host country, so they have to make a decision based on the "average profitability" of a typical firm headquartered in the same country; (2) firms choose technologies after they know their own profitability in each host country, so they make a decision based on this information. To differentiate between these two timing assumptions, I construct a firm-level index of the average host country capital abundance, weighted by the firm's revenue in all its production locations (including the home), and run a horse race between the home country

[9] The estimated β_1 and β_2 vary across specifications and have non-negligible standard errors. The standard error of β_1 tends to be larger than that of β_2, largely because the identification of β_1 only comes from variation in the country-level capital-to-labor ratios and the standard errors have been clustered at the home country level. As discussed in Section 4, I target one set of the the regression coefficients (Column 3 in Table 1) when calibrating the quantitative model using indirect inference. I examine the sensitivity of my quantitative results by recalibrating the model using different targeted values of β_1 and β_2 in Appendix A.2.

and average host country capital abundance.[10] According to the first timing assumption, the impact of the former should dominate the latter, and vice versa according to the second timing assumption.

Table 2: The Impact of Home Country and Alternative Definitions of Technology Origin

	Dependent Var: log(total assets/wage bill)					
	(1)	(2)	(3)	(4)	(5)	(6)
Home country $\log(K_i/L_i)$	0.268**	0.277**	0.264**	0.274**		
	(0.125)	(0.123)	(0.124)	(0.123)		
Average host $\log(K_l/L_l)$ (firm weights)	0.0168	0.0193				
	(0.0470)	(0.0459)				
Largest host $\log(K_l/L_l)$			0.0235	0.0198		
			(0.0389)	(0.0402)		
Average host $\log(K_l/L_l)$ (agg weights)					0.302**	0.322**
					(0.131)	(0.127)
log(Revenue)	0.0555***	0.0437***	0.0555***	0.0436***	0.0548***	0.0425***
	(0.00994)	(0.0107)	(0.00996)	(0.0107)	(0.0104)	(0.0112)
debt-to-equity ratio		0.00368***		0.00369***		0.00336***
		(0.000645)		(0.000646)		(0.000581)
# of firms	55,000	45,000	55,000	45,000	53,000	44,000
# of host countries	21	21	21	21	21	21
# of host * industry	4,111	3,735	4,110	3,736	3,860	3,503
# of home countries	22	22	22	22	18	18
# of foreign links	33,000	26,000	33,000	26,000	32,000	25,000
R-squared	0.463	0.483	0.463	0.484	0.464	0.484

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. Only multinational firms are included in the regression. Average host $\log(K_l/L_l)$ (firm weights) is the average host country capital abundance of the MNE, weighted by all its affiliates Largest host refers to the host country where the multinational corporation has the largest revenue (home country included). Standard errors are clustered at both home country and host country * industry levels. Significance levels: * 0.10 ** 0.05 *** 0.01. Number of observations is rounded to thousands of firms.

In Columns 1 and 2 of Table 2, I reported the horse race regressions, using data on the MNE affiliates only, since these two key regressors are exactly the same for non-MNE affiliates. One caveat about these regressions is that the firm-level index of average host country capital abundance may contain measurement errors due to incomplete coverage of the Orbis data, so its coefficient may be estimated with an attenuation bias. With this caveat in mind, Columns 1 and 2 show that that the impact of the home country endowment dominates that of the average host country, therefore supporting the first timing assumption. In Columns 3 and 4, I replace the average host country capital abundance with the capital abundance of the largest host country in terms of revenue (possibly the home country), and find similar patterns. Finally, according to the first timing assumption, the best measure

[10] I thank a referee for proposing this measure.

to use should be the average host country capital abundance weighted by the *aggregate MP sales* instead of firm-level revenue in each location. Columns 5 and 6 show that this variable strongly predicts the affiliates' capital-labor ratios. However, this measure has a correlation of 0.995 with the home country capital abundance, so there is not enough variation for me to perform a horse race between them.[11]

In Online Appendix OA.2, I perform further analysis and various robustness checks. The technology origin and size effects are robust to controlling gravity variables between the home and host countries, controlling for host-country-industry-revenue/age-bin fixed effects where I divide firms in each host-country-industry cell into ten equally sized bins based on their revenue and age, further controlling for heterogenous financing costs and using alternative ways of defining technology origins. Due to space limit, I relegate all the additional empirical results to the online appendix.

To summarize, the technology origin and size effects reveal that multinational firms use technologies with systematically different capital intensities than do non-MNEs. These patterns are missing in heterogeneous-firm models where firms differ only in Hicks-neutral productivities. In the next section, I develop a model that can replicate these two features and can be taken to the data.

3 Model

In this section, I build a quantitative model of trade and multinational production (MP) in which firms differ in their capital intensities. I incorporate two new mechanisms into the trade and MP model in Arkolakis et al. (2018) (hereinafter ARRY): technology-capital complementarity and endogenous technology choice. Technology-capital complementarity is modeled following the factor-biased production function in Burstein and Vogel (2017), while endogenous technology choice is modeled by assuming the firm chooses factor-augmenting

[11] In contrast, the correlation coefficients between home country capital abundance and the two alternative measures, the average host country capital abundance weighted by firm revenue in each location and the capital abundance of the firm's largest host country, are only 0.48 and 0.47, respectively.

productivities from a technology menu (Caselli and Coleman (2006), Oberfield and Raval (2014)). When both mechanisms are shut down, all firms worldwide have the same capital-labor ratios given a set of factor prices. I further characterize the choices of technologies and MP costs analytically in the model under certain simplifying assumptions.

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, and factor markets are perfectly competitive. I assume both factors are immobile throughout the analysis except for in Appendix A.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 and engaging in monopolistic competition in the product market. Varieties available in market i are combined using a CES aggregator for final consumption. The price index of the composite final good is

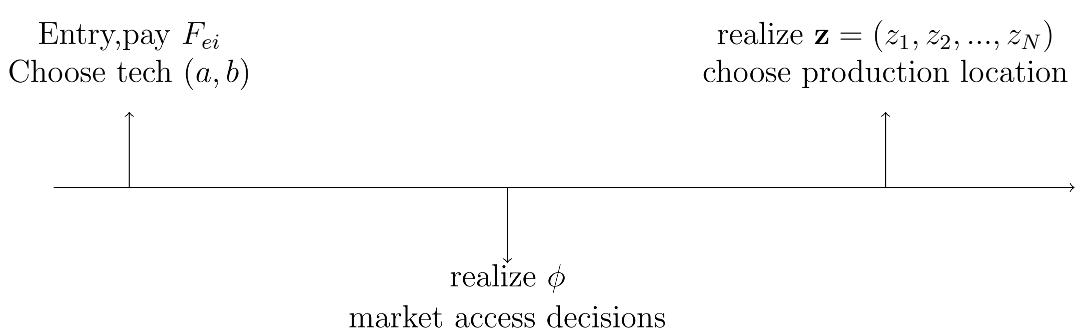
$$P_i = \left(\int_{\omega \in \Omega_i} p_i \left(\omega \right)^{1-\sigma} d\omega \right)^{1/(1-\sigma)}, \tag{2}$$

where $p_i(\omega)$ is price of variety ω in market i and Ω_i is the set of varieties available in country i.

3.1 The Firm's Problem

Timing and Technology

Figure 1: Timing of Firms' Activities



Firms' activities are divided into three stages, as shown in Figure 1. First, firms pay an entry cost, F_{ei} units of the composite final good in country i, to set up a headquarter there, and they 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

$$\phi \sim F(\phi) = 1 - (\phi/\phi_{\min})^{-k}, \tag{3}$$

which determines their overall efficiency no matter where they produce and the Pareto tail parameter k governs the dispersion of the overall efficiency. In this stage, firms also need to decide which market(s) to serve. They have to pay a marketing cost, F units of the composite final good in the destination country, to access its market.[12] 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

$$z_l \sim \exp\left(-T_{il} z^{-\chi}\right), \; l = 1, \ldots, N, \tag{4}$$

where the location parameter T_{il} determines the average quality of ideas and χ 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 to the CES production function

$$q = z_l \left(\lambda^{1/\varepsilon} \left(a\phi^{1-\xi/2} K \right)^{\frac{\varepsilon-1}{\varepsilon}} + (1-\lambda)^{1/\varepsilon} \left(b\phi^{1+\xi/2} L \right)^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}}, \tag{5}$$

[12] Unlike one-factor trade and MP models, it is unclear whether the marketing and entry costs should be paid in capital or labor in my model. I take a natural alternative and assume they are paid in composite goods. This assumption, however, is likely to cause the model to have different welfare predictions from ARRY. In Appendix A.4, I discuss alternative setups and the robustness of the calibration and the quantitative predictions of the model.

