Firm-Level Distortions, Trade, and International Productivity Differences

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Abstract

Developing countries typically exhibit small firm size, high dispersion of marginal productivity of factors across firms, and low trade-to-output ratios. They also tend to export particularly less to more distant and smaller markets. To rationalize these facts, this paper develops a flexible, multi-country general equilibrium model of production and trade in which heterogeneous producers face both domestic size-dependent distortions (SDD) and costly entry into exporting. Since larger firms have greater export-market participation, misallocation induced by SDD reduces the economy's overall market access, trade volumes, and gains from trade, reinforcing the contraction in aggregate total factor productivity. I explore the quantitative properties of the model calibrated to firm-level and aggregate data from the manufacturing sector of 77 major economies. I find that productivity gains from reducing SDD are significantly larger when economies are open to trade. Enhanced firm selection and factor allocation across firms fully explain this amplification, whereas the contribution from changes in firm creation is actually dampened by trade. Furthermore, cross-country variation in SDD explains a substantial share of international productivity differences, but only when countries are integrated through trade. **JEL classification: F12, F63, L25, O11, O47**

Keywords: Misallocation, Firm-Level Distortions, Gravity Equation, International Trade

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1 Introduction

One of the major recent advances in the macroeconomics and international trade literatures has been the focus on firm-level data. Two regularities have emerged from the micro datasets: firm-level revenue per unit of inputs is highly heterogeneous, particularly in developing countries (Banerjee and Duflo [2005], Hsieh and Klenow [2009], Bartelsman et al. [2013], and Asker et al. [2014]), and large and more productive firms tend to export whereas small and less productive ones do not (Bernard et al. [2007] and Eaton et al. [2011]). The first fact has been interpreted as indicative of the existence of allocative inefficiencies across firms, with negative effects at the aggregate level. The second fact points to the importance of large producers in shaping international trade and of inter-firm reallocations in driving the gains from trade.

These observations give rise to a host of questions. Firstly, does opening to international trade exacerbate or alleviate the aggregate losses from domestic micro frictions? On the one hand, imports offer an opportunity for consumers and firms to substitute away from domestic producers plagued by misallocation. In this case, trade could mitigate the effects of distortions. On the other hand, when trade costs and international competition turn exporting into mostly a prerogative of large and highly productive firms, domestic inefficiencies could indirectly jeopardize the economy's access to foreign markets, in which case the losses could be amplified. Whichever the case may be, a related inquiry is that of if taking trade into account is quantitatively relevant in assessing the macro effects of misallocation. Lastly, are domestic distortions to firm size important to explaining aggregate trade performance and the gains from trade?

The goal of this paper is to address the questions above both theoretically and empirically. On the conceptual side, the basic insight is that, in open economies with firm selection into exporting, domestic distortions that misallocate capital and labor from high- to low-productivity firms indirectly affect the economy's overall market access, trade volumes, and gains from trade. These mechanisms add to the standard closed-economy channels through which micro-level misallocation depresses aggregate TFP. On the empirical side, I first show that, in general equilibrium, these interactions between trade and domestic distortions considerably augment the aggregate losses from misallocation. I then demonstrate that such effects are quantitatively important in understanding the large differences in trade openness, geography of exports, and aggregate productivity between rich and developing countries.

I start out by revisiting key facts about firms and international trade in developing economies. Such countries typically exhibit **(i)** small average firm size, **(ii)** high within-industry dispersion of both revenue and physical firm-level productivity, and **(iii)** low trade-to-output ratios. I add a new fact: **(iv)** developing economies export particularly less to more distant and smaller markets. Compared with sales from rich economies, their exports increase faster with importer market size but also decrease faster with bilateral geographic barriers. This finding indicates that developing countries' access to export markets is systematically smaller than what their geography would predict.

The canonical multi-country trade model with heterogeneous firms reviewed in Arkolakis et al. [2012] (ACR henceforth) does not square with the facts above. First, the model predicts that market-based reallocation should eliminate within-industry dispersion of revenue (marginal) productivity across firms.[1] With CES demand, marginal costs invariant to scale, and monopolistic competition, a highly productive firm should expand its size to the point that its revenue productivity equalizes that of its less productive competitors. Second, the model assumes that the firm size distribution is invariant across countries. With Pareto distribution of firm size, this invariance implies that trade elasticities are also the same across exporters. Finally, the theory predicts that *higher* firm heterogeneity should lead to *larger* incentives to trade and to aggregate exports that are *less* sensitive to trade costs - the opposite of what is observed in the data.

To reconcile the theory and facts, I introduce two central elements of the macro-development literature into a quantitative multi-country model of production and trade in the spirit of Eaton et al. [2011] and Di Giovanni and Levchenko [2012]. First, I allow for the Pareto shape parameter that controls the distribution of micro technologies to be country specific. This assumption gives the model flexibility to match the fact that the dispersion of firm-level physical productivity is higher in developing economies.[2] Second, and more importantly, I assume that firms face output distortions that covary with firm size, which I refer to as *size-dependent distortions* (SDD). These distortions capture domestic policies, institutions, and market frictions typical in developing countries that effectively penalize larger and more productive producers relative to smaller and less productive ones.[3] The remaining elements of the model are standard. Economies are comprised of a competitive service sector and a tradable sector with monopolistic competition, CES demand, and free entry. Markets are separated by iceberg and fixed trade costs, and labor and capital are mobile within but not between countries.

SDD play a dual role in the model. First, they lead high-productivity plants to employ less capital and labor than in the first-best equilibrium relatively to low-productivity plants. This raises the dispersion of revenue productivity across firms. Second, due to the fixed costs to enter foreign markets, SDD reduce firms' incentives to start exporting. These distortions also compress the sales distribution of incumbent exporters. These two factors together make the extensive margin of aggregate exports more sensitive to trade costs and importer market size. As distortions rise, an increase in trade costs crowds out of the export sector a larger number of marginal firms, whose sales volumes are closer to the sales of inframarginal exporters. As a result, the proportional reduction in

[1] The presence of fixed costs can also create dispersion of revenue productivity. However, when these costs are calibrated to match usual estimates of survival rates, the amount of dispersion generated is way lower than what is found in the data. See Bartelsman et al. [2013] and Hsieh and Klenow [2014].

[2] See Hsieh and Klenow [2009] and Porzio [2016].

[3] SDD are also known as *correlated distortions* according to the terminology in Restuccia and Rogerson [2008]. Examples of detailed mechanisms that would map into SDD include quality of the managerial delegation environment (Akcigit et al. [2016]), frictions in factor markets (Hopenhayn and Rogerson [1993] and Midrigan and Xu [2014]), rent-seeking and unequal regulation enforcement (Aterido et al. [2007]), size-dependent policies (Guner et al. [2008], Garicano et al. [2016], and Martin et al. [2017]), and markup dispersion (Peters [2013]).

aggregate exports grows. Therefore, more distorted economies export less in general and particularly less to "harder" destinations, i.e., smaller and more distant markets.

Equipped with a model that reconciles both trade and firm-level facts, I turn to analyzing the channels through which SDD affect macro performance. I first demonstrate that the aggregate TFP in an open economy is a function of two separable components: one representing the closed-economy TFP, and another capturing the gains from trade. The first term encapsulates the basic channels highlighted by the literature based on closed-economy models. More severe SDD decrease the expected value of entry, reducing the mass of firms in the economy (Bento and Restuccia [2017]). SDD also hinder the expansion of the most efficient firms, which in equilibrium worsens the selection of producers in the market (Bartelsman et al. [2013] and Yang [2016]). Finally, distortions increase the dispersion of marginal productivity across firms, aggravating the misallocation of factors across incumbent producers (Hsieh and Klenow [2009]).

The contribution of trade to aggregate TFP, by its turn, depends on only two terms: the home share of spending on tradable goods (an inverse measure of trade openness) and the trade elasticity with respect to variable trade costs. Therefore, in the spirit of the sufficient statistics literature, the effect of SDD on these two components subsumes all the general equilibrium interactions between misallocation and trade. Firstly, by hindering the reallocation of factors from low-productivity to high-productivity producers, SDD increase the trade elasticity and, therefore, reduce the gains from trade for any given level of trade openness. This effect contributes to the amplification of the aggregate losses from micro-level misallocation in open economies. Secondly, SDD also affect the economy's equilibrium trade openness. If openness decreases in domestic distortions, as is the case when distortions compromise the economy's overall export performance, then the aggregate losses from misallocation are unambiguously larger with trade. If not, then trade could potentially mitigate those losses by allowing the economy to substitute imports for low-productivity domestic producers.

To quantify the economic forces described above, I first assemble a cross-country dataset that combines aggregate information on manufacturing production, bilateral trade flows, and trade costs with establishment-level data on revenues and input use. I then measure the model's parameters using a combination of estimation and calibration. The procedure consists of three steps. The first step estimates country-specific SDD in the manufacturing sector using micro data from the *World Bank Enterprise Survey* (2016).[4] Applying the Hsieh and Klenow [2009] methodology, I estimate the schedule of SDD[5] as the *within-sector* elasticity of firm-level revenue productivity with respect to firm-level physical productivity.

The second step recovers exporter-specific structural trade elasticities through the estimation of the log-nonlinear gravity equation that emerges from the model. The non-

[4]Earlier versions of this dataset have been used by other studies in the literature - see Asker et al. [2014], Porzio [2016] and Bento and Restuccia [2017].

[5]The functional form of SDD adopted in this paper is traditional in the macro-development literature. See Hsieh and Klenow [2014], Buera and Fattal-Jaef [2014], and Bento and Restuccia [2017].

linearity stems from the fact that the contribution of importer-specific factors to the extensive margin of aggregate bilateral trade varies according to the exporter's firm size distribution. For instance, a larger market size (or lower import tariffs) is proportionately more important in boosting exports from countries with smaller firm size or more severe SDD. This relationship allows me to exploit the variation in importer fixed effects, together with the usual variation in tariffs, to leverage bilateral trade datasets and estimate one elasticity for each exporter. Finally, the third step calibrates trade costs and technology parameters such that the model perfectly matches the empirical world matrix of bilateral trade in manufactures.

According to my estimates, SDD significantly decrease with development. In developing economies, the gap in revenue productivity between high-productivity and low-productivity firms is two to three times greater than in OECD countries, as if more efficient producers faced disproportionately higher barriers to expand in the developing world. At the same time, trade elasticities are also lower in richer countries. Whereas elasticities range between 4 and 5 for OECD members,[6] developing economies exhibit much higher values, varying between 7 and 12. Importantly, there is no evidence that differences in the sectoral composition within the manufacturing sector are driving this cross-country variation in trade elasticities.

The combination of the two findings above strongly supports the main prediction of the model: more severe distortions at the micro level show up in the aggregate as higher trade elasticities. Indeed, a one standard deviation increase in SDD leads to a .5 standard deviation increment in trade elasticities. Moreover, measures of firm-level heterogeneity explain 21% of the cross-sectional variation in aggregate elasticities. The calibrated model also successfully reproduces a number of non-targeted features of both the micro and aggregate data. For instance, the model captures the large international differences in output per worker, the positive correlation between development, firm size and share of firms that export, and the cross-country variation in the dispersion of firm-level physical and revenue productivity.

To quantify the output losses from SDD in open economies, I endow each country in the sample - one at a time - with the "US efficiency" and then compute the new general equilibrium. The US benchmark is crucial in this context because elements like overhead costs, adjustment costs, and markup variation can generate dispersion in revenue productivity even in the absence of firm-level distortions.[7] I find a cross-country average gain in aggregate TFP of 29.2%, which represents approximately one-third of the TFP gap between the US and the average country in my sample. The average gain

[6]Recent papers, mainly based on manufacturing trade between developed countries, have found values in this same interval. See Costinot and Rodriguez-Clare [2013] and Simonovska and Waugh [2014a].

[7]Bartelsman et al. [2013] emphasize that if data on input use include overhead costs, then average revenue productivity is no longer proportional to marginal revenue productivity. In this case, we could observe both within-sector dispersion in revenue products *and* equalization of marginal products across establishments. Asker et al. [2014] show that in the presence of adjustment costs, high time-series volatility in revenue productivity can generate high cross-section dispersion in the marginal product of capital. Finally, imperfect goods markets can generate dispersion of revenue productivity as shown by Bernard et al. [2003] and Peters [2013].

in the closed-economy case is just 17.9%. Therefore, international trade increases the effect of SDD on aggregate TFP by 63%.

Exploring the composition of the aggregate gains from the reduction of SDD, I find that 89% of the average gain is due to improved firm selection and enhanced allocation of factors across firms, and 11% is due to increased firm creation. Further, I find that on average 40% of the amplification due to international trade comes from increases in the gains from trade *given* the initial level of trade openness and 60% stems from the expansion of trade openness itself. This trade-creation mechanism is particularly relevant for economies that are more closed to trade in the initial equilibrium.

In the last counterfactual exercise, I address the following question: in a world economy integrated through trade, what would be the international productivity distribution if *all countries* shared the "US efficiency"? In this scenario, two factors raise a country's productivity: the direct effect examined earlier and the "trade-transmitted" spillover stemming from improvements in allocative efficiency elsewhere. I find that the international inequality in output per worker decreases substantially - the variance of log productivity decreases by 39.4%, and the 90^{th} to 10^{th} percentile ratio decreases by 47.8%. This convergence effect is not observed in a world without international trade. Therefore, domestic allocative distortions contribute to a significant share of international income differences mainly because they inhibit developing countries trade performance.

Related Literature

This paper contributes to a recent research agenda on the interplay between firm-level heterogeneity, the business environment, and aggregate economic performance. One branch of this literature has studied the effect of specific micro frictions on aggregate productivity in closed-economy models - see Buera et al. [2011] and Moll [2014] for financial frictions, Lagos [2006] for labor market frictions, Jones [2011] and Jones [2013] for intermediate inputs, and Peters [2013] for imperfect competition in output markets. Another body of work, based on the seminal contributions of Melitz [2003] and Bernard et al. [2003], has investigated how trade-induced inter-firm reallocations affect industry performance.

On the interaction between trade and domestic distortions, Manova [2013] studies the effect of capital misallocation across firms on export performance. Ho [2010] develops a two-country model to study the interplay between trade and firm-level distortions in the context of India's 1991 trade liberalization. Epifani and Gancia [2011], Edmond et al. [2015], and Arkolakis et al. [2015] study the contribution of trade openness to the reduction of markup distortions. Finally, Tombe [2015], Swikecki [2017], and Caliendo et al. [2017] introduce sectoral frictions into quantitative trade models.

My contributions to this literature are twofold. First, I show that in the presence of firm selection into domestic and export markets, international trade is a natural and quantitatively relevant multiplier of the aggregate effects from size-dependent distortions. This finding is relevant because the quantitative results from the closed-economy literature, despite being substantial in absolute terms, still fall short at explaining the large international differences in aggregate TFP. According to Hopenhayn [2014a], even in the extreme case where the entire difference in firm size distribution between the US and developing countries is attributed to distortions, the aggregate TFP losses from distortions are still too low.[8] In my experiments, converging to the "US efficiency" reduces the productivity gap by 30% in Mexico, 55% in China, and 78% in India. Second, I show that cross-country differences in firm size distribution and in domestic allocative distortions matter for assessing the differential benefits of international trade for developing and rich countries.

This paper also contributes to the literature on gains from trade and firm heterogeneity. ACR highlight that trade models with firm heterogeneity result in the same macro predictions and aggregate gains from trade as models with representative firms. This equivalence rests on two results. First, under the standard assumptions on the distribution of micro-level heterogeneity, the same equation describes the gains from trade in the two classes of models, and this equation depends on only two sufficient statistics: the home share of spending on tradable goods (which is observed) and the elasticity of trade with respect to variable trade costs. Second, the estimation of trade elasticities is not model-specific because both frameworks deliver the same estimating gravity equation.[9]

I show that if the distribution of firm size varies across countries, then the second result no longer holds. In this case, the gravity equation, the estimation of trade elasticities, which are now origin-country-specific, and the magnitude of gains from trade will differ across models.[10] Methodologically, my contribution is close to Simonovska and Waugh [2014b]. They show that models with micro heterogeneity imply different estimates of trade elasticities, and therefore different gains from trade, than representative-firm models.

Relatedly, this paper extends the workhorse quantitative multi-country trade model to allow for country-specific distributions of firm size. I develop a numerical strategy to compute the general equilibrium in this highly nonlinear environment.[11] I also prove that, under mild and empirically verifiable assumptions, the general equilibrium exists and is unique. Spearot [2016] also introduces rich cross-country heterogeneity in a multi-country gravity model. My paper differs from this study in two respects. Methodologically, I solve and estimate the model in levels instead of in differences. My strategy is

[8]The losses are approximately 7% for Mexico and India, and 1% for China. These estimates do not take into account the effect of distortions on the selection of producers.

[9]The structural interpretation of the trade elasticity still differs across models. In representative-firm models, it captures the elasticity of substitution across varieties; in models with firm heterogeneity, it captures the dispersion of micro-level productivity. For methods to estimate trade elasticities, see Mayer [2014] and Caliendo and Parro [2014].

[10]Melitz and Redding [2015] also stress that the equivalence result is not valid under more general distributions of firm-level productivity. My results show that even in the standard case with untruncated Pareto distribution, the selection effects highlighted by the new trade models matter in the aggregate precisely because they interact with the distribution of firm size, which is a country-specific object.

[11]My numerical method combines bisection and fixed-point algorithms, and it easily applies to a setting with an arbitrarily large number of countries. Yang [2017] develops a gravity model with log-normal distribution of firm-level productivities in which the dispersion of draws varies across export countries. His quantitative exercises, however, are limited to a world economy with ten countries.

more costly because it requires the calibration of all structural parameters of the model. However, it allows me to perform a broader set of counterfactual exercises in general equilibrium, beyond those based on changes in trade costs. Empirically, I show that the cross-country variation in trade elasticities is correlated with differences in firm-level distortions observed in the micro data. More generally, this paper relates to recent work on nonlinear gravity models like Adao et al. [2017], Bas et al. [2017], and Lind and Ramondo [2017], which explores the consequences of relaxing the ACR assumptions.

Finally, this paper develops a mechanism to rationalize the results in Helpman et al. [2008] and Waugh [2010]. These papers find that trade costs derived from gravity equations are asymmetric, with developing countries facing systematically higher costs to export their goods. I show empirically that this asymmetry in part captures differences in domestic SDD.[12] Furthermore, I find that gravity estimates of export costs no longer covary with development once cross-country differences in firm size distribution are taken into account. The distinction between trade costs and firm size distribution is not only of theoretical interest but also crucial for policy recommendation. On the one hand, if high trade costs are the main bottleneck to exports, policies targeted at improving transportation infrastructure and at promoting trade agreements are the right remedy. On the other hand, if export performance is weak because firms are too small to overcome costs to access foreign markets, domestic institutional reforms are a better alternative.

Road Map

Section 2 documents the salient facts about development, firms, and trade. Section 3 presents the model. Section 4 describes the empirical implementation of the model and the main empirical results. I present the counterfactual exercises in Section 5 and Section 6 concludes. Appendices A, B, C, D, E contain mathematical proofs, Monte Carlo simulations, details of data construction, additional results, and tables.

2 Empirical Motivation

This section presents four facts to motivate the theoretical model. I focus on manufactured goods since they comprise the bulk of international trade values. The data are for the year 2006 unless otherwise noted.

2.1 Data

Average Firm Size The data on manufacturing firm size are from Bento and Restuccia [2017] and are based on national censuses, representative surveys, and registry datasets of 134 countries for the period 2000-2012. This dataset is particularly suitable for cross-country analysis for two reasons. First, it covers both registered and unregistered estab-

[12] Fieler [2011] shows that this asymmetry can also be rationalized by the introduction of nonhomothetic preferences and multiple classes of goods into a Ricardian gravity model.

lishments. Second, it includes paid and unpaid workers in its definition of employment. These features are relevant in our context because informal and family-owned establishments tend to be both smaller and more prevalent in developing economies. Firm size is defined as the average number of persons engaged per establishment.[13]

Establishment Data The establishment data come from the World Bank Enterprise Survey (WBES) 2016. The WBES is an ongoing research project to collect micro-level data of firms from a broad cross-section of countries. The information is collected through face-to-face surveys in the most important economic areas of each country. The sample used in this paper was collected during the period 2005-2016 and contains 42,996 observations from 118 countries disaggregated at the 2-digit sector level.[14] The dataset includes OECD members (e.g., Chile, Spain, Israel, Sweden, and Ireland), emerging economies (e.g., Brazil, Russia, India, China, and Indonesia) and developing countries (e.g., Nigeria, Cambodia, and Bolivia). The dataset contains establishment-level information on total sales, spending on raw materials and intermediate goods, net book value of assets, and total cost of labor. The median country has approximately 500 firms distributed across 19 industries. A well-known feature of this survey is that it tends to oversample large firms. Despite being a disadvantage in other contexts, this characteristic is actually beneficial for this study, which focuses on the constraints experienced by large producers.

Production, Trade, and Geography I use trade data from COMTRADE and production data from UNIDO to assemble a dataset that contains manufacturing market size, valued added, and bilateral trade disaggregated at the 3-digit sector level for 77 major economies. I combine this information with Mayer and Zignago [2006] data on bilateral geographic variables. Finally, I measure development using output per worker and aggregate TFP from the Penn World Tables 8.0 (PWT).

In the construction of the stylized facts that follow, I include all countries for which the relevant data are available. In the final sample used in the structural model, I work with a subset of 77 economies that comprise more than 90% of the global GDP and manufacturing trade.

2.2 Facts

Fact I: Firm Size and Development

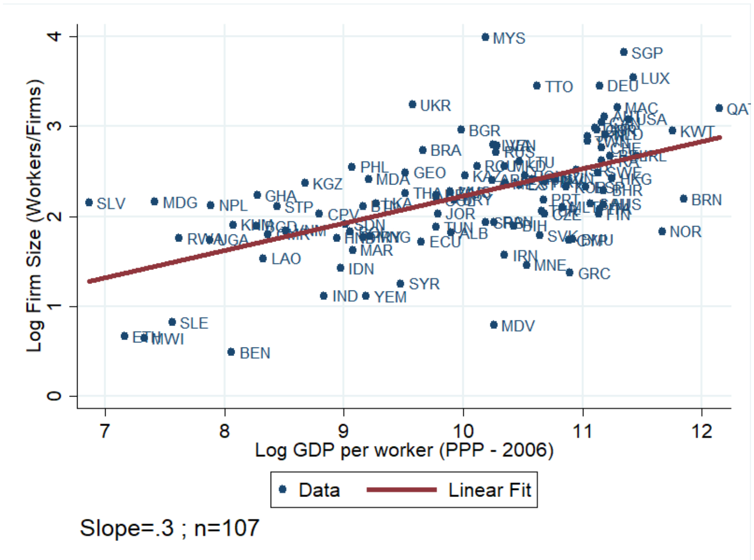
Small production units carry out a high share of the economic activity in developing countries. In the agricultural sector, Adamopoulos and Restuccia [2014] document a 34-fold difference in the average operational scale of farms between rich and developing countries. Lagakos [2016] documents stark cross-country differences in the retail sector: developing economies have employment concentrated in traditional, small-scale shops and advanced countries in modern big-box stores.