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-labor ratios 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, as in Burstein and Vogel (2017).[13] 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

$$\frac{K}{L} = \frac{\lambda}{1-\lambda}\phi^{\xi(1-\varepsilon)}\left(\frac{a}{b}\right)^{\varepsilon-1}\left(\frac{r_l}{w_l}\right)^{-\varepsilon}. \tag{6}$$

From this expression, it is clear how the core productivity ϕ leads to a positive correlation between a firm's capital-labor ratio and its size when $\xi(1-\varepsilon) > 0$: higher core productivity leads to both higher output and a 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. On the other hand, the endogenous choice mechanism will help to match the technology origin effect in the data as long as firms from more capital-abundant countries choose technologies with higher $(a/b)^{\varepsilon-1}$, which I show to be the case under simplifying assumptions in Section 3.3 analytically and in the calibrated full model quantitatively.

Following Caselli and Coleman (2006) and Oberfield and Raval (2014), the menu of all

[13] ARRY show that, in their setting, a model with affiliates draw z_l from a multivariate-Pareto distribution is observationally equivalent to one with the setup here (firms first draw ϕ from a Pareto distribution and then draw z_l from Fréchet distribution). I do not use the multivariate-Pareto setup because of the need to have a single overall efficiency measure to determine the capital intensity.

feasible technologies is characterized by the set

$$\Theta \equiv \left\{ (a,b) \left| \theta(a,b) \right. = \left(a^{1-\eta} + b^{1-\eta}\right)^{1/(1-\eta)} \leq 1 \right\}, \tag{7}$$

with the additional parameter restriction $\eta + \varepsilon < 2$ which ensures the technology to be an interior solution.[14] Given the amount of capital and labor, a firm's output in any production location l increases in both a and b. Therefore, the firm always chooses a technology on the technology frontier, $\theta(a,b) = 1$. The parameter η governs the shape of the technology frontier, thus the trade-off between high capital- and high 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 lowering one factor-augmenting productivity does not increase the possible range of the other. Therefore, firms always choose $(a,b) = (1,1)$ in this limiting case, and the mechanism of endogenous technology choice is completely shut down.

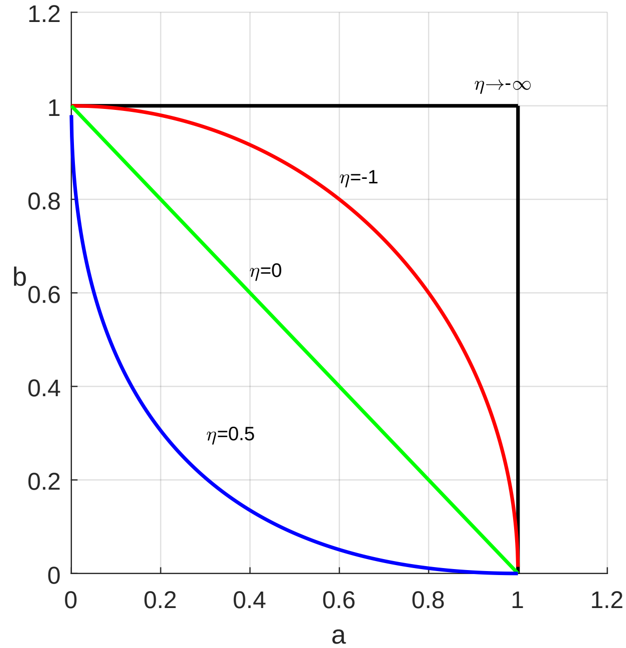
Another way to see the economic meaning of the parameter η is to consider a firm producing in a closed economy l. The firm takes factor prices (r_l, w_l) as given and minimizes its cost by choosing both (a,b) and (K,L). One can solve the problem in two steps: first solve the optimal (K,L) given (a,b), and then solve the optimal technology (a,b). Using this procedure, one can show that the total response of K/L with respect to r_l/w_l becomes

$$\varepsilon^{tot} \equiv \frac{d\ln(K/L)}{d\ln(r_l/w_l)} = \varepsilon + \frac{(1-\varepsilon)^2}{2-\varepsilon-\eta}, \tag{8}$$

Therefore, the total response can be decomposed into the *extensive* margin (optimal choice of (a,b), governed by parameter η) and the *intensive* margin (adjusting K/L after (a,b) has

[14] The lemma in the Online Appendix OA.3.4.1 establishes this result. When $\varepsilon + \eta \geq 2$, one can show that the marginal cost is monotonic in a/b when firms face one set of factor prices. Thus the optimal technology would be either $(a,b) = (0,1)$ 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 prefers using one input.

Figure 2: Technology Menu under Different η



been chosen, governed by parameter ε).

Though this decomposition has been discussed in Oberfield and Raval (2014), they are not able to distinguish between the intensive and extensive margins using domestic plant-level data. Using multinational firm data combined with the assumption that (a, b) is common within a firm across its affiliates, I am able to separately estimate the two parameters, ϵ and η. When an affiliate produces in a country with different factor prices, the intensive margin still allows it to substitute between capital and labor. However, since the affiliate's technology is potentially different from firms from other origins producing in the same host country, its capital-labor ratio differs and the difference is informative about the extensive substitution.

Firm Optimization

I solve for the firm's problem backwards from Stage 3. After all shocks are realized, the unit cost of a country i firm producing in country l is

$$C_l\left(\phi, z_l, a, b\right)=\frac{1}{z_l}\left(\lambda\left(\frac{r_l}{a \phi^{1-\xi/2}}\right)^{1-\varepsilon}+(1-\lambda)\left(\frac{w_l}{b \phi^{1+\xi/2}}\right)^{1-\varepsilon}\right)^{1/(1-\varepsilon)}, \tag{9}$$

which can be derived from cost-minimizing using the CES production function (5). The marginal cost to serve market n from country l for a firm headquartered in country i is

$$C_{iln}\left(\phi, \mathbf{z}, a, b\right)=\gamma_{il} C_l\left(\phi, z_l, a, b\right) \tau_{ln}, \tag{10}$$

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.

In Stage 3, a 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. The derivation of the probability of serving market n via production in country l and the expected operating profit associated with market n follows Arkolakis et al. (2018) closely. Interested readers can find the expressions in the online appendix.

In Stage 2, a firm chooses the markets that it will serve. Given the expected operating profit $\pi_{i \cdot n}\left(\phi, a, b\right)$, a firm enters market n if and only if the expected profit from that market is larger than the monetary value of the marketing costs $P_n F$. Under the assumption that both capital- and labor-augmenting productivities increase with the core productivity ϕ (i.e., $-2<\xi<2$), a higher ϕ strictly increases $\pi_{i \cdot n}\left(\phi, a, b\right)$. Therefore, there exists a unique cutoff ϕ_{in}^* above which firms will enter.

Unlike Arkolakis et al. (2018), there is no closed-form expression for ϕ_{in}^*, since ϕ affects the marginal cost not only through the overall efficiency but also through factor intensities. When I shut down technology-capital complementarity, i.e., set $\xi=0$, I recover a closed-form expression for ϕ_{in}^* and gravity-type expressions for aggregate trade and MP shares as in ARRY. The detailed derivation can be found in Online Appendix OA.3.3.

In Stage 1, the firm chooses the optimal technology (a, b) upon entry by maximizing the expected global profit $E_\phi [\pi_i (\phi, a, b)]$, where $\pi_i (\phi, a, b)$ is defined as

$$\pi_i (\phi, a, b) \equiv \sum_n \mathbf{1} [\pi_{i \cdot n} (\phi, a, b) \geq P_n F] (\pi_{i \cdot n} (\phi, a, b) - P_n F) . \tag{11}$$

The free entry condition implies that firms headquarter in home country i if and only if the expected global profit is no less than the monetary value of the entry costs $P_i F_{ei}$.

Implications for Firms' Capital-Labor Ratios

According to the timing assumptions, firms choose optimal technology before the core productivity ϕ is realized. Therefore, there is no heterogeneity across firms from the same country at this stage, and all firms from the same country will choose the same technology as long as the optimal technology choice is unique. I assume that the choice is made before rather than after ϕ is realized for three reasons. First, as is shown in Table 2, the home country capital abundance rather than average host country capital abundance weighted by firm-host-country level sales predicts the affiliate capital intensities. This suggests that firms' technologies are chosen before they have a good sense about where they are going to produce.

Second, this timing assumption is a reduced-form way to capture the dynamic process of developing technology and expansion of multinational production in a static model. For example, when Toyota developed lean production, it might have not expected that it would expand its production into other countries such as the United States and China. Therefore, at the time of the technology development, domestic factors were most likely to be concerned. Finally, this assumption greatly simplifies the firm's problem and thus the solution of the model. If I assumed that the choice is made after ϕ is realized, I would need to solve for the firm's problem for different values of ϕ, which would greatly increase the computational burden. With the current setup, I only need to solve for one pair of (a, b) for each home country. In Section 3.3, I further discuss how the intuition of the main analytical results still holds if firms choose technologies after ϕ is known.