[13] I use the terms firm and establishment interchangeably.

[14] The bulk of establishments are classified in the manufacturing sector (ISIC revision 3 digits 15 through 36).

A similar pattern applies to the manufacturing sector. For instance, the average manufacturing firm in the United States and Germany has 21 and 31 workers, but only 3 in India. Figure 1 presents the relationship between average firm size and aggregate productivity for a large sample of countries. A twofold increase in income per worker is associated with a 30% rise in average size. This relationship still holds when differences in the industrial composition of the manufacturing sector are controlled for (see Poschke [2014]) and is also present in time-series data. Poschke [2014] documents this phenomenon in the US during the twentieth century and Buera and Fattal-Jaef [2014] show that growth in firm size and aggregate productivity followed structural reforms in Japan, South Korea, Singapore, and Chile.

Figure 1: Firm Size and Development



Note: The horizontal axis is the logarithm of output per worker in 2006 PPP dollars and the vertical axis is the logarithm of average firm size measured as the number of engaged persons per establishment. Data on firm size is from the period 2000-2012. **Source:** Bento and Restuccia [2017] and PWT 8.0.

Fact II: Dispersion of Firm-Level Productivity and Development

To introduce the second fact, I need to impose more structure on the data. As Hsieh and Klenow [2009], I assume that each manufacturing sector s is monopolistically competitive with CES demand controlled by $\sigma > 1$. I also assume that firm i's value-added production function is Cobb-Douglas and α_s is the output elasticity with respect to physical capital. Firms face an idiosyncratic revenue wedge $\tau_{s,i}$, with higher $\tau_{s,i}$ representing lower distortions. Under these assumptions, firm-level physical productivity is proportional to the ratio between deflated revenue and factor use

$$TFPQ_{s,i} \equiv \frac{Y_{s,i}}{K_{s,i}^{\alpha_s} L_{s,i}^{1-\alpha_s}} \propto \frac{(P_{s,i}Y_{s,i})^{\frac{\sigma}{\sigma-1}}}{K_{s,i}^{\alpha_s} L_{s,i}^{1-\alpha_s}} \tag{1}$$

and idiosyncratic distortions are proportional to the average revenue productivity ($TFPR_{s,i}$)

$$TFPR_{s,i} \equiv \frac{P_{s,i}Y_{s,i}}{K_{s,i}^{\alpha_s}L_{s,i}^{1-\alpha_s}} \propto (\tau_{s,i})^{-1} \propto (MRPK_{s,i})^{\alpha_s}(MRPL_{s,i})^{1-\alpha_s} \tag{2}$$

where $MRPK$ and $MRPL$ are the marginal revenue product of capital and labor adjusted for human capital.

Equation (2) shows that a firm with high revenue productivity is also a high-marginal-product firm. Supposing $TFPR$ is not equal across firms within a sector, the model connects high dispersion of revenue productivity to micro allocative inefficiency.

I assume $\sigma = 3$ and use the U.S labor shares $\{1-\alpha_s\}_{s=1}^{S}$ from the NBER Productivity Database[15] combined with estimates from Gollin [2002].[16] I measure capital input as the sum of reported values of machinery, vehicles, land, and buildings and labor input as the sum of wages, salaries, bonuses, and social security payments.[17] The benchmark estimation includes both domestic producers and exporters.[18] Finally, I compute country j's within-sector dispersion of revenue productivity as

$$Sd(log(TFPR)_j) \equiv Sd\left(log\left(\frac{TFPR_{j,s,i}}{\overline{TFPR}_{j,s}}\right)\right) \tag{3}$$

where Sd stands for standard deviation. To compute this moment, I use the sampling weights provided by the WBES. A similar formula applies to the dispersion of physical productivity.[19]

Figure 2 shows a significant negative association between micro dispersion and development. I estimate that a two-fold increase in aggregate productivity leads to a .31 (.34) standard deviation reduction in the dispersion of TFPQ (TFPR). Appendix D presents a comparison between the dispersion statistics calculated with the WBES dataset and values based on more comprehensive firm-level datasets compiled by national statistical bureaus. I find that the there is no systematic difference between the two measures and, overall, the WBES provides a very good approximation of the datasets commonly used in single-country studies.

[15] As Hsieh and Klenow [2009], I adjust the labor shares to correct for the omission of social security contributions in the computation of labor compensation in the NBER data.

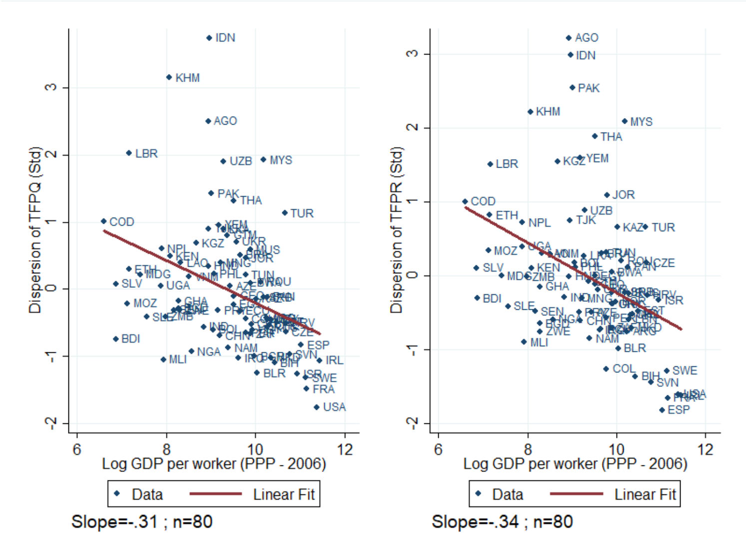
[16] The elasticity of output with respect to labor is equal to the labor share of value added in an imperfectly competitive environment only under the assumption that monopoly rents are distributed to capital and labor accordingly to their output elasticities.

[17] The advantage of using wages instead of the number of workers is to control for unobserved differences in the composition of human capital across firms.

[18] Appendix C describes the construction of the final sample. Appendix D shows that results remain the same if the analysis is restricted to domestic firms.

[19] $\overline{TFPQ}_s \equiv \left(\sum_i TFPQ_{s,i}^{\sigma-1}\right)^{\frac{1}{\sigma-1}}$ and $\overline{TFPR}_s \equiv \sum_i \frac{P_{s,i}Y_{s,i}}{P_sY_s} TFPR_{s,i}$.

Figure 2: Dispersion of Firm-Level Productivity and Development



Note: The horizontal axis is the logarithm of output per worker in 2006 PPP dollars and the vertical axis is the standardized measure of dispersion of firm-level productivity. The left panel shows the results for physical productivity; the right, for revenue productivity. **Source:** Author's calculation based on the WBES dataset, Hsieh and Klenow [2009] for the US, and Bellone et al. (2013) for France.

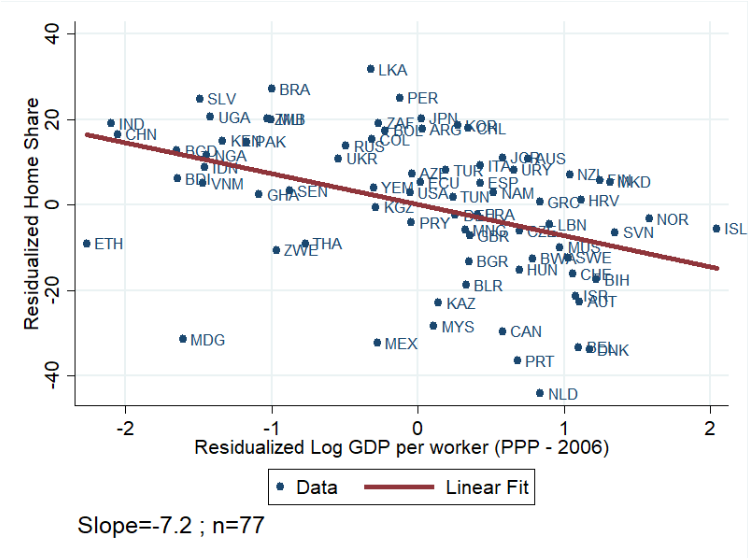
Fact III: Trade Openness and Development

Fact three is the positive correlation between trade openness and development. Fieler [2011] and Caron et al. [2014] document this fact for aggregate trade flows. The same pattern holds for trade in manufactures. To capture the openness in the manufacturing sector, I compute the domestic share of spending as:

$$s_{jj} = \frac{X_{jj}}{\sum_{i=1}^{N} X_{ji}} \tag{4}$$

where X_{ji} is country j's spending on manufactures from i. X_{jj} is not directly observed, but can be recovered with trade and production data using the identity $X_{jj} \equiv Y_j - \sum_{i \neq j} X_{ij}$, where Y_j is j's manufacturing gross production. The domestic share is an inverse measure of trade openness, and it will prove very convenient in the theoretical model. Figure 3 presents a scatterplot of home trade shares, s_{jj}, and output per worker. Both measures are net of variation in country total output. A two-fold increase in output per worker is associated with a reduction of 7.2 percentage points in manufacturing home share. As a baseline, the average domestic share is 47%.

Figure 3: Trade Openness and Development



Note: The horizontal axis is the residualized logarithm of output per worker in 2006 PPP dollars, and the vertical axis is the residualized home share. Residualized x variable corresponds to the residuals of a regression of x on the logarithm of country total output. **Source:** Author's calculation based on data from COMTRADE, UNIDO, and PWT 8.0.

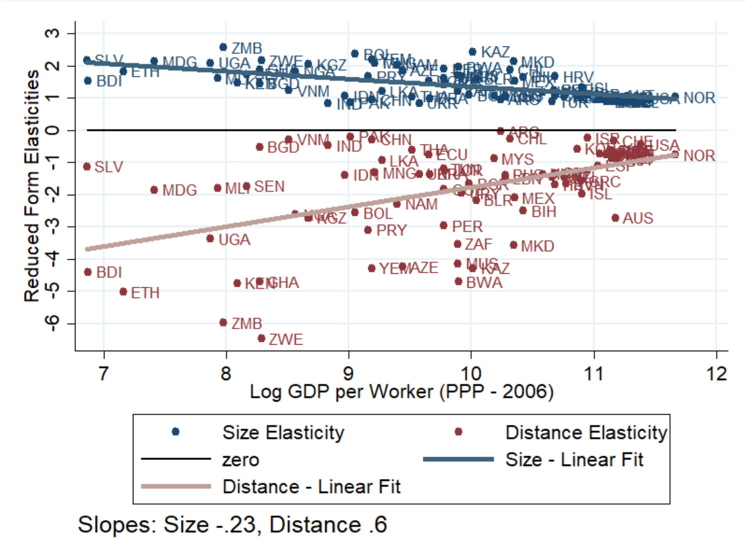
Fact IV: Geography of Exports and Development

The last fact is about the differences in the geography of exports between rich and developing countries. As a first step, consider for each source country i the following regression:

$$x_{ji} = \beta_0^i + \beta_{size}^i x_j + \beta_{dist.}^i d_{ji} + \epsilon_{ji} \tag{5}$$

where x_{ji} is sales from i to j, x_j is total spending on manufactures in j, and d_{ji} is bilateral distance. All variables are in logs, so the coefficients are the reduced-form elasticities of exports with respect to market size and distance. I exclude zeros from the estimation, which reduces the sample size by 3%. Figure 4 plots the elasticities against exporter's output per worker.

Figure 4: Reduced Form Trade Elasticities and Development



Note: The horizontal axis is the logarithm of output per worker in 2006 PPP dollars and the vertical axis is the reduced form trade elasticities. The sample contains bilateral trade in manufactures among 77 countries. **Source:** Author's calculation based on data from COMTRADE, UNIDO, and Penn World Tables 8.0.

There is large and systematic cross-country variation in the reduced form elasticities. First, the elasticity of sales with respect to market size decreases with exporter productivity. Whereas sales from rich countries are approximately homothetic (the coefficients cluster around 1) exports from developing nations tend to increase faster than importer market size. Second, the elasticity of sales with respect to distance becomes less negative with exporter productivity. Whereas sales from the developed world tend to decrease proportionately with bilateral distance the reduction in sales of developing countries is more than proportional. These results imply that developing economies tend to sell disproportionately more to larger and less distant markets.

Standard structural gravity models predict the invariance of trade elasticities only when import prices are kept constant. Thus, the reduced-form results above could be just a result of model misspecification instead of true heterogeneity in the underlying structural parameters.[20] To address this concern, I include importer fixed effects in the regression. Consider the following specification:

$$x_{ji} = \alpha_i + \delta_j + \beta_{size}(x_j y_i) + \beta_{dist} d_{ji} + \beta_{int}(d_{ji} y_i) + \epsilon_{ji} \tag{6}$$

where y_i represents labor productivity at the origin country, α_i and δ_j are exporter and importer fixed effects. An absence of heterogeneity in elasticities implies I would fail

[20]In addition, variation in the elasticity of trade with respect to distance can reflect dispersion in the elasticity of trade with respect to trade costs, in the elasticity of trade costs with respect to distance, or both. In the structural section, I use import tariffs as cost shifters to identify structural trade elasticities and show that the reduced-form results of this section, in fact, reflect variation in trade-cost elasticities.

to reject the hypothesis $\beta_{size} = \beta_{int} = 0$. Table 1 presents the results. The effects of market size and distance are still large and statistically significant. Sales from developing economies are still more elastic with respect to importer market size and distance. Moreover, sharing a language or a border promotes bilateral trade, but less so for more productive exporters. Similar results hold when specification (6) is estimated at finer levels of sectoral disaggregation - see Appendix D.

Table 1: Reduced Form Trade Elasticities and Development

VARIABLES	(1) Trade Value
(Importer Size)*(Exporter GDP per Worker)	-0.228***
	(0.0158)
Distance	-1.617***
	(0.0752)
Distance*(Exporter GDP per Worker)	0.648***
	(0.0532)
Language	1.940***
	(0.145)
Language*(Exporter GDP per Worker)	-0.838***
	(0.104)
Border	0.318
	(0.315)
Border*(Exporter GDP per Worker)	-0.117
	(0.261)
Observations	5,852
R-squared	0.778

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Regression includes exporter and importer fixed effects. Both trade and distance are in logs. Zeros are excluded from the sample. Exporter's productivity is standardized such that its average is zero and standard deviation is one. The sample contains bilateral trade in manufactures among 77 countries. **Source:** Author's calculation based on data from COMTRADE, UNIDO, and PWT 8.0.

For a smaller sample of countries, I can decompose total bilateral trade in manufactures into number of exporters and mean sales per exporter using the World Bank Exporter Dynamics Database (WBED) from Fernandes et al. [2016]. I use these data to test if the cross-exporter differences in the elasticity of aggregate sales with respect to distance stems from the intensive margin (average exports per firms) or the extensive margin (number of firms).

Table 2 presents the results. Similarly to other papers in the gravity literature, I find a proportional relationship between trade and distance: the elasticity is -1. 30% of this effect is due to the mean sales decreasing with distance. The remaining 70% is due to the extensive margin, i.e., fewer firms entering more distant markets. Moreover, the interaction between distance and exporter's productivity is entirely driven by the extensive margin. The evidence indicates that the number of export firms decreases

13% faster in bilateral distance for developing economies. The reduction of mean sales associated with distance, by its turn, is the same for rich and developing exporters.

Table 2: Extensive and Intensive Margin Gravity

VARIABLES	(1) Total Sales	(2) Mean Sales	(3) Number of Exporters
Distance	-1.015***	-0.310***	-0.705***
	(0.0175)	(0.0118)	(0.0115)
Distance*(Exporter GDP per Worker)	0.0295***	-0.00237	0.0318***
	(0.00595)	(0.00428)	(0.00386)
Observations	10,263	10,263	10,263
R-squared	0.798	0.688	0.793
Difference Distance Elast. pc	8	-2	13

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: All specifications include importer and exporter fixed effects, and geographic controls like existence of common border and common official language. The first column reports the coefficients for the specification with total sales as the dependent variable. The second column reports the results for the specification with mean sales as the left-hand side variable. The third column reports the results for a specification with number of exporters as the left-hand side variable. The last row reports the percentage decrease in the absolute value of trade-distance elasticities caused by an increase of exporter's output per worker from the 5th to the 95th percentile of the productivity distribution. **Source:** Author's calculation based on data from the WBED.

3 Model

A minimal theoretical framework necessary to study the facts described above must contain: (i) distributions of firm-level physical productivity that vary across countries; (ii) SDD representing cross-country differences in the business environment; (iii) bilateral trade costs that reflect both geographic and institutional barriers to trade; and (iv) endogenous entry and exit of firms into domestic and export markets. It is important that the inclusion of these features does not compromise the model's amenability to quantitative analysis. Therefore, in my choices of distributions and functional forms I try to balance flexibility with tractability.

3.1 The Environment

Service Sector

Consider a world economy with N countries indexed by i. Each economy is comprised of two sectors: services and manufacturing. Country i is endowed with L_i workers and K_i units of capital. Factors are mobile within but not between countries. The representative consumer's utility is linear in the nontradable final good (C_i) and her budget constraint is $Y_i = w_i L_i + r_i K_i + \Pi_i$. Income is the sum of total factor payments and distributed profits (Π_i). The service sector is perfectly competitive and produces the final good according to the Cobb-Douglas production function

$$C_i = (K_{i,s}^{\alpha}(h_i L_{i,s})^{1-\alpha})^{\mu} Q_i^{1-\mu} \tag{7}$$

where the subscript s refers to service sector, h_i represents human capital, Q_i is a bundle of intermediate inputs, and α is the capital share in value added. The parameter μ controls the share of employment in the service sector. The input bundle is a CES aggregator of intermediate varieties

$$Q_i = \left(\int_{\Omega_i} q(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}} \tag{8}$$

where $q(\omega)$ is the quantity of variety ω and the elasticity of substitution, σ, is greater than one. The set Ω_i is determined endogenously and includes both domestic and imported varieties. Expenditure on variety ω is

$$x_i(\omega) = \left(\frac{p_i(\omega)}{P_i} \right)^{1-\sigma} Z_i \tag{9}$$

where Z_i is the service sector's spending on inputs and P_i is the input bundle price.[21] Perfect competition implies $Z_i = (1-\mu)Y_i$.

Manufacturing Sector

A steady state equilibrium of firms in monopolistic competition characterizes the manufacturing sector. An endogenous mass M_i of ex-ante identical entrepreneurs pays an exploration cost of $w_i f_i^e$ to start a firm. This cost captures the direct and indirect costs of licenses, regulations, and permits required to open a business. After the payment, the producer ω learns her production function

$$q_i(\omega) = A_i \omega (K_i(\omega))^{\alpha} (h_i L_i(\omega))^{1-\alpha} \tag{10}$$

The distribution of micro technologies (ω or, equivalently, TFPQ) is Pareto with cumulative distribution function

$$G_i(\omega) = 1 - \omega^{-\theta_i} \tag{11}$$

where $\omega \geq 1$. Pareto is the most common choice in the literature on trade with heterogeneous firms for a number of reasons. First, it gives tractability to the solution and estimation of multi-country general equilibrium models. Second, standard processes of innovation give rise to Pareto techniques (see Arkolakis [2016]). Third, empirical evidence shows that the firm size distribution, which derives from the distribution of ω in the basic model, is well approximated by Pareto (see Axtell [2001] and Di Giovanni et al. [2011]).

In this framework, the parameters A_i and θ_i fully characterize country i's technology. A_i controls average productivity and reflects factors that equally affect all firms

[21] $P_i \equiv \left(\int_{\Omega_i} p_i(\omega)^{1-\sigma} d\omega \right)^{\frac{1}{1-\sigma}}$

in the economy. For instance, growth of A_i improves overall technology while keeping constant the relative technologies between any pair of firms. The parameter θ_i controls the dispersion of firm-level productivity because:

$$Sd(log(TFPQ)_i) = \theta_i^{-1} \tag{12}$$

Therefore, the dispersion of micro technologies is inversely proportional to θ_i. Assuming country-specific dispersion gives the model the necessary flexibility to match the cross-country patterns of firm-level heterogeneity. It also prevents the theory from loading all cross-country differences in size distribution on differences in distortions. Even in the absence of firm-level frictions, countries differ in their size distribution for technological reasons.[22] Finally, the assumption is important because the aggregate gains from selection and reallocation crucially depend on the heterogeneity of TFPQ.

The total cost of selling q units of variety ω from origin i to destination j is:

$$c_{ji}(\omega, q) = \frac{q d_{ji} \overline{c}_i}{\tilde{A}_i \omega} + w_i f_{ji} \tag{13}$$

where $\overline{c}_i$ is the Cobb-Douglas price of inputs[23] and $\tilde{A}_i \equiv A_i h_i^{1-\alpha}$. The term $d_{ji} \geq 1$ is the iceberg trade cost[24] and f_{ji} is the fixed cost of serving destination j, such as search and contractual costs, non-tariff barriers, and costs to adapt the product to local standards and regulations. Domestic trade costs, d_{ii} and f_{ii}, are normalized to one, so I interpret the domestic fixed cost as the entrepreneur's opportunity cost of running a business.[25] Bilateral iceberg and fixed trade costs can be asymmetric, reflecting both geographic and policy barriers to international trade.

Firm ω from country i faces an idiosyncratic revenue distortion denoted by $\tau_i(\omega)$. Therefore, the after-tax revenue from sales to destination j is

$$r_{ji}(\omega) = \tau_i(\omega) x_{ji}(\omega) \tag{14}$$

where $x_{ji}(\omega)$ is j's spending on i's variety ω as defined in equation (9). If $\tau_i(\omega) > 1$, then the distortion works as a subsidy; if $\tau_i(\omega) < 1$, as a tax.[26] In this context, revenue wedges serve as a parsimonious representation of the set of policies and institutions that distort resource allocation across firms. I model firm-level distortions using the following deterministic log-linear function:

$$\tau_i(\omega) = \omega^{-\gamma_i} \tag{15}$$

[22] More generally, one can interpret ω as a composite of firm-level technical efficiency and an idiosyncratic demand shifter capturing product's quality or appeal. See Hsieh and Klenow [2009].

[23] $\overline{c}_i = \left(\frac{r_i}{\alpha}\right)^{\alpha} \left(\frac{w_i}{1-\alpha}\right)^{1-\alpha}$

[24] To avoid arbitrage opportunities, I assume $\forall\ i, j, l\ d_{il} \leq d_{jl} + d_{ij}$.

[25] Kehoe et al. [2016] shows that the aggregate outcomes of a Melitz model are the same as in a model with occupational choice a la Lucas [1978] if fixed costs are interpreted as the entrepreneur's forgone wage.

[26] It is straightforward to demonstrate that this revenue wedge is isomorphic to an idiosyncratic tax on variable factors of production. See Hsieh and Klenow [2009].

with $\gamma_i \geq 0$. This functional form has been applied in many recent papers in the macro-development literature (see Buera and Fattal-Jaef [2014], Hsieh and Klenow [2014], Poschke [2014], and Bento and Restuccia [2017]) and has many advantages. First, the severity of distortions depends on only one parameter (γ_i), which is easily estimable with firm-level data. Second, as demonstrated by Hopenhayn [2014b], micro distortions that increase proportionately with firm productivity are much more likely to generate the large observed international differences in aggregate TFP than frictions independent from firm efficiency. Third, the undistorted economy is represented by the special case with $\gamma_i = 0$. Finally, as I show in section 4, there is no empirical evidence that the dispersion of uncorrelated distortions (distortions that are not systematically related to firm size) covaries with development. This finding implies that the cross-country variation in dispersion of TFPR presented in section 2 stems mainly from differences in correlated distortions, i.e., differences in the distortion-productivity elasticity γ_i.