In this setup, suppose all firms from country i choose the same technology (a_i, b_i). The capital-labor ratio of a firm from i producing in country l with core productivity ϕ can be written as

$$\frac{K_{il}(\phi)}{L_{il}(\phi)} = \frac{\lambda}{1-\lambda}\phi^{\xi(1-\varepsilon)}\left(\frac{a_i}{b_i}\right)^{\varepsilon-1}\left(\frac{r_l}{w_l}\right)^{-\varepsilon}. \tag{12}$$

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), which helps to match the technology origin effect in the data. Beyond this effect, country i firms producing in country l still differ 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 are 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 ratios both because of the intensive substitution term and its impact on the ex-ante technology choice (a_i, b_i). However, when multinational firms are available, it is possible to separate these two margins because the dataset contains firms whose producing location is not its home country $(i \neq l)$.

3.2 Aggregation and Equilibrium

The aggregation of the model is similar to ARRY despite the fact that there is no analytical gravity. By integrating over firms of different core productivities, one obtains the aggregate three-way sales from country i firms producing in country l and selling to market n, which I denote with X_{iln}. The bilateral trade and MP shares, λ^T_{ln} and λ^M_{il}, are defined in standard ways:

$$\lambda_{ln}^{T} = \frac{\sum_i X_{iln}}{\sum_{i,l} X_{iln}}, \quad \lambda_{il}^{M} = \frac{\sum_n X_{iln}}{\sum_{i,n} X_{iln}}. \tag{13}$$

In equilibrium, capital, labor and goods markets clear in all countries. Firms make optimal entry and technology choices. I allow the existence of an exogenous current account surplus/deficit in each country, which shows up in the goods market clearing condition. Moreover, since the marketing and entry costs are paid using the composite final goods, they also appear in the goods marketing clearing condition. All the market clearing conditions can be found in Online Appendix OA.3.2.

Due to the complication introduced by non-neutral technologies and firms' option 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.[15]

3.3 Analytical Results

So far, I have not shown that firms from capital-abundant countries necessarily chose more capital-intensive technologies in the model, while the data suggest this is the case. I now prove this in a special case of the model without technology-capital complementarity (i.e., $\xi = 0$), but with endogenous technology choice (i.e., $\eta > -\infty$). In addition, I make the following simplifying assumptions:

Assumption 1 (Within-Region Symmetry) *There are N_N countries in the North and N_S countries in the South. Countries within the same region are symmetric in the following sense:*

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: $K_N/L_N > K_S/L_S$.*

[15] 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}.

2. *Entry costs F_{ei} are common within a region. Exogenous current account surpluses are allowed but have to be the same within a region.*

3. *MP and trade costs are the same for all country pairs, except for the domestic MP and trade costs, which are normalized to 1, i.e., $\gamma_{ii} = \tau_{ii} = 1, \gamma_{il} = \gamma > 1, \tau_{il} = \tau > 1, \forall i \neq l$.*

Though these assumptions make the model far more restrictive than the full model with realistic trade/MP costs and rich heterogeneity across countries regarding factor endowments, this setup is sufficient to highlight the working of the endogenous technology choice mechanism. Under these assumptions, I can prove the following proposition:

Proposition 1 (Technology Origin Effect) *Assume foreign trade and MP costs satisfy one of the two restrictions, (1) $\gamma \geq \tau > 1$ or (2) $\tau = \infty, \gamma > 1$, and assume that, in equilibrium, entrants with the lowest core productivity $\phi_{\min}$ do not sell in any markets. Then, in a symmetric equilibrium,*[16]

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), i.e., $(a_N/b_N)^{\varepsilon-1} \geq (a_S/b_S)^{\varepsilon-1}$.*

3. *Northern firms enjoy a cost advantage in the North while Southern firms enjoy a cost advantage in the South, i.e., $C_l(a_i, b_i) \geq C_i(a_i, b_i), \forall i, l \in \{N, S\}, i \neq l$, where $C_l(a_i, b_i) \equiv \left(\lambda (r_l/a_i)^{1-\varepsilon} + (1-\lambda)(w_l/b_i)^{1-\varepsilon}\right)^{1/(1-\varepsilon)}$.*

Proof. See Online Appendix OA.3.4.2 for the proof. ■

The intuition for these results comes from the fact that bilateral MP costs γ are greater than one.[17] This implies that production in other countries is less efficient than that in the

[16] In a symmetric equilibrium, equilibrium variables such as prices and the mass of entrants are the same for countries within the same region.

[17] I can only prove the proposition when trade costs are sufficiently small or sufficiently large. However, the above predictions may still hold when trade costs are in the intermediate range. In fact, in the full calibrated model, though bilateral trade costs are sometimes larger than MP costs, the capital intensities of technologies are highly correlated with home country capital abundance.

home country. Therefore, when choosing the optimal technology, firms give more weight to the expected profit obtained from producing in the home market. This makes 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.

It is worth discussing which other model assumptions are essential to this result. Crucially, I have assumed that a firm chooses only one technology and apply it wherever it produces. If firms can switch technologies without any costs, they will adapt to the optimal technology in the production country according to its factor prices, regardless of their home country factor prices. However, this extreme case is inconsistent with the observed technology origin effects.

In Section 3.1, I have discussed why I assume that firms choose technologies before the core productivity ϕ is realized. However, the intuition of the technology origin effect still holds if one assumes technology-capital complementarity and assume that technologies are chosen after ϕ is realized but before the location-specific productivities are realized. Under this alternative timing assumption and applying the same argument as in the proof of Proposition 1, one can show that, a Northern firm with sufficiently high ϕ chooses a more capital-intensive technology compared to a Southern firm with the same ϕ, as long as the North has relatively cheap capital (see Online Apeendix OA.3.4.3). Unfortunately, the factor demand equations are no longer tractable in this case and it is not obvious how to show the North has indeed relatively cheap capital.

Part (3) of Proposition 1 highlights the endogenous costs for firms to produce in countries with different endowment structures. To see this more clearly, consider the marginal cost of a country i firm with $\phi = 1$, producing in l and selling to n:

$$\zeta_{iln}\left(a_i, b_i\right) \equiv \gamma_{il} C_l\left(a_i, b_i\right) \tau_{ln}. \tag{14}$$

In this expression, the iceberg MP costs, γ_{il}, are exogenously given and are home-host country specific. The middle term, $C_l(a_i, b_i)$, is also home-host country specific, but it is endogenous to firms' technology choices. I therefore call γ_{il} the "exogenous MP costs" and $C_l(a_i, b_i)$ the "endogenous MP costs".[18] In Proposition 1, though the exogenous MP costs γ_{il} are assumed to be common for all country pairs, the endogenous choice of (a_i, b_i) makes $C_l(a_i, b_i)$ larger for cross-region MP (North-to-South or South-to-North) than within-region MP (North-to-North or South-to-South). This difference provides a supply-side explanation for the empirical pattern that firms invest relatively more in countries with income levels similar to their home country. (see Fajgelbaum et al. (2015) for a demand-side explanation) I quantify the relevance of this supply-side explanation in Section 4.4.

4 Calibration

To understand the quantitative importance of technology-capital complementarity and endogenous technology choice, I calibrate the model to match both affiliate-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 affiliate-level data help to discipline three important parameters in the model. The size and technology origin effects, discussed above in Section 2, will discipline the strength of the technology-capital complementarity ξ and the extensive elasticity of substitution η. Using variation across affiliates of the same firm, I can 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 untargeted aggregate and firm-level moments.

[18] Though both γ_{il} and $C_l(a_i, b_i)$ are called "MP costs", only the former reflects frictions in MP that may be reduced by policies. The latter is caused by firms' optimal choice of technologies and cannot be seen as a friction.

4.1 Parameters Calibrated without Solving the Model

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

$$\frac{r_l K_a}{w_l L_a} = \phi_f^{(1-\varepsilon)\xi} \left(\frac{a_i}{b_i}\right)^{\varepsilon-1} \left(\frac{r_l}{w_l}\right)^{1-\varepsilon}, \tag{15}$$

where i and l denote the home and host countries and f denotes the firm that the affiliate belongs to. Since each firm is mapped to a unique home country, I can control the first two terms with firm fixed effects. 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:

$$\log\left(\frac{r_l K_a}{w_a L_a}\right) = (1-\varepsilon)\log\left(\frac{r_l}{w_l}\right) + \delta_{f\times s} + u_a, \tag{16}$$

where s and f denote the industry and firm that the affiliate belongs to. 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 $w_a L_a$ as the denominator on the left-hand side. Finally, since the host-country rental rate r_l appears on both the left- and right-hand sides of the equation, I instrument for $\log(r_l/w_l)$ with the endowment, $\log(K_l/L_l)$, to avoid mechanical correlation caused by measurement errors in r_l.[19]

The cross-sectional data lack a measure of affiliates' real capital stock K_a. I construct a host-country-specific asset deflator and then deflate affiliates' total assets using the deflator. The asset deflator assumes that affiliates' capital stock has been growing at a constant rate

[19] The country-level wages and rental rates are backed out using the labor share data from Karabarbounis and Neiman (2014). In particular, I attribute GDP to labor income and capital income using the labor shares and divide them by efficient units of labor and real capital stock, respectively.