The first part of the firm's problem is to maximize after-tax profits ($\pi_{ji}(\omega)$) in each potential destination. Optimal price is

$$p_{ji}(\omega) = \underbrace{(\tilde{\sigma}\omega^{\gamma_i})}_{Markup} \underbrace{\left(\frac{\overline{c}_i d_{ji}}{\tilde{A}_i \omega}\right)}_{MarginalCost} \tag{16}$$

where $\tilde{\sigma} \equiv \frac{\sigma}{\sigma-1}$ is the undistorted markup. After-tax revenue, which is proportional to after-tax profit, is

$$r_{ji}(\omega) = (\tilde{\sigma}\overline{c}_i d_{ji})^{1-\sigma} \tilde{A}_i^{\sigma} (Z_j P_j^{\sigma-1}) \omega^{\sigma-1-\sigma\gamma_i} \tag{17}$$

In principle, γ_i could be so high that after-tax sales and profits become decreasing in TFPQ, reverting the competitive advantage of more efficient producers. To avoid this extreme case, I assume that the following **non-ranking reversal** condition is true for all i:

$$\epsilon_i \equiv \sigma - 1 - \sigma\gamma_i > 0 \tag{18}$$

Intuitively, condition (18) assures that, despite heavier distortions, more productive firms still make higher after-tax profits and, therefore, sell more than their less productive competitors. I show in the empirical section that the estimates of $\{\gamma_i\}_{i=1}^N$ satisfy this condition for the values of σ usually employed in the trade and macro literatures. The second part of the firm's problem is to choose which destinations to serve, domestic market included. Firm ω enters market j if and only if $\pi_{ji}(\omega) \geq 0$. For each pair (j, i) there is a threshold productivity ω_{ji}^* defined by $\pi_{ji}(\omega_{ji}^*) = 0$, above which it's profitable for i's firms to enter j's market.

Aggregation and Equilibrium

Country j's input price index, P_j, is the implicit solution of the equation

$$P_j^{1-\sigma} = \sum_{i=1}^{N} M_i \int_{\omega_{ji}^*}^{\infty} p_{ji}(\omega)^{1-\sigma} dG_i(\omega) \tag{19}$$

where P_j affects the right-hand side through the selection of foreign sellers (ω^*_{ji}). The integrals converge if, and only if, the following **regularity condition** is satisfied for all i:

$$\chi_i \equiv \theta_i + (\sigma - 1)(\gamma_i - 1) > 0 \tag{20}$$

Condition (20) includes the regularity condition of traditional gravity models with Pareto or Frechet distributions of micro technologies ($\theta > \sigma - 1$). This condition rules out the case in which buyers can achieve an arbitrarily low price index by concentrating demand on a few extremely productive inputs. In particular, it rules out the Zipf's law case ($\theta = \sigma - 1$). Under condition (20), all the aggregate objects in the model are well defined. I now have all the elements necessary to define the general equilibrium. I demonstrate in Appendix A that for parameters $\{\sigma, \alpha, \mu\}$ and $\{A_i, L_i, \gamma_i, \theta_i, f^e_i\}_{i=1}^N$ that satisfy conditions (18) and (20), and trade costs $(f_{ji}, d_{ji})_{i,j=1}^N$ that satisfy the triangular inequality, there exists a unique (up to scale) vector $\{w_i, r_i, P_i\}_{i=1}^N$ and a sequence of measures $\{M_i\}_{i=1}^N$ such that:

- Consumers and firms behave optimally
- Goods and factor markets clear
- **Balanced Trade** $Z_i = \sum_{j=1}^N X_{ji}$ for all i
- **Free Entry** $\Pi_i = 0$ for all i
- P_i satisfies equation (19) for all i

3.2 SDD, Dispersion of Firm-Level Productivity, and Trade

The goal of this subsection is to characterize the theoretical relationships between size-dependent distortions, dispersion of firm-level productivity, and trade elasticity. As in Hsieh and Klenow [2009], revenue productivity is proportional to the marginal revenue products of factors. What is particular about my framework is that the distortion schedule (15) causes marginal products to be proportional to physical productivity with elasticity regulated by γ_i. For a purely domestic firm in country i, the following relationship holds:

$$TFPR_i(\omega) \propto MRPK_i(\omega)^\alpha MRPL_i(\omega)^{1-\alpha} \propto \omega^{\gamma_i} \tag{21}$$

Therefore, the dispersion of revenue productivity among domestic producers measures the dispersion of marginal productivity. Moreover, the gap in marginal productivities between high-productivity and low-productivity firms increases in γ_i. The properties of the Pareto distribution imply that for any set of active domestic producers we have:

$$Sd(log(TFPR)_i) = \frac{\gamma_i}{\theta_i} = \gamma_i Sd(log(TFPQ)_i) \tag{22}$$

The next step is to characterize the relationship between SDD and trade elasticities. Combining equations (9) and (16), aggregate exports from country i to country j are

$$X_{ji} = \overline{T}_i Z_j P_j^{\sigma-1} d_{ji}^{1-\sigma} \int_{\omega^*_{ji}}^{\infty} \omega^{-(\chi_i+1)} d\omega \tag{23}$$

The term $\overline{T}_i$ captures i's competitiveness at the intensive margin[27] (how large are sales for active exporters). More important are the terms χ_i and ω^*_{ji}. The first relates to the sales distribution of incumbent firms, and the second relates to firm selection into markets. In the next proposition, I present the relationship between dispersion of firm-level productivity, SDD, and dispersion of firm-level sales.

Proposition 1. *For any set of active firms and for all j, $Sd(log(x_{ji})) = \frac{(\sigma-1)(1-\gamma_i)}{\theta_i}$. Thus: $\frac{\partial Sd(log(x_{ji}))}{\partial \theta_i} < 0$ and $\frac{\partial Sd(log(x_{ji}))}{\partial \gamma_i} < 0$.*

Proof. It follows from equation (20) and properties of the Pareto distribution. □

SDD constrain disproportionately more the size of high-productivity firms, and this effect compresses the distribution of both export and domestic sales. Therefore, more severe SDD reduces the sales difference between marginal and inframarginal firms. Note that the relationship between dispersion of revenue productivity and dispersion of revenues is ambiguous. According to equation (22), both higher dispersion of TFPQ and higher SDD lead to larger dispersion of TFPR. However, while the former increases the dispersion of sales, the latter reduces it.

The next step is to analyze the effect of distortions on the selection of firms into exporting. Using the zero-profit condition, the marginal firm in the $j - i$ link is:

$$\omega^*_{ji} = \left(\frac{w_i f_{ji} \sigma (\tilde{\sigma} \overline{c}_i d_{ji})^{\sigma-1}}{\tilde{A}_i^{\sigma-1} Z_j P_j^{\sigma-1}} \right)^{\frac{1}{\sigma-1-\sigma\gamma_i}} \tag{24}$$

The partial equilibrium elasticity of the threshold productivity with respect to trade costs and market size is increasing in SDD. This implies that it is particularly more difficult for firms from more distorted economies to enter "harder" markets, i.e., more distant and smaller destinations. The next proposition highlights this result.

Proposition 2. *For all destinations, the partial equilibrium elasticities of the threshold productivity with respect to trade shifters increases (in absolute value) in γ_i. More specifically: $\frac{\partial \left| \frac{\partial log(\omega^*_{ji})}{\partial log(d_{ji})} \right|}{\partial \gamma_i} > 0$, $\frac{\partial \left| \frac{\partial log(\omega^*_{ji})}{\partial log(f_{ji})} \right|}{\partial \gamma_i} > 0$, and $\frac{\partial \left| \frac{\partial log(\omega^*_{ji})}{\partial log(Z_j)} \right|}{\partial \gamma_i} > 0$.*

Proof. Follows from equations (18) and (24). □

Now we have all the elements to analyze the impact of distortions on the elasticities of aggregate trade flows with respect to trade shifters. Defining s_{ji} as the share of j's spending on tradables devoted to i's goods, the combination of equations (23) and (24)

[27] $\overline{T}_i \equiv M_i \tilde{\sigma}^{1-\sigma} \left(\frac{\tilde{A}_i}{\overline{c}_i} \right)^{\sigma-1}$

results in the following equation:

$$s_{ji} = \frac{T_i (Z_j P_j^{\sigma-1})^{\left(\frac{\beta_i}{\sigma-1}-1\right)} d_{ji}^{-\beta_i} f_{ji}^{\left(1-\frac{\beta_i}{\sigma-1}\right)}}{\sum_{k=1}^{N} T_k (Z_j P_j^{\sigma-1})^{\left(\frac{\beta_k}{\sigma-1}-1\right)} d_{jk}^{-\beta_k} f_{jk}^{\left(1-\frac{\beta_k}{\sigma-1}\right)}} \tag{25}$$

where the term T_i captures country i's competitiveness when both the extensive and intensive margins are taken into account and is given by

$$T_i = \frac{M_i \theta_i \tilde{A}_i}{\chi_i (\tilde{\sigma} \overline{c}_i)^{(\sigma-1)\left(1+\frac{\chi_i}{\epsilon_i}\right)} (w_i \sigma)^{\frac{\chi_i}{\epsilon_i}}} \tag{26}$$

and the structural trade elasticity β_i is

$$\beta_i \equiv (\sigma - 1)\left(1 + \frac{\chi_i}{\epsilon_i}\right) = (\sigma - 1)\left(1 + \frac{\theta_i + (\sigma - 1)(\gamma_i - 1)}{\sigma - 1 - \sigma\gamma_i}\right) \tag{27}$$

Equations (25), (26), and (27) constitute the backbone of the model. If $\gamma_i = 0$ and $\theta_i = \theta$ for all i, then β_i becomes equal to θ and equation (25) becomes the standard gravity formula in Eaton et al. [2011] and Di Giovanni and Levchenko [2012]. In this special case, trade elasticities no longer vary across exporters by definition, and trade shares do not depend on market size, so the term $(Z_j P_j^{\sigma-1})^{\left(\frac{\theta}{\sigma-1}-1\right)}$ vanishes from equation (25). In addition, exporter competitiveness (T_i) is solely determined by factor prices, technology and mass of firms - as shown in equation (26).

In the general case, SDD affect export performance both through its effects on exporter competitiveness (T_i) and trade elasticity (β_i). Given factor prices, more severe distortions reduce T_i by affecting the endogenous mass of firms (M_i) and distorting the allocation of market shares across incumbent exporters. To this extent, the effect of micro-level distortions on aggregate exports is isomorphic to the one from changes in aggregate technology (A_i). This result highlights the importance of the interaction between size-dependent distortions and selection into export markets: without selection, an economy with severe micro-level misallocation behaves in the aggregate just like an economy with low aggregate technological capabilities. In this sense, taking micro considerations into account does not yield any extra insight about the behavior of the aggregate economy that is not already present in aggregative models. With selection, however, micro-level misallocation brings novel aggregate implications because of its effect on the structural trade elasticity.

Structural trade elasticities are higher for exporters with less dispersed technologies and more severe SDD. These results derive directly from propositions (1) and (2). Higher SDD simultaneously increase the number of marginal exporters and reduce disproportionately more the sales of inframarginal ones. As a result, the aggregate exports from more distorted economies become more sensitive to trade shifters like trade costs and importer market size. On the one hand, this effect leads to disproportionately small sales to distant destinations. In this respect, higher distortions work just like larger export costs. On the other hand, it implies disproportionately large sales to big markets.

Another feature of equation (27) is that the trade elasticity reflects both extensive and intensive margin effects. Although trade models with micro heterogeneity generally exhibit this characteristic, the assumption of Pareto or Frechet distributions results in trade elasticities that are independent from intensive-margin parameters (see and Arkolakis et al. [2012] for examples with CES preferences and Arkolakis et al. [2015] for models featuring more general demand systems). Under these distributional assumptions, the trade elasticity based on gravity estimators identifies the dispersion of TFPQ - a result that has been intensely exploited by the recent quantitative literature in international trade and economic geography. This is no longer the case in the presence of SDD that vary across source countries.

The elasticity of trade with respect to fixed trade costs is decreasing in the demand elasticity as in Chaney [2008]. Unlike it, however, the elasticity of trade with respect to variable trade costs is also decreasing in σ. Therefore, the gains from trade, instead of decreasing in the degree of substitutability across goods as in Krugman [1980], *increase* in σ. The intuition for this result is that trade promotes a movement of factors from low-productivity to high-productivity establishments. The larger is the substitutability across goods, the more important is the productivity advantage of the latter firms and, therefore, the larger are the gains from such reallocation. I summarize this discussion in the next proposition.

Proposition 3. *The structural trade elasticity β_i controls the partial equilibrium effect of trade shifters like trade costs and importer market size on aggregate exports. The effects of dispersion of firm-level productivity, size-dependent distortions, and demand elasticity on this elasticity are $\frac{\partial \beta_i}{\partial \theta_i} > 0$, $\frac{\partial \beta_i}{\partial \gamma_i} > 0$, and $\frac{\partial \beta_i}{\partial \sigma} < 0$.*

Proof. Follows from equation (27). □

3.3 SDD and Aggregate TFP in Open Economies

In this environment, SDD affect aggregate TFP through four channels: firm entry, resource allocation among active firms, firm selection, and trade. The goal of this subsection is to describe in detail each of these channels. Before doing that, I need to define one last endogenous object: the mass of firms M_i. By combining the free-entry condition with the equilibrium in the tradable sector one can show that:[28]

$$M_i = \frac{(\sigma - 1 - \sigma\gamma_i)}{\sigma\theta_i f_i^e}\frac{(1-\mu)}{(1-\alpha)}L_i \tag{28}$$

Since $\frac{\partial M_i}{\partial \gamma_i} < 0$, more severe SDD reduce the measure of manufacturing firms. Intuitively, distortions disproportionately decrease profits from higher efficiency draws, making entry

[28]See derivation in Appendix A.

less appealing. Equation (28) also reveals complementarity between policies that reduce costs to start a firm and policies that improve allocative efficiency among existing firms. For example, the effect of allocative reforms on firm creation is larger when entry barriers are smaller.

Defining $m_i^d \equiv \frac{\sigma-1-\sigma\gamma_i}{\sigma-1}$ as the ratio between the distorted and undistorted mass of firms, one can show that the economy aggregate TFP is

$$TFP_i \equiv \frac{C_i}{K_i^{\alpha}(h_iL_i)^{1-\alpha}} = \Lambda s_{ii}^{\frac{-(1-\mu)}{\beta_i}} TFP_i^c \tag{29}$$

where

$$TFP_i^c \equiv \left(\frac{m_i^d(\sigma-1)(f_i^e)^{-1}}{\theta_i + (\sigma-1)\left(\theta_i Sd(log(TFPR)_i) - 1\right)}\right)^{\frac{1-\mu}{\beta_i}} \left(A_i L_i^{\frac{1}{\sigma-1}}\right)^{1-\mu} \tag{30}$$

Λ is a collection of constants and TFP_i^c is the total factor productivity when the economy is in autarky ($s_{ii} = 1$). Starting with the closed-economy effects, γ_i affects aggregate TFP through its effects on m_i^d, $Sd(log(TFPR)_i)$, and β_i.

First, more severe SDD reduce entry in the manufacturing sector, decreasing the measure of inputs available for the service sector. This effect is akin to the effect of higher entry costs. Second, for any given set of active producers, a higher γ_i increases the dispersion of marginal products among them, contracting aggregate TFP. This effect is also called *intensive margin misallocation* and has been an important topic in literature following Restuccia and Rogerson [2008] and Hsieh and Klenow [2009].

Finally, changes in γ_i affect the selection of producers into the domestic market through their effect on β_i. The sign of the selection effect depends on parameters. In the empirically relevant case, more severe SDD will protect less productive producers from its more productive competitors. This worsens selection and creates *extensive margin misallocation*. Intuitively, low-efficiency firms that would not be active in the first-best equilibrium survive and employ productive factors in the distorted economy.[29]

According to equation (29), gains from trade in this economy depend on only three statistics: the home share of expenditures, the size of the tradable sector, and the trade elasticity. These are the same sufficient statistics as in the quantitative trade models described in ACR. However, the trade elasticity is now a combination of demand and supply-side parameters. In addition, these elasticities vary across source countries according to their dispersion of firm-level physical and revenue productivity. The total effect of SDD on TFP in an open economy is

$$\underbrace{\frac{\partial log(TFP_i)}{\partial \gamma_i}}_{\text{Total Effect}} = \underbrace{\left(log(s_{ii})\frac{(1-\mu)}{\beta_i^2}\frac{\partial \beta_i}{\partial \gamma_i} - \frac{(1-\mu)}{\beta_i}\frac{\partial log(s_{ii})}{\partial \gamma_i}\right)}_{\text{Trade Channel}} + \underbrace{\frac{\partial log(TFP_i^c)}{\partial \gamma_i}}_{\text{Closed-Economy Effect}} \tag{31}$$

[29] A higher γ_i could also improve the selection of producers. At the calibrated parameters, this latter case is rare, and the positive effects tends to be negligible.

SDD affect the gains from trade through two channels. The first term is the trade-efficiency term and it captures the fact that a less distorted economy is better at reaping the reallocation gains from trade at any given level of trade openness. Since $s_{ii} < 0$ and $\frac{\partial \beta_i}{\partial \gamma_i} > 0$, this term is always negative. The second term represents the effect of distortions on trade openness itself. Unlike the first term, its sign is ambiguous. On the one hand, the reduction in distortions is akin to a positive aggregate productivity shock that increases the demand for the domestic product, which reduces trade openness $\left(\frac{\partial log(s_{ii})}{\partial \gamma_i} < 0\right)$. On the other hand, a lower γ_i also eases the access to export markets by increasing firms after-tax profits relative to export entry costs, which in equilibrium tends to increase trade openness $\left(\frac{\partial log(s_{ii})}{\partial \gamma_i} > 0\right)$. In this sense, lower SDD operate in the aggregate like a reduction in trade costs. Ultimately, the contribution from the trade channel depends on the relative magnitude of these two forces in general equilibrium.

It is instructive to analyze the trade channel in a model without fixed costs to illustrate the interaction of SDD, selection, and trade costs. Assuming no fixed costs, the trade elasticity is constant across exporters ($\beta_i = \sigma - 1$ and $\frac{\partial \beta_i}{\partial \gamma_i} = 0$) and gains from trade no longer stem from factor reallocation across domestic firms. Since all firms sell to all markets, more severe SDD do not reduce access to exporting either. In this environment, a superior micro allocation increases the mass of firms in the economy and improves allocative efficiency. It can be shown that the aggregate effects from these channels are equivalent to the effect of an improvement in aggregate technology (A_i). In an open economy, these gains are moderated by depreciation of terms of trade $\left(\frac{\partial log(s_{ii})}{\partial \gamma_i} < 0\right)$. Thus, without endogenous selection into markets, international trade alleviates, instead of magnifies, the aggregate effects of SDD. The corollary of this result is that the complementary effect of SDD and trade on aggregate productivity relies on the fact that large producers are much more likely to access export markets than small producers.

3.4 Simple Numerical Examples

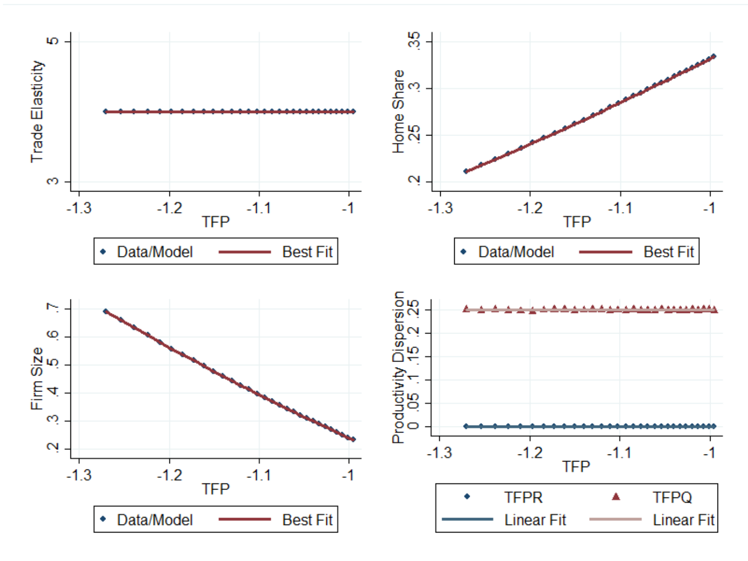
In a world in which entry and trade costs are the same everywhere, the international distribution of aggregate TFP depends only on the distribution of $\{A_i, \theta_i, \gamma_i\}_{i=1}^{N}$. The goal of this subsection is to study the separate effects of each of these variables on aggregate TFP, trade elasticities, trade openness, firm size, and dispersion of firm-level productivity. I evaluate which process of development, A-driven, θ-driven or γ-driven, is compatible with the cross-country patterns of firm size distribution and trade observed empirically.

Figure 5 presents the results for the A-driven process. This kind of technological heterogeneity reflects the common approach of modeling international productivity differences in the quantitative gravity literature (see Waugh [2010], Fieler [2011], and Bertoletti et al. [2015]). However, this process delivers predictions at odds with the data. By construction, the trade elasticity is constant across countries. Second, as countries get more productive, they start buying relatively more, not less, from themselves.

Therefore, to match the empirical fact about trade openness and development within this framework, we would need to resort to exogenous differences in trade costs. Third, this process delivers a negative relationship between firm size and TFP. Finally, the process is not flexible enough to create the observed covariances between development and dispersion of firm-level productivity - it even fails to generate within-country dispersion of revenue productivity.

Admittedly, one can always relax the standard model's hypothesis about technology and demand structure to reconcile the A-driven process with the empirical facts. A possible modeling strategy could, for example, combine alternative distributions of firm-level efficiency (log-normal or truncated Pareto) with a demand system that allows for markup variation across producers. The first assumption makes trade elasticities to vary across exporter-importer pairs (see Bas et al. [2017]) whereas the second yields dispersion of revenue productivity across firms (see Melitz and Ottaviano [2008]). The disadvantages of such approach are lack of tractability and computational complexity. In addition, in the absence of cross-country variation in the dispersion of technologies, this approach would rely solely on selection effects to generate the observed international patterns of dispersion of firm-level productivity.