(the same rate as that of the nation's aggregate capital stock) for a decade. Together with a constant, country-specific growth rate of investment prices and inflation rate, I derive the asset deflator and deflate the total assets of the firm to obtain K_a.[20]

Table 3: Estimate the Intensive Elasticity ε

	OLS		IV Regression			
	(1)	(2)	(3)	(4)	(5)	(6)
$log(r_l/w_l)$	0.636		0.490		0.462	0.525
	(0.0744)		(0.113)		(0.110)	(0.118)
$log(r_l/w_a)$		0.405		0.452		
		(0.0397)		(0.0975)		
N	23517	23517	23517	23517	23517	23517
Implied ε	0.364	0.595	0.510	0.548	0.538	0.475
Assumed Affiliate Age	10	10	10	10	5	20
# of firm-industry	6423	6423	6423	6423	6423	6423
# of host countries	21	21	21	21	21	21
# of home countries	22	22	22	22	22	22
First-stage F			145.5	74.2	145.5	145.5

Dependent variable is log of affiliates' capital expenditure divided by total wage bills in all regressions. The affiliate is indicated by a, and l indicates the host country of the firm. In the IV regressions (columns 3-6), factor prices are instrumented with host country endowment, $\log(K_l/L_l)$. In all regressions, I control for firm $\times$ NACE 4-digit industry fixed effects. Columns also differ in the firm ages assumed when calculating the asset deflator of each country, which are displayed in the bottom of the panel. Standard errors are two-way clustered at home and host country level. The number of observations excludes singletons that are not used in the regression.

Column 1 shows the OLS estimate of equation (16), which implies an intensive elasticity of 0.364. In Column 2, I use the affiliate-level wage instead of the country-level wage to calculate the relative factor prices on the right-hand side, and the estimated intensive elasticity becomes higher. I instrument the host country relative factor prices with relative capital abundance in columns 3 and above. Columns 3 and 4 replicate the OLS regressions using the IV approach, and the estimated elasticities are 0.51 and 0.55, respectively, with slightly larger standard errors. In Columns 1 to 4, I deflate firms' total assets by an asset deflator that assumes all firms have accumulated capital for ten years. Columns 5 and 6 shows that the estimates are robust when I assume that firms have accumulated capital for five and twenty years, respectively.

[20]See Online Appendix OA.1.2 for detailed derivation of the asset deflator and data used for each component.

The estimates suggest that the intensive elasticity is below one. It contrasts some estimates obtained using aggregate time-series data (Chirinko (2008)), but is in line with estimates that use micro data (e.g., Oberfield and Raval (2014)). In my calibration, I choose Column 3 as my preferred specification and set ε to be 0.51. Since the estimates depend on the specifications and the standard errors are non-negligible, I examine the sensitivity of the calibration and counterfactuals to in Section 4.2 and Appendix A.1.

4.2 Parameters Calibrated by Matching Moments

Table 4: Baseline Calibration - Targets and Parameters

Parameters	Values/Normalization	Targets
τ_{il}	$\tau_{ii} \equiv 1$	bilateral trade shares
γ_{il}	$\gamma_{ii} \equiv 1$	bilateral MP shares
F_{ei}		probability serving home market 0.7
η	0.545	technology origin effect 0.277
ξ	0.580	coefficient of revenue 0.054
k	4.201	unrestricted trade elasticity 4.3
χ	10.932	restricted trade elasticity 10.9
λ	0.313	average labor share 0.520

All of the other parameters of the model – γ_{il}, τ_{ln}, k, χ, η, ξ and λ – are calibrated to match the model's endogenous outcomes. As discussed before, I decide to perfectly match trade and MP shares so the location parameter of the productivity distribution, T_{il}, cannot be separately identified from the iceberg MP costs γ_{il}. I simply normalize T_{il} to 1 for all i and l.

A difficult question is how to calibrate the lower bound of the core productivity ϕ_{min}, fixed marketing cost F and entry costs F_{ei}. In Online Appendix OA.4.2, I prove that, without technology-capital complementarity, one can normalize all these parameters and calibrate an observationally equivalent equilibrium as long as $\phi^*_{in} > \phi_{min}$ for all i, n, an assumption maintained in ARRY. Extra data moments are needed if one wants precise values of these parameters.[21] Unfortunately, the calibration of my model with technology-capital complementarity is not neutral to the values of these parameters. Instead of searching for extra data to pin down these parameters, I decide to set ϕ_{min} and F to one and calibrate F_{ei} such that the fraction of entrants that end up serving their domestic markets is 70% in all countries. I then experiment with alternative strategies, such as lowering this target to 10% for all countries, or calibrating $F_{e,US}$ to match a probability of 70% in the US and assuming entry costs in other countries are the same. However, the other calibrated parameters and the quantitative predictions of the model under these alternative assumptions are very similar to the baseline (see Online Appendix OA.5.5), which make the calibration strategy of these parameters less of a concern.

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 equation (13)), 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 Online Appendix OA.1.1.

Note that the calibration of the MP and trade costs is different from ARRY. ARRY use an "extended Head and Reis" approach which adds the restriction that the MP and trade costs are symmetric for bilateral pairs of countries. The benefit of their approach is that they are able to identify the country-level innovation capabilities (source country effect in T_{il}) and

[21] For example, the mass of entrants in each country and the fraction of entrants serving the domestic market are good candidates for disciplining the entry costs F_{ei}, but these data are difficult to obtain for a large cross section of countries. Without these measures, di Giovanni and Levchenko (2013) use information such as the amount of time required to set up a business to discipline the entry costs in each country relative to the United States. However, they need to set the entry costs in the US to target a somewhat arbitrary entry rate (see their footnote 14) since it is unclear how to map the time to set up a business to the level of entry costs in units of labor.

the production capabilities (destination country effect in T_{il}), at the cost of not perfectly matching all trade and MP shares. Since identifying countries' innovation and production capabilities is not the main purpose here, I choose to keep T_{il} unidentified and use γ_{il}, τ_{il} to perfectly match MP and trade shares. This approach is more suitable for answering questions such as the impact of declining MP costs on factor prices. As a sanity check, Table OA.22 in the online appendix shows that the calibrated trade and MP costs correlated with gravity variables in meaningful ways.

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 0.313.

Restricted and Unrestricted Trade Elasticities

As is shown in ARRY, the Fréchet shape parameter χ and the Pareto shape parameter k are well disciplined by the "restricted" and "unrestricted" trade elasticities, respectively. The "restricted trade elasticity" is the elasticity of the three-way sales X_{iln} with respect to the trade costs between the production country and the destination market, τ_{ln}, conditional on the trade flows being generated by firms from home country i. In ARRY, one can express the log of three-way sales as

$$\ln X_{iln} = \delta^r_{il} + \delta^r_{in} - \chi \ln \tau_{ln}, \tag{17}$$

where δ^r_{il} and δ^r_{in} are home-host and home-destination fixed effects. Therefore, they estimate χ directly using data on X_{iln} and tariff without solving the model. In my model, because there is no analytical gravity ($\xi \neq 0$), the restricted trade elasticity can differ from χ. However, given guesses of other parameters, I can back out all the trade costs τ_{ln} and solve for the equilibrium three-way sales X_{iln}. I therefore adjust the value of χ (together with other parameters) to ensure the restricted trade elasticity estimated using the model-implied τ_{ln}

and X_{iln} matches the OLS estimate in ARRY (10.9). The calibrated χ is 10.932, very close to the targeted elasticity.

Similarly, I discipline the parameter k to match the "unrestricted trade elasticity", the elasticity of bilateral trade flows X_{ln} with respect to trade costs τ_{ln}. In particular, I run the following regression using model-implied X_{ln} and τ_{ln}:

$$\ln X_{ln} = \delta_l^u + \delta_n^u - \beta^u \ln \tau_{ln} + \epsilon_{ln}, \tag{18}$$

where δ_l^u and δ_n^u are host and destination fixed effects and β^u is the unrestricted trade elasticity. One can show that β^u can be directly used as an estimate of k if $\xi = 0$ and MP costs are prohibitively high. When $\xi \neq 0$ and MP costs are finite, β^u is still informative about the value of k. I adjust k so that β^u in equation (18) match the unrestricted trade elasticity estimated using data on X_{ln} and tariff in ARRY (OLS estimate, 4.3). The calibrated k is 4.206, in line with the calibrated value in ARRY (4.5).

Technology Origin and Size Effects

As discussed earlier, 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 above, the size effect was found to typically be between 0.04 and 0.08 and the technology origin effect to range from 0.14 to 0.30. In the calibration, I pick one set of the estimates as targets and discuss the sensitivity of the calibration to the targeted coefficients below.