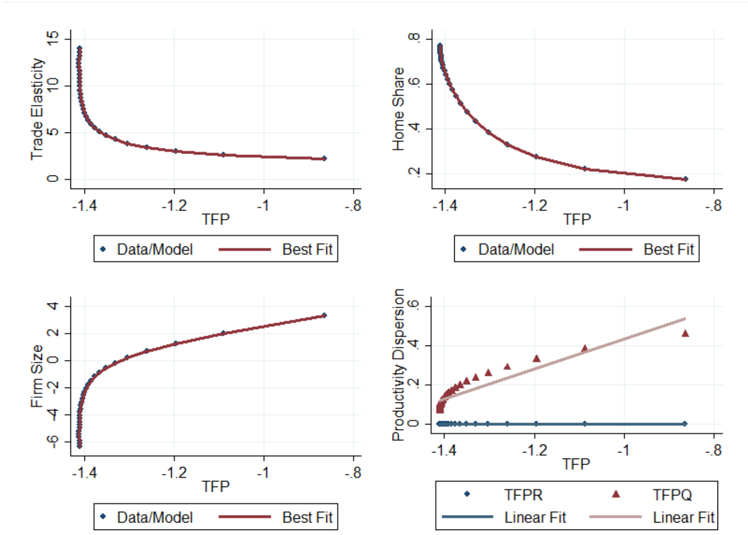
Figure 5: A-driven Process



Note: Number of countries = 30. Parameters: $f = 4$, $f^e = 1$, $c = 1.3$, $\{\theta_i, \gamma_i\} = \{4, 0\}$, and $A_i \in [1, 3]$. Upper-left panel shows the relationship between aggregate TFP and trade elasticity. The upper-right panel shows the behavior of home shares. The bottom-left panel shows the variation in average firm size, and the bottom-right, in dispersion of firm-level productivity. **Source:** Author's simulated data.

Figure 6 presents the results for the θ-driven process. In this case, lower θ leads both to higher dispersion and greater average firm-level productivity, boosting aggregate output. The covariances now are qualitatively aligned with the empirical facts **(i)**, **(iii)**, and **(iv)**: more productive economies have larger firms, higher trade openness, and lower trade elasticities. However, the process fails to yield positive dispersion of revenue productivity and, importantly, generates a *positive* covariance between aggregate TFP and dispersion of firm-level physical productivity. Therefore, a model based only on technological differences cannot simultaneously match facts **(ii)** and **(iv)**.

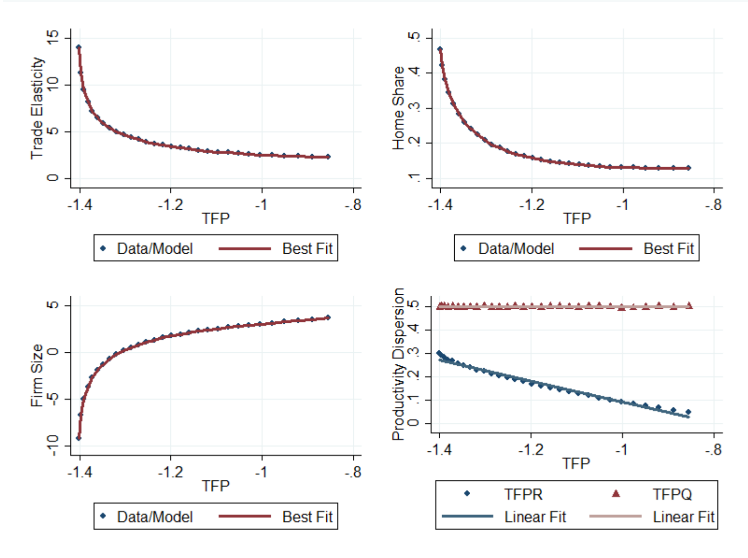
Figure 6: θ-driven Process



Note: Number of countries = 30. Parameters: $f = 4$, $f^e = 1$, $c = 1.3$, $\gamma_i = 0$, $A_i = 1$, and $\theta_i \in [2.2, 14]$. Upper-left panel shows the relationship between aggregate TFP and trade elasticity. The upper-right panel shows the behavior of home shares. The bottom-left panel shows the variation in average firm size, and the bottom-right, in dispersion of firm-level productivity. **Source:** Author's simulated data.

Finally, figure 7 depicts trends more coherent with the data. It illustrates a development process driven by the removal of SDD. As SDD fall, aggregate TFP increases, trade elasticity decreases - so countries start to export relatively more to more distant and smaller markets - trade openness and average firm size increase, and the dispersion of firm-level revenue productivity decreases. Despite its relative success, this process is still not flexible enough to match the negative relationship between TFP and dispersion of firm-level physical productivity. This motivates the need for cross-country variation in both γ_i and θ_i in the quantitative analysis that follows next.

Figure 7: γ-driven Process



Note: Number of countries = 30. Parameters: $f = 4$, $f^e = 1$, $c = 1.3$, $\gamma_i \in [.1, .6]$, $A_i = 1$, and $\theta_i = 2$. Upper-left panel shows the relationship between aggregate TFP and trade elasticity. The upper-right panel shows the behavior of home shares. The bottom-left panel shows the variation in average firm size, and the bottom-right, in dispersion of firm-level productivity. **Source:** Author's simulated data.

4 Taking the Model to the Data

The goal of this section is to quantify the model and present the main empirical results. I divide the calibration into three sequential steps. In the first part, I estimate SDD $\{\gamma_i\}_{i=1}^N$ for a large cross-section of countries using establishment-level data from the WBES. The next step computes the trade elasticities $\{\beta_i\}_{i=1}^N$ through the estimation of the structural gravity equation (25). The third part combines data on factor endowments, entry costs, geography, and tariffs with the structure of the model to recover the structural trade costs $\{d_{ji}, f_{ji}\}_{i,j=1}^N$ and technology levels $\{A_i\}_{i=1}^N$. The model perfectly matches the world matrix of manufacturing trade $\{s_{ji}\}_{i,j=1}^N$ and successfully predicts a number of non-targeted moments like: (i) the world distribution of output per worker; (ii) the relationship between aggregate productivity, average firm size, and firm participation in exporting; and (iii) cross-country variation in within-industry dispersion of firm-level productivity.

4.1 Size-Dependent Distortions

For estimation purposes, I adopt the following stochastic version of the distortion schedule (15):

$$\tau_{s,i} = b_s \omega_{s,i}^{-\gamma} exp(u_{s,i}) \tag{32}$$

where s indexes sectors, and i, firms. Since I estimate the schedules on a country-by-country basis, I omit country subscripts for notational convenience, but all parameters controlling the distribution of distortions are allowed to vary across countries. The constant b_s represents sector-specific distortions (like taxes, subsidies, and other sectoral policies) which may yield inter-sectoral (but not intra-sectoral) misallocation. For instance, a sector with access to subsidized interest rates, or lower import tariffs on inputs, obtains a higher constant.

The normal shock $u_{s,i} \sim N(0, \sigma_u^2)$ captures idiosyncratic revenue shocks that are *independent* from firm productivity, and the parameter σ_u^2 controls its dispersion. If the shock is realized before the entry/exit decisions are made, then endogenous selection into production will introduce a correlation between $u_{s,i}$ and $\omega_{s,i}$ in the sample of observed firms. This holds even under the assumption the shock is *ex-ante* independent from core productivity. Intuitively, if we observe a low ω firm active in the market, then it is more likely that it received a higher revenue shock (higher τ). Therefore, I proceed under the assumptions that entry and exit decisions are based on expected productivity only and occur before the realization of the independent shock. In a version available upon request, I show that the introduction of uncorrelated revenue distortions adds an extra white noise to the distribution of firm-level variables and changes the expression of mass of firms and average firm size. However, all the other theoretical predictions remain intact, and the quantitative findings are minimally affected.

As in Hsieh and Klenow [2009], the statistics TFPQ and TFPR introduced in section 2 identify $\omega_{s,i}$ and $\tau_{s,i}^{-1}$ up to a sectoral constant.[30] Therefore, one can estimate the distortion schedule as the slope coefficient of the following regression[31]

$$log\left(\frac{TFPR_{s,i}}{\overline{TFPR}_s}\right) = \tilde{\beta} + \gamma log\left(\frac{TFPQ_{s,i}}{\overline{TFPQ}_s}\right) + \epsilon_{s,i} \tag{33}$$

The estimator of the dispersion of independent shocks is the standard deviation of the regression residuals. In this framework, larger γ means that marginal products grow faster in firm productivity. This effect increases the gap between the marginal product of high-productivity and low-productivity establishments. Relative to the first-best equilibrium, the former become too small and the latter too large. Admittedly, a $\gamma > 0$ does not imply the existence of SDD. The existence of overhead production costs or adjustment costs can introduce a positive covariance between physical and revenue productivity even when the underlying marginal products are equalized across firms. For this reason, the estimates of a potentially distorted economy should always be compared with the numbers from a benchmark, relatively undistorted country.

Figure 8 presents the estimated slopes. There is a significant negative relationship between SDD and aggregate productivity. For instance, the US slope is .09, and the

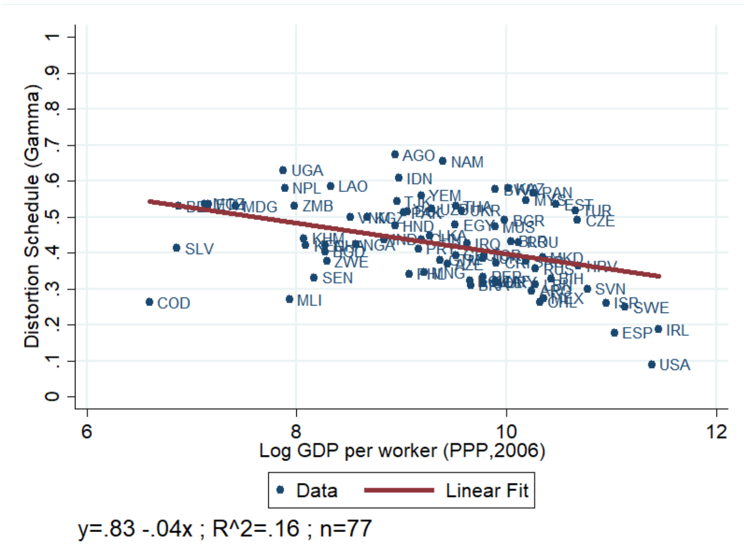
[30] The advantage of this procedure is that it allows one to recover establishment physical productivity (or appeal) without data on establishment prices. However, it relies on strong assumptions on demand and market structure.

[31] Where I have defined $\tilde{\beta} \equiv E(\tilde{\beta}_s) = E(\gamma log(\overline{TFPQ}_s) - log(\overline{TFPR}_s))$ and $\epsilon_{j,i} \equiv -(u_{s,i} + E(\tilde{\beta}_j) - \tilde{\beta}_j)$.

slopes of other OECD economies are all below .3 (e.g., .2 in Spain and Ireland, .25 in Israel and Sweden, and .26 in Chile). Middle income countries have values in the range of .3 (Brazil) to .5 (Turkey). Finally, slopes above .5 concentrate in former socialist countries (e.g., .52 in Ukraine and .53 in Estonia) and Sub-Saharan Africa (e.g., .54 in Ethiopia and .58 in Botswana). These results suggest that the gap in marginal products between high- and low-productivity establishments in the developing world could be two to three times greater than the OECD average (.19). A similar negative relationship holds when aggregate TFP is used to measure productivity.

These numbers are close to estimates from more comprehensive, administrative datasets. For example, Chen and Irarrazabal [2015] find a slope of .29 for Chile in 1995. My estimate based on data for the 2000's is .26. Hsieh and Klenow [2009] find a slope of .53 for China in 2005; my estimate is .44. Hsieh and Klenow [2014] find a slope of .5 for India. My estimate is .44. These similarities confirm that the WBES dataset provides a good approximation of cross-country differences in size-dependent distortions. In Appendix D, I show that the estimates above are robust to different sample definitions.