Specifically, I use the estimates for the multinational subsample (Column 3 in Table 1) where the technology origin and size effects are estimated to be 0.277 and 0.0543, respectively.[22] In contrast to previous moments, these targets are regression coefficients from an

[22] One may also consider using the firm's global revenue to estimate the "size effects". Note that both the global and affiliate-level revenue are imperfect measures of the core productivity. They are endogenous to the entire vector of location-specific productivities and equilibrium outcomes such as factor prices in each location. Therefore, neither is superior as a moment to match in the indirect inference approach. In practice, I prefer to use the affiliate revenue because Orbis may not cover all affiliates of a multinational firm, so the

affiliate-level dataset. Therefore, for each guess of model parameters, I solve for the general equilibrium and then simulate a set of multinational affiliates. (Online Appendix OA.4.3 discusses the detailed algorithm) 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 0.545 and that of ξ is 0.580, as shown in Table 4.

Sensitivity of Calibrated Parameters

Before I move onto the discussion about the fit of the model, I briefly discuss the sensitivity of the calibration with respect to the targeted moments, which also sheds light on how the key parameters are identified. A more detailed discussion, regarding both the parameter values as well as the quantitative predictions of the model, are contained in Appendix A.

First, I change the elasticity of capital and labor at the intensive margin, ε, to lower and higher values (0.4 and 0.6) than the baseline estimate (0.51), and recalibrate the model. The two parameters sensitive to the value of ε are the extensive elasticity, η, and the parameter that governs the technology-capital complementarity, ξ. The former changes with ε quite a bit but keeps $\varepsilon^{tot} - \varepsilon$ relatively stable, because I still target the same technology origin effect (see definition of ε^{tot} in equation (8)). The latter rises with ε because the elasticity of affiliates' capital-labor ratios with respect to the core productivities is $\xi(1-\varepsilon)$, which should be stable because the targeted size effect has not changed.

Second, I examine the calibrated parameters when I vary the targeted technology origin and size effects. Specifically, I pick three values of the technology origin effect (0.1, 0.2 and 0.3) and three values of the size effect (0.025, 0.05 and 0.075). These moments correspond to low, medium and high values of η and ξ, respectively. It is clear from Table A2 that η (thus $\varepsilon^{tot} - \varepsilon$) responds strongly and increases monotonically with the targeted technology origin effect, and that ξ increases with the targeted size effects. The other parameters are less responsive to the choice of these two moments. Therefore, the technology origin and size effects are the most informative about the two key parameters in the model, η and ξ,

revenue aggregated from Orbis will systematically underestimate firms' true global revenue. I choose to use affiliate revenue in the empirical analysis as well as in the simulated regressions.

and should be targeted in the calibration.

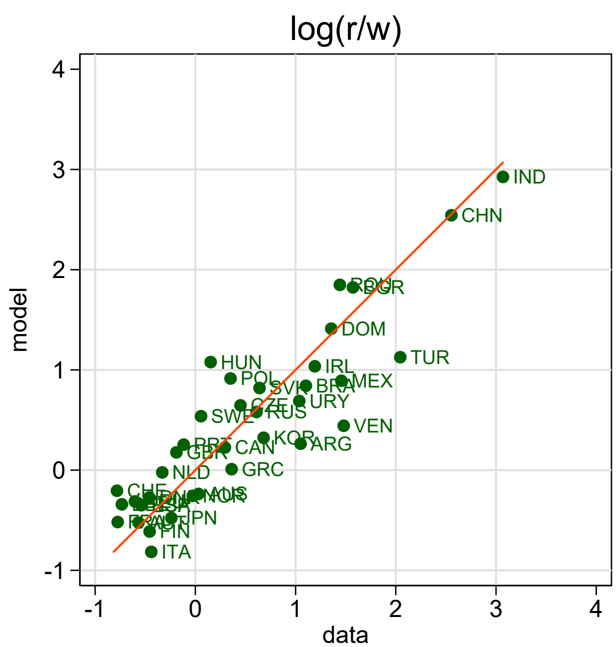
4.3 Model Fit

In this section, I discuss the fit of the model. I first examine the fit of the factor prices across countries, since I later apply the model to study the change in labor shares. I then discuss the fit of other untargeted moments, such as firm-level statistics.

Factor Prices

Since one of the main applications of the model is to examine its predictions on changes in factor prices, I want to make sure that the model fits the prices well. Figure 3 plots the predicted values of the relative factor prices in each country, $\log{(r/w)}$, against those in 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. The correlation between the model and the data is 0.9.

Figure 3: Model Fit – Factor Prices



Note: Log of r/w in the model and in the data. Wage in the US is normalized to 1.

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, in a world economy with no MP ($\gamma_{il} = \infty$ for all $i \neq l$), the total elasticity (equation (8)) dictates the relationship between r/w and K/L. The calibrated value of η (0.55) together with the intensive elasticity $\varepsilon = 0.51$ implies a total elasticity of 0.77. 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 $\varepsilon = 0.51$. A lower total elasticity implies that factor prices have to respond more to factor endowments to make the factor markets clear. This intuition is confirmed by estimating the elasticity of relative factor prices r/w with respective to country-level capital-labor ratios. In the data, the elasticity of countries relative factor prices with respect to capital abundance is 1.33 (s.e.=0.07), while the baseline calibration with technology origin effect predicts a coefficient of 1.29 (s.e.=0.02), 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 regression using the predicted factor prices from this alternative model.[23] The estimated elasticity is 1.81 (s.e.=0.01), much larger than that in the data. Therefore, the technology origin effect is important for matching the relationship between the relative factor prices and capital abundance across countries.

Firm-Level Moments

The simulated sample of firms allows me to compare the untargeted firm-level moments in the data and those in the model. Bernard et al. (2007) report the fraction of exporting firms in the United States as 4 percent in 2000, whereas in my calibration the corresponding number is 1.1 percent. The smaller share of exporters is likely due to the lack of fixed costs of setting up a plant abroad. The same reason also leads to a higher number of production

[23] The calibrated parameters of this alternative model can be found in Online Appendix OA.5.1.

locations of multinational firms in the model compared to the data. For example, the model predicts that the average German multinational firm produces in 2.5 foreign countries, while in the data it is 1.57 (Tintelnot (2017)). Although the calibration does not directly target the firm-size distribution, it is able to generate firm size heterogeneity as observed in the data. Using the simulated affiliate-level data from the model, I estimate the power law exponent for affiliates' revenue in each country. For US firms, the estimated exponent is 1.14, slightly higher than the estimates 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, in line with the estimates presented in di Giovanni and Levchenko (2013).

4.4 MP Patterns Explained by Endogenous MP Costs

Besides explaining the technology origin effect as observed in the data, the endogenous choice of technology can also help to explain MP patterns. Fajgelbaum et al. (2015) document that countries tend to invest in other countries of similar income levels. They provide a demand-side explanation: firms from the North develop high quality products which 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 as their home market. In contrast, the technology origin effect provides a 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 1 states this argument formally: the normalized 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 higher endogenous MP costs between countries with larger differences in endowment structures.

To see the quantitative importance of the mechanism in explaining MP patterns, I deviate from the baseline calibration and force firms to adopt the "average world technology."

The counterfactual setup still incorporates the "technology-capital complementarity" (TCC) mechanism but not the endogenous technology choice mechanism. 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 the optimal technology of country i firms 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 match the data perfectly.

In Columns 1 and 2 of Table 5, I regress $\lambda_{il}^{M,base}$ and $\lambda_{il}^{M,TCC}$ on differences in capital abundance between the home country i and host country l, controlling for home and host country fixed effects. In column 1, I find a similar pattern as in Fajgelbaum et al. (2015): 1% differences in capital abundance between i and l reduces MP sales from i to l by 0.84%.[24] However, when I assume away the endogenous technology choice (column 2), this effect becomes much weaker - about 88% smaller than that in the data. The effect is still negative, which reflects the fact that the calibrated exogenous MP costs γ_{il}^{base} are larger between countries with different capital abundance (column 3). Based on the difference between column 1 and 2, the endogenous technology choice explains about 88% of the correlation between bilateral MP sales and difference in capital abundance, while the rest 12% might be due to other mechanisms such as dissimilarity in demand.[25] Adding additional gravity controls (columns 4-6) barely changes these results.

[24] Strictly speaking, Fajgelbaum et al. (2015) uses per capita income instead of capital abundance to measure country similarities. Since these two variables are highly correlated, the patterns presented in Table 5 are robust if I use their measure. The results can be found in Online Appendix Table OA.23.

[25] This is a very rough decomposition between the endogenous choice mechanism and other explanations such as demand dissimilarity. Without firm-level data on prices and market shares, it is hard to quantify how product quality is systematically different across firms thus hard to quantify the importance of the demand-side mechanism. The decomposition here is meant to provide a convenient assessment of the importance of the endogenous technology choice mechanism in accounting for the bilateral MP patterns rather than distinguishing between the relative importance of the supply- and demand-side explanations.

Table 5: MP Shares, MP Costs and Country Endowment 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) $log(\gamma_{il}^{base})$
$\lvert \log(K_i/L_i) - \log(K_l/L_l) \rvert$	-0.842	-0.108	0.0984	-0.916	-0.183	0.110
	(0.152)	(0.135)	(0.0252)	(0.146)	(0.133)	(0.0242)
log(dist)	-1.741	-1.770	0.375	-1.852	-1.889	0.391
	(0.0963)	(0.101)	(0.0183)	(0.114)	(0.120)	(0.0212)
contiguity				-1.151	-1.195	0.177
				(0.240)	(0.242)	(0.0365)
common language				0.238	0.223	-0.0518
				(0.246)	(0.240)	(0.0447)
colony				1.068	1.003	-0.160
				(0.333)	(0.329)	(0.0600)
N	1089	1089	1089	1089	1089	1089
R^2	0.784	0.780	0.902	0.793	0.789	0.906
T-stat		3.610			3.715	

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. All regressions control host and home country fixed effects. Standard errors clustered at host-country level. Differences in country characteristics are absolute differences in log values. The T-stat is calculated based on a T-test for whether the coefficients before country differences in Columns 1 and 2 (or Columns 4 and 5) are the same. It assumes that the observations in the two regressions are independent.

5 Multinational Production and the Labor Shares

In this section, I use the calibrated model to study how the rise of multinational production affects aggregate outcomes especially the labor shares. I first estimate the change in MP costs and examine how the changes in these costs affects the factor prices and labor shares from 1996 to 2011. Next, I consider other factors that affect labor shares and decompose the change in labor shares in each country into changes in trade costs, MP costs, endowments and technologies using the model and examine the contribution of each component.

5.1 The Impact of the Change in MP Costs up to 2011

Over the past two decades, multinational production has become more prevalent in the global economy. To assess the increase in multinational production in each country, I combine data from OECD and Eurostat and calculate average MP shares in a later period, 2006-2011 for 23 countries, a subset of the countries in the baseline calibration. Online Appendix OA.1.1 details the construction of the data. I estimate the new bilateral MP costs γ'_{il} using the new MP data and examine how the change in the MP costs affects aggregate outcomes such as factor prices and welfare.

Columns 1 and 2 of Table 6 report the total inward MP shares for the baseline period (1996-2001) and the later period . The total inward MP share is the share of total non-financial output produced by foreign firms (sum of bilateral MP shares λ_{il}^M excluding λ_{ll}^M). Of the 23 countries, 19 saw an increase in this statistic. The average increase is 9.6 percentage points. Emerging economies 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 experienced further increases during this period.

Table 6: Counterfactual of Reduction in Bilateral MP Costs

	Data			Baseline Model				Model: TCC only	
Country	(1) Δinward MP share	(2) Δoutward MP share	(3) Δlabor share	(4) $\overline{\log(\hat{\gamma}_{il})}$ for each l	(5) $\overline{\log(\hat{\gamma}_{il})}$ for each i	(6) Δlabor share	(7) Δlog real income	(8) Δlabor share	(9) Δlog real income
AUT	6.2		-2.5	-25.2	-20.5	0.2	2.6	-0.9	2.7
BEL	5.7		-2.1	17.4^i	-6.9	-1.4	-1.2	-1.5	-1.1
BGR	28.3		-7.5	-38.8	-29.6^i	-6.6	2.0	-2.8	1.1
CHN	13.0		-4.6	-4.2^i	-22.1	-2.6	-0.3	-0.0	-0.5
CZE	15.3		-0.8	-22.8	-18.1	-2.1	0.6	-2.1	0.3
DEU	-1.2	3.7	-5.1	-11.6	-10.3	0.6	2.1	0.0	2.2
DNK	12.2		2.1	-28.4	-7.5	-0.3	2.5	-1.2	2.7
ESP	5.7	6.2	-0.3	-15.1	-2.6	0.2	1.4	-0.2	1.4
FIN	2.9	10.5	3.3	-16.1	-12.0	0.3	3.3	-0.7	3.3
FRA	5.4	15.1	1.2	-21.9	-16.1	0.8	3.0	-0.0	2.9
GBR	8.7	6.7	0.0	-36.0	-20.4	0.1	1.2	-0.3	1.2
HUN	10.9	7.3	-4.6	-16.2	-27.5^i	-2.0	4.8	-1.1	4.0
IRL	15.3		5.8	-23.3	-12.4	-4.2	8.7	-2.9	7.9
ITA	5.5	5.1	3.1	-12.6	-15.1	0.5	0.7	-0.2	0.8
JPN	0.1	7.3	-2.1	-14.8^i	-22.4	1.4	3.0	0.0	3.1
NLD	-3.0		-1.3	-15.3	-8.0	1.4	-5.3	0.6	-5.2
NOR	14.1	4.6	-6.4	-26.3	-1.2	-1.1	0.8	-1.9	1.0
POL	15.4		-13.3	-28.2	-22.7	-2.0	0.5	-1.2	0.1
PRT	-13.7	4.6	1.2	-10.4	-6.0	1.9	1.9	1.6	1.9
ROU	36.9		-4.1	-34.3	-1.9^i	-7.9	0.2	-2.6	-1.5
SVK	29.9		-4.6	-15.5	-19.2^i	-3.9	2.2	-3.0	1.5
SWE	7.5		-1.1	-23.1	-13.1	-1.0	2.7	-0.9	2.6
USA	-1.8	3.3	-4.4	-5.7	-11.6	0.8	1.5	0.1	1.7
Mean	9.5		-2.1	-18.6	-14.2	-1.2	1.7	-0.9	1.5

Counterfactual experiment of changing bilateral MP costs such that MP shares match those in 2006–2011. All numbers are in percentage points or 100× change in log points. Column 2 shows the change in outward MP share for the 11 countries that I estimate the home-country component of the change in MP costs. Columns 4 and 5 report the average change in bilateral MP costs by destination and origin, respectively. When calculating these statistics, I ignored observations that correspond to MP shares less than 10^{-6} in 2006-2011 to avoid extreme changes in MP costs. The superscript i indicates averages that are calculated based on fewer than 10 observations.

To understand the impact of the influx of multinational activities, I estimate 37*36=1332 new MP costs γ'_{il} to match the new MP shares $\lambda^{M\prime}_{il}$, holding all other model primitives and parameters fixed. Unfortunately, I lack data for 14 destination countries as well as some bilateral shares for the 23 destination countries with data. Despite that the bilateral share matrix is incomplete, many countries report the total outward or inward MP sales. I therefore make the following identification assumptions to deal with the missing values and to use all the information contained in bilateral MP shares and total inward and outward MP sales.

1. If $\lambda^{M\prime}_{il}$ is known, I will estimate a value for γ'_{il} to match $\lambda^{M\prime}_{il}$. I set $\gamma'_{il} = \infty$ if $\lambda^{M\prime}_{il} = 0$ as in my baseline calibration. There are 533 positive bilateral MP shares to match and 66 zero bilateral MP shares in 2006 – 2011.

2. If $\lambda^{M\prime}_{il}$ is unknown and λ^{M}_{il} is zero, I assume $\gamma'_{il} = \gamma_{il} = \infty$, therefore the new MP share is still zero. There are 206 such cases.

3. For the remaining cases, I assume the change in MP costs can be decomposed into a source and a destination effect, i.e., $\gamma'_{il}/\gamma_{il} = \gamma^S_i \gamma^D_l$. I target γ^D_l to match the total inward MP shares and γ^S_i to match the total outward MP shares.[26] For countries that lack information on these two variables in the later period, I assume γ^D_l or γ^S_i equals one.[27]

Columns 3 and 4 in Table 6 present summary statistics of the calibrated change in MP costs for the 23 countries considered here. I calculate the average log change for each of the 23 host and home countries. The average change by host country is 18.6 log points, while the average change by home country is 14.2 log points. There is slightly more variation in

[26] Total outward MP share of country i is defined as the total MP sales made by country i firms abroad divided by the total output of country i.

[27] I estimate γ^D_l for 19 countries and calibrate γ^S_i for 11 countries. I have data on total inward MP sales on the 23 countries listed in Table 6. For four of them, I have complete information on the bilateral MP shares, so I do not need to infer γ^D_l. Though OECD and Eurostat also report total outward MP sales for 20 countries, it is well known that outward MP statistics can be inconsistent with inward MP statistics, due to different data sources and survey approach (Totland, 2013). I found that for seven countries, total outward MP sales are smaller than those aggregated from bilateral MP sales reported by the host countries. I therefore drop these seven countries, together with Austria and Poland, whose total outward MP sales are already very close to those aggregated from bilateral MP sales. The 11 countries for which I calibrate γ^S_i are those with non-missing values in Column 2 of Table 6.

the change by host country (with standard deviation of 12.1 log points) than the change by home country (with standard deviation of 8.1 log points). Both the host- and home-country components of the change in bilateral MP costs are important.

As discussed earlier, in my model, changes in MP reallocate production across firms with different factor intensities. This changes the relative demand for capital and labor and, therefore, leads to changes in relative factor prices and labor shares. As can be seen in Column 5 of Table 6, the model predicts declines in labor shares in 13 out of the 23 sample countries in response to the estimated changes in MP costs. In the model, the average decline in the labor shares is 1.2 percentage points across countries, while the average decline in the data was 2.1 percentage points (Column 6). Therefore, the change in MP activity can explain about 56 percent of the average decline in the labor shares.[28]

The predicted changes in the labor shares vary across countries. In the counterfactual, the labor share declines as much as 7.9, 6.6 and 3.9 percentage points in Romania, Bulgaria and Slovakia, respectively. The magnitude of the predicted decline is consistent with the observed labor share decline in these countries. However, the model fails to predict the labor share declines in developed countries such as the United States and Germany, largely because there is little change in their inward MP costs (more explanation below). Overall, the model is able to capture the broad variation in the changes of 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 (coef = 0.54, standard error = 0.29 and p-value = 0.08), while the correlation between these two variables is 0.33.

To examine the model predictions on welfare, I computed the changes in real wages, real rental rates and real per-capita income. Due to limited space, I only show changes in real per-capita income in Column 7 of Table 6 and present the first two variables in Table OA.24 of the online appendix. Most countries see an increase in real income per capita after reductions in MP costs and the average increase is 1.5 log points. However, this measure

[28] In Appendix A, I examine the sensitivity of these results with respect to key model parameters as well as assumptions on capital mobility across countries and the entry/marketing costs.

captures welfare well only when assets are equally distributed across workers. As is shown in Table OA.24, 9 out of the 23 countries see a rise in real rental rates but and a decline in real wages. Therefore, the lower prices brought by more MP cannot fully compensate the workers unless they also own assets and benefit from the rise in real rental rates.

To understand the variation of labor share declines across countries, I relate the changes in the labor shares to the changes in the total inward MP shares. Column 1 of Table 7 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 in my model. This single variable captures 84 percent 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 larger declines in their labor shares for a given increase in their total inward MP shares.

In Column 3, I interact the change in the total inward MP shares with the average source country capital abundance, weighted by the change in bilateral MP shares.[29] The weighted average measures the change in the composition of the inward MP and is larger if a country receives more Northern MP during the period of study. The interaction term is negative as expected, but it is less precise than the interaction term in Column 2. This is understandable since most of the inward MP comes from capital abundant countries, and this weighted average has much smaller variation (standard deviation = 0.22) than the host country capital abundance (standard deviation = 0.68) .

In Columns 4-6, I replicate these regressions using labor share changes in the data. Though the estimates are noisier than those in Columns 1-3, the coefficients have the same signs and are of similar magnitudes, and none of them was explicitly targeted in the calibration.

[29]The source country capital abundance is measured in the baseline period.

Table 7: Labor Shares and Inward MP Shares

Δ Labor Share in Country l	Baseline Model			Data		
	(1)	(2)	(3)	(4)	(5)	(6)
Δ inward MP share for l	-0.205***	-0.990***	-0.158**	-0.124**	-1.034	-0.102
	(0.0252)	(0.123)	(0.0709)	(0.0491)	(0.718)	(0.248)
$\times$ $\log(K_l/L_l)$		0.0792***			0.0918	
		(0.0126)			(0.0727)	
$\times$ weighted source $\log(K_i/L_i)$ for l			-0.141			-0.0760
			(0.182)			(0.740)
N	23	23	20	23	23	20
R^2	0.844	0.923	0.854	0.114	0.154	0.117

Dependent variable is percentage point change in labor shares. Robust standard errors in parentheses. Columns 1-2, 4-5 include all 23 countries considered in this counterfactual. For column 3 and 6, I dropped Belgium and China, for which I do not observe a breakdown of their total inward MP sales, and also Japan, for which I only observe one inward bilateral MP sales so I cannot construct a reliable weighted average.

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 (TCC) mechanism operates essentially through selection. MP liberalization leads to more competition in the host economy, which drives out small and labor-intensive firms. This mechanism should operate in all countries that receive more MP, regardless of their capital abundance. Since developed countries such as the United States and Germany do not experience an influx of inward MP, the model does not generate declines in labor shares in these countries. Second, the endogenous technology choice (ETC) mechanism affects the labor share when the host country is receiving multinational production from home countries with different endowment structures. Since the majority of multinational production is performed by firms from capital-abundant countries, it is the capital-scarce countries that are most affected by the technology transfer of capital-intensive production technologies. Therefore, ETC contributes further to the decline of the labor shares in these countries.

With the structural model, I can decompose the effects of the two mechanisms (TCC v.s. ETC). In particular, I recalibrate the model imposing $\eta \to -\infty$, so that all firms from all countries choose the same technology $(a, b) = (1, 1)$, and TCC is the only mechanism that generates heterogeneity in firms' capital intensities. In Column 8 of Table 6, I present the change in labor shares for each country under this alternative model. The in model predicts labor shares to decline by 0.90 percentage points on average, which is around 75% of the predicted decline in the full model. The ETC mechanism, capturing around 25% of the total effect on average, is more important for less developed countries. For example, for the six East European countries in my sample (Bulgaria, the Czech Republic, Hungary, Poland, Romania and Slovakia), ETC accounts for around 39% of the total effect.

Table 8: The Effect of Outward MP on Labor Shares

Δ Labor Share in Country i	Model: TCC only		Baseline Model		Data	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ outward MP share	0.0338*		0.0630***		0.0920	
	(0.0164)		(0.0153)		(0.0884)	
Δ weighted host $\log(K_l/L_l)$ for i		0.00628		-0.0837**		-0.0459
		(0.0217)		(0.0384)		(0.179)
Δ inward MP share for i	-0.0844***	-0.0895***	-0.178***	-0.176***	-0.118*	-0.131**
	(0.0130)	(0.0133)	(0.0302)	(0.0323)	(0.0558)	(0.0562)
N	18	18	18	18	18	18
R^2	0.858	0.830	0.886	0.882	0.169	0.146

Notes: Weighted host countries' $\log(K_l/L_l)$ refers to the average log of aggregate capital to labor ratio weighted by the MP sales X_{il} in the baseline and new periods. Capital and labor are measured in the baseline period. The sample contains all countries listed in Table 6 except four countries without total outward MP statistics in 2006-2011 (Bulgaria, China, Denmark, Netherland) and Ireland. The four countries without total outward MP are excluded because I cannot ensure that the model-predicted outward MP sales X_{il} cover the majority of the total outward MP. Ireland is excluded because it has a large increase in outward MP into the capital-abundant countries both in the data and in the model, which can be caused by profit-shifting activities.

TCC and ETC also have implications on how labor shares in the home countries respond to outward MP flows. Due to TCC, when MP costs into foreign countries decline, productive and capital-intensive firms are likely to relocate their production abroad, which will lead to an increase in labor shares at home. This can be seen from Column 1 of Table 8, where I regress the change in labor shares on both changes in total outward and inward MP shares predicted by the model where I shut down ETC (only TCC is operating). At the same time, ETC can also leads to a positive relationship between outward MP and labor shares. This is because, when capital-scarce countries lower their MP costs, firms at home will choose more labor-intensive technologies so that they can be more profitable in those foreign countries. Indeed, the full model with both TCC and ETC prescribes a stronger relationship between the change in labor shares and in outward MP shares (Column 3). In the data, there is a positive relationship between the two, but the coefficient is insignificant (Column 5).

To see the effect of outward MP on labor shares through ETC more clearly, I construct a measure of average host country capital abundance, using the base period aggregate capital-labor ratio of each production location (including the home country), and relate the change in labor shares to this variable using regressions in Columns 2 and 4 of Table 8. In the baseline model, countries whose firms increase MP in capital-scarce countries see a larger reduction in labor shares (Column 4). However, such effects are muted when I shut down endogenous technology choice (Column 2). In the data, the effect of the change in average host country capital abundance on home country labor share is negative, though it is imprecisely estimated likely due to other factors that affect labor shares (Column 6).

In summary, the period of 1996–2011 saw great progress in MP liberalization in many countries. Such liberalization tends to benefit capital more than labor in the majority of the sample countries. The model captures the decline in labor shares in emerging economies with large inflows of MP activities well. It also predicts that outward MP, especially those to capital-scarce countries, may increase the labor share in the home countries. This prediction is not strongly supported by the data. Finally, the change in MP costs do not explain the decline in labor shares in developed countries such as Germany and the United States – other mechanisms are needed to understand the experience of these countries.

5.2 Other Factors that Affect the Labor Shares

In the previous section, I focus on how changes in MP costs affect the labor share in different countries. However, many other factors may also have affected the labor shares during the period of study. Moreover, incorporating changes in other factors may influence the estimated new MP costs γ'_{il}. In this subsection, I consider such possibilities and examine the role of changes in trade costs, endowments and home-country technologies together with the changes in MP costs.

In particular, I first feed into the model the observed changes in capital and labor for each country from the baseline period to 2006–2011. I then jointly estimate the new bilateral MP costs, bilateral trade costs and home-country technologies by exactly matching the new trade shares, MP shares and changes in labor shares. To match the changes in the labor shares, I assume that each home country experiences exogenous changes in the capital share shifter λ. Therefore, though all countries start with the same calibrated λ in the base period, they end up with different λ_i' ten years later. This, of course, is a reduced-form approach to model capital-biased technological change. One can simply view λ_i' as a residual term that captures all the changes in labor shares that cannot be explained by changes in other model primitives. The goal here is not to understand what caused λ_i to change, but to understand how the other three factors have affected the labor shares.

During the period of study, all the 37 sample countries except Brazil saw an increase in aggregate capital stock per capita. The average country experienced a 27-log-point increase. With the elasticity of substitution between capital and labor smaller than one, this implies the labor share increases because of capital accumulation. To counter this force and match the labor share decline, the calibration reveals that λ_{ki} has increased in most of the countries. The calibration also reveals declines in trade and MP costs in most of the countries, which is intuitive given the increases in trade and MP shares. Online Appendix OA.4.8 reports the changes for each country.

Table 9: Step-by-step Decomposition of Changes in the Average Labor Share

(1)	(2)	(3)	(4)	Total
τ	γ	(K_i, L_i)	λ_i	
0.6	-2.1	2.2	-2.8	-2.1
γ	τ	(K_i, L_i)	λ_i	
-2.3	0.8	2.2	-2.8	-2.1
(K_i, L_i)	τ	γ	λ_i	
2.1	0.7	-2.0	-2.8	-2.1
(K_i, L_i)	γ	τ	λ_i	
2.1	-2.2	0.8	-2.8	-2.1

The above table shows the percentage point change in labor shares by introducing changes in trade costs τ, MP costs γ, endowments (K_i, L_i) and country-specific technologies λ_i one at a time. Changes in endowments are obtained from the data, while changes in the other three model primitives are jointly calibrated by targeting the changes in trade shares, MP shares and labor shares. Each column shows the additional impact on the labor share after introducing the change. The four components add up to the total effect on labor shares (last column), which is, by construction, the same as the change in the average labor share in the data.

To decompose the impact of each factor, I start from the base period and add the changes one at a time. In principle, the order of adding these changes matters for the decomposed effects. In Table 9, I present each component's impact on the average labor share under four different orderings. Whether I introduce changes in endowments first or changes in trade and MP costs first, changes in endowments increase the average labor share by around 2.1 percentage points. In contrast, exogenous technology changes (i.e., changes in λ_{ki}) reduce the average labor share. Changes in trade costs increase the average labor share by 0.6 to 0.8 percentage point, depending on the ordering, while changes in MP costs reduce the average labor share by 2.0 to 2.3 percentage points, larger than the effects obtained in Section 5.1. This result suggests that, during the sample period, increase in multinational production rather than trade helps to explain the decline in labor shares through the lens of the model. This is because the model features strong substitutability between trade and MP, and decline in trade costs tends to reduce MP and thus increases the labor shares.

6 Conclusion

Multinational firms differ in many ways from domestic firms. This paper departs from standard quantitative multinational production models by incorporating firm heterogeneity in non-neutral technologies. I document two empirical regularities regarding firms' capital intensities: (1) larger firms on average use more capital-intensive technologies and (2) firms from capital abundant countries tend to 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 non-neutral technologies. The model can be applied to explain bilateral MP patterns and the decline in labor shares.

There are several ways to extend the current model in future research. First, the model assumes a single sector, which abstracts from conventional Heckscher-Ohlin forces. Incorporating such forces would require data on industry-level bilateral MP statistics (Alviarez, 2017), and will provide more precise predictions on factor prices and income shares. Second, the paper makes somewhat arbitrary assumptions on the capital intensities of headquarter activities. MP liberalization can induce countries to specialize in innovation or production activities (ARRY), and such specialization may also have a large quantitative impact on factor prices if their capital intensities differ. Such mechanisms can be quantified using better data on headquarter activities. Finally, the model can be used to study other technology heterogeneities across firms, such as the heterogeneity in skill intensities, and to shed light on the impact of multinational production on the skill premium.

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Appendices

A Sensitivity Analyses

In this section, I conduct a range of sensitivity analyses regarding model parameters. I illustrate the sensitivity of results using mainly the application in Section 5.1 and focus on the prediction for the change in labor shares due to the estimated decline in MP costs.

A.1 Intensive Elasticity ε

In my calibration, I estimate the elasticity of substitution between capital and labor directly using the variation of factor usage and prices across affiliates in different countries within a multinational firm. 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 (0.4) and a higher value (0.6) than the baseline calibration (0.51). 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.

It is clear from Table A1 that the labor share decline induced by the estimated reduction in MP costs becomes larger when ε is smaller. Intuitively, the reallocation of factors across firms with different capital intensities after liberalizing MP can be viewed as capital-biased technical change at the aggregate level. 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, 0.6, the predicted decline is quite close to that in the baseline calibration.[30]

Table A1: Sensitivity to the Intensive Elasticity ε

Specification	Re-calibrated Parameters						Counterfactual (Section 5.1)
ε	η	Implied ε^{tot}	ξ	k	χ	λ_k	Δlabor share
0.40 (low)	-0.07	0.62	0.45	4.24	10.95	0.32	-1.38
0.51 (baseline)	0.54	0.76	0.58	4.20	10.93	0.31	-1.18
0.60 (high)	0.84	0.89	0.69	4.18	10.91	0.28	-1.01

Average change in the labor shares across 23 countries, in percentage points. Each column corresponds to calibration with the intensive elasticity ε set to 0.4, 0.51 (baseline) and 0.6. All other parameters are recalibrated except for σ, which is set at 4 without calibrating the model.

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

A.2 Size and Technology Origin Effects

In the baseline calibration, I chose to match the size effect and technology origin effect estimated using the multinational subsample. Though the magnitudes of the coefficients are similar across specifications and robust to additional controls, there is still some variation and the standard error on each coefficient is not negligible. In this subsection, I experiment with different values of the two coefficients. When I target lower values of these two coefficients, I expect both technology-capital complementarity and endogenous technology 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 correspond 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 combination. After the calibration, I repeat the exercise in Section 5.1 and examine the model prediction for the declines in the labor shares over the ten-year period.

Table A2 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 0.277 and the size effect to be 0.054, turns out to be at the high end among all different combinations. However, even when the two targeted effects are reduced to 0.1 and 0.025, respectively, the predicted change (–0.7 percentage point) still accounts for one-third of the average decline in labor shares in the data.

Table A2: Sensitivity to Size and Technology Origin Effects

Specification		Re-calibrated Parameters						Counterfactual (Section 5.1)
Size Eff	Tech Origin Eff	η	Implied ε^{tot}	ξ	k	χ	λ_k	Δlabor share
0.025	0.10	-1.53	0.59	0.25	4.00	10.91	0.38	-0.67
0.025	0.20	0.07	0.68	0.26	3.99	10.91	0.37	-0.83
0.025	0.30	0.61	0.78	0.26	3.99	10.90	0.35	-0.93
0.050	0.10	-1.41	0.59	0.51	3.96	10.96	0.34	-0.98
0.050	0.20	0.16	0.69	0.50	3.95	10.94	0.33	-1.07
0.050	0.30	0.65	0.79	0.49	3.94	10.92	0.30	-1.13
0.075	0.10	-1.32	0.60	0.77	3.91	11.01	0.30	-1.16
0.075	0.20	0.24	0.70	0.77	3.87	10.97	0.28	-1.23
0.075	0.30	0.69	0.81	0.77	3.85	10.95	0.25	-1.25

Average change in the labor shares across 23 countries, in percentage points. Each row corresponds to calibration with different targeted size and technology origin effects. All other parameters are recalibrated except for σ and ε.

A.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 still ask how capital market integration affects the above results. Instead of modeling and quantifying international capital market frictions, I simply consider an alternative version of the model in which capital markets are perfectly integrated. Because my model features monopolistic competition and increasing returns to scale, the reward to the immobile factor (labor) is not equalized across countries despite 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 exercise in Section 5.1. With cross-country flows of capital, the average decline in the labor shares is reduced to 0.4 percentage point, which, however, still captures 21 percent of the average decline in labor shares in the data. Moreover, the alternative model also 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 OA.5.3 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.

A.4 Assumption on Marketing and Entry Costs

In the baseline model, I assume that the marketing and entry costs are paid in units of composite goods. Assuming that they are paid in primary factors helps to make the model more comparable to ARRY, but I need to make additional assumptions on the labor shares of the marketing and entry activities. In Online Appendix OA.5.4, I calibrate such a version of the model, assuming that (1) marketing costs are paid by combining capital and labor in the destination country in a Cobb-Douglas fashion with the labor share being the same as in the 1996-2001 data for that country and (2) entry costs are paid by combining capital and labor in the home country with the same technology. I show that, under this setup, the model still predicts similar factor prices and average declines in labor shares after MP liberalization.