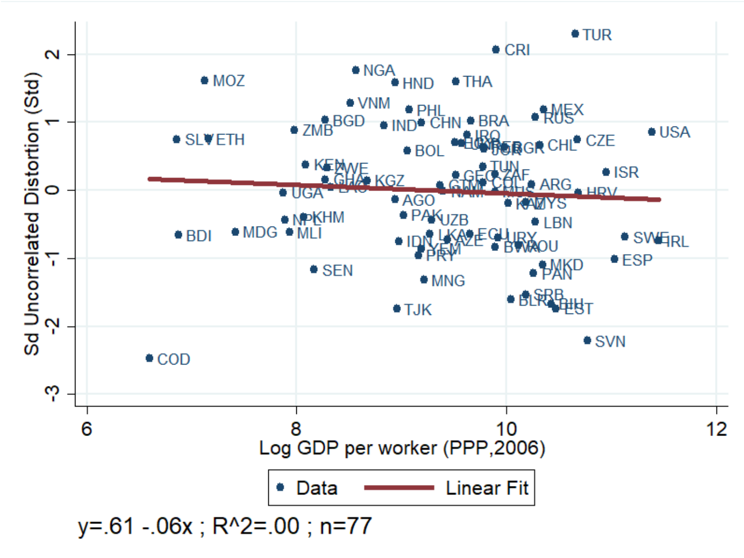
Figure 8: SDD and Development



Note: Estimates are the within-sector elasticity between firms' $TFPR$ and $TFPQ$. I include only countries with sample size above 90 observations after trimming outliers. The median number of observations per country is 293 and the average is 509. The median number of ISIC 2-digit sectors per country is 19. All regressions include time fixed effects. Observations are weighted according to establishment size. **Source:** Author's calculation based on data from the WBES and PWT 8.0. The estimate for the US economy comes from Hsieh and Klenow [2014].

Figure 9 presents the standardized dispersion of independent shocks (σ_u^2). Interestingly, I do not find a significant correlation between this measure and development - a regression of the former on the latter yields an $R^2 = .00$. Therefore, the negative correlation between dispersion of revenue productivity and development reported in section 2 is primarily driven by differences in SDD. This finding provides an empirical justification for my approach to modeling firm-level distortions.

Figure 9: Uncorrelated Distortions and Development



Note: Estimates are the within-sector dispersion of $TFPR$ that is not explained by variation in $TFPQ$. I only include countries with sample size above 90 observations after trimming outliers. The median number of observations per country is 293 and the average is 509. The median number of ISIC 2-digit sectors per country is 19. All regressions include time fixed effects. Observations are weighted according to establishment size. **Source:** Author's calculation based on data from the WBES and PWT 8.0. The estimate for the US economy is inferred from Hsieh and Klenow [2014].

4.2 Structural Trade Elasticities

The second step of the calibration recovers trade elasticities $\{\beta_i\}_{i=1}^N$ through the estimation of the structural gravity equation (25). This step serves two purposes. First, with information on trade elasticities and SDD, I can recover the dispersion of technologies $\{\theta_i\}_{i=1}^N$ consistent with equation (27). Second, I use these statistics to test propositions (1) and (3), which connect aggregate trade performance to the dispersion of firm-level productivity observed at the micro level.

Since the estimation of the gravity equation can be performed without data on manufacturing market size, I expand the trade data of section 2 to include 21,942 bilateral trade flows in manufactures between 160 sources and 138 destinations. I employ import tariffs from UNCTAD's *Trade Analysis Information System* (TRAINS) as trade costs shifters. For every pair of importer a and exporter b, TRAINS computes the *Effectively Applied Tariff* (AHS) charged by country a on country b's exports in each manufacturing sector c. The aggregate import tariff is then calculated as the weighted average of sectoral tariffs, with weights given by the share of sector c in total sales from b to a. If

AHS tariffs are not available, I use *Most-Favored Nation* (MFN) tariffs. Finally, I use data on bilateral geographic distance, shared borders, and common official language as controls.

Using the price equation (19), one can rewrite the gravity equation in terms of aggregate trade flows

$$X_{ji} = T_i(Z_j^{\frac{1}{\sigma-1}} P_j f_{ji}^{\frac{-1}{\sigma-1}})^{\beta_i} d_{ji}^{-\beta_i} f_{ji} \tag{34}$$

To estimate the equation above, I need to assume functional forms for iceberg and fixed trade costs. Following Caliendo and Parro [2014], I model iceberg trade costs as a log-linear function of tariffs and transportation costs:

$$d_{ji} = (1 + t_{ji}) exp(x_i^d + m_j^d + \mathbf{z}'_{ji}\delta_i^d) \tag{35}$$

where t_{ji} is the *ad-valorem* import tariff, x_i^d is the exporter fixed effect, m_j^d is the importer fixed effect, and $\mathbf{z}_{ji}$ is a vector of observed geographic trade barriers. This specification allows for the effect of geography on trade costs (δ_i^d) to vary across exporters, capturing differences in the quality of transportation and communication infrastructures. Tariffs enter the model only as cost shifters on imported goods and do not generate revenues.[32] In a similar vein, I model fixed trade costs as a function of exporter x_i^f and importer m_j^f fixed effects, geography, and an unobserved trade barrier as follows:

$$f_{ji} = exp(x_i^f + m_j^f + \mathbf{z}'_{ji}\delta_i^f + \bar{\epsilon}_{ji}) \tag{36}$$

The advantage of these specifications it to allow for a rich pattern of asymmetric trade costs. This flexibility is fundamental for my analysis of trade elasticities. A gravity model with symmetric costs would load all the differences in export performance unexplained by the exporter fixed effect on trade elasticities, thereby overestimating the cross-exporter dispersion in elasticities.[33] The equations above yield the following estimating gravity equation:

$$\tilde{X}_{ji} = \Pi_i + \xi_j + \beta_i\zeta_j - \beta_i log(1 + t_{ji}) + \mathbf{z}'_{ji}\delta_i + \epsilon_{ji} \tag{37}$$

where $\tilde{X}_{ji} \equiv log(X_{ji})$. $\{\Pi_i, \beta_i, \delta_i\}_{i=1}^N$ and $\{\xi_j, \zeta_j\}_{j=1}^N$ are parameters, $\{\tilde{X}_{ji}, \mathbf{z}_{ji}, t_{ji}\}_{i,j=1}^N$ are data, and ϵ_{ji} is a random error term capturing bilateral barriers independent from other fundamentals. The novel feature of this equation is the nonlinear term $\beta_i\zeta_j$. This object reflects that the effect of importers' structural characteristics (like market size, price, and importer-specific trade costs) on import flows depends on the firm size distribution of the origin country. This term, combined with variation in tariffs, identifies $\{\beta_i\}_{i=1}^N$. I estimate this gravity equation by Nonlinear Least Squares using the iterative fixed-point algorithm proposed by De la Roca and Puga [2017].

To grasp the intuition behind the identification of $\{\beta_i\}_{i=1}^N$, it is useful to go through the iterative structure of the estimator. The algorithm consists of two steps. The first

[32] When tariffs generate revenues, the gravity equation assumes a different form. For more on this topic, see Caliendo et al. [2015].

[33] See the symmetric gravity models of Fieler [2011] and Lashkaripour [2015].

step estimates a vector β *given* a vector ζ through an OLS regression where ζ is treated as data. The second step combines the results from the first part and the structure of the model to update the value of ζ. Starting with a first guess $\zeta^{(1)} = 0$, the bilateral variation in tariffs identifies $\beta^{(1)}$. This step also produces residuals $\hat{\epsilon}^{(1)}_{j,i}$. The second step calculates $\zeta^{(2)}$ based on importer-specific covariances between $\hat{\epsilon}^{(1)}_{j,i}$ and $|\beta^{(1)}|$. If this covariance is large (small), then the algorithm increases (decreases) $\zeta^{(2)}$ relative to $\zeta^{(1)}$. Intuitively, if country j imports relatively more from high-elasticity exporters (or, equivalently, if j imports relatively more *despite* the exporters' high trade elasticities) then j must have a combination of larger market size, higher prices, or lower import costs. The algorithm then returns to the first step, which combines variation in the updated $\zeta^{(2)}$ with variation in tariffs to estimate $\beta^{(2)}$ and so on and so forth. The estimator stops when a fixed point is achieved. I show in Appendix B that this algorithm recovers with precision the vector of trade elasticities in Monte Carlo experiments.

Table 3 presents the estimates from the new model and compares them with those from the standard gravity specification, which constrains elasticities to be homogeneous across exporters. The new estimator fits the data better than the standard model, as evidenced by the F-Test. The gain in goodness-of-fit is approximately 4.4%. This is a substantial improvement once we take into account that the constrained model is already saturated with importer and exporter fixed effects. More importantly, the new model delivers large cross-country differences in trade elasticities, which range from 2 to 14. The average elasticity is 7.4, which is close to the Eaton and Kortum [2002] preferred estimate (8.28) but way above the ballpark of estimates for manufacturing trade among developed countries established in recent research. For example, Eaton et al. [2011], Simonovska and Waugh [2014a], and Caliendo and Parro [2014] preferred estimates are between 4 and 5.

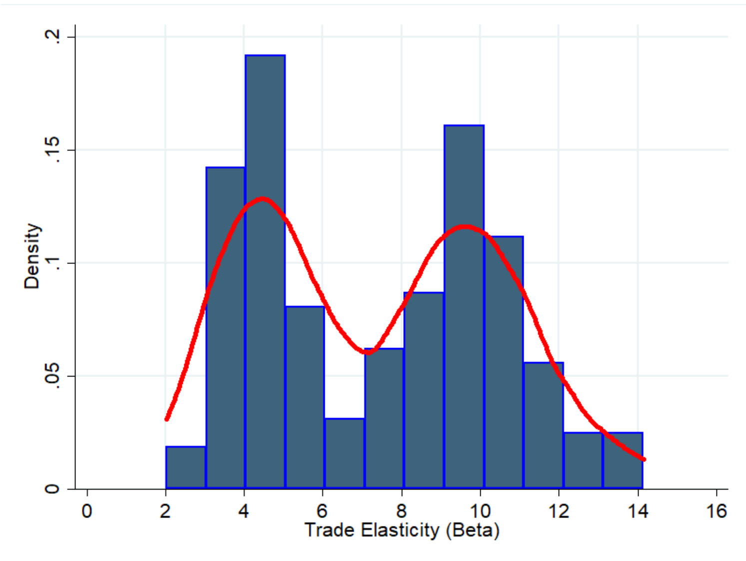
Table 3: Estimates of Structural Trade Elasticities

	Homogeneous	Heterogeneous
Min	-	2.03
Max	-	14.1
Mean	8.85	7.38
Adj R2	0.738	0.771
N.obs	21,942	21,942
Improved Fit (%)	4.36	
F-stat	8	

Note: The column on the left-hand side presents the estimate of the constrained model, which assumes that trade elasticities are constant across exporters. On the right-hand side are the estimates of the unconstrained model. Standard errors are clustered by importer and exporter using the multi-way cluster formula from Cameron et al. [2011]. The F-test rejects the hypothesis of equivalence between the two models at 1% of significance level. 23% of the country pairs report zero trade flows. I apply the transformation $log(1 + X_{ji})$ in those cases. Results remain the same if zeros are replaced with inputed trade flows from a traditional gravity equation instead. Table 19 presents the full set of trade elasticities and standard errors. **Source:** Author's calculation based on data from COMTRADE, WITS, and CEPII.

Figure 10 sheds light on the cause of the apparent discrepancy. The distribution of estimates is bi-modal with one peak around 4 and another peak around 9. According to these results, two sets of countries characterize the export side of manufacturing trade: (i) low-elasticity exporters and (ii) high-elasticity exporters.

Figure 10: Estimates of Trade Elasticities



Note: Blue bars represent the density on unit intervals of elasticities. The red line is the kernel density estimate. Sample size=160 countries. **Source:** Author's calculation based on data from COMTRADE, WITS, and CEPII.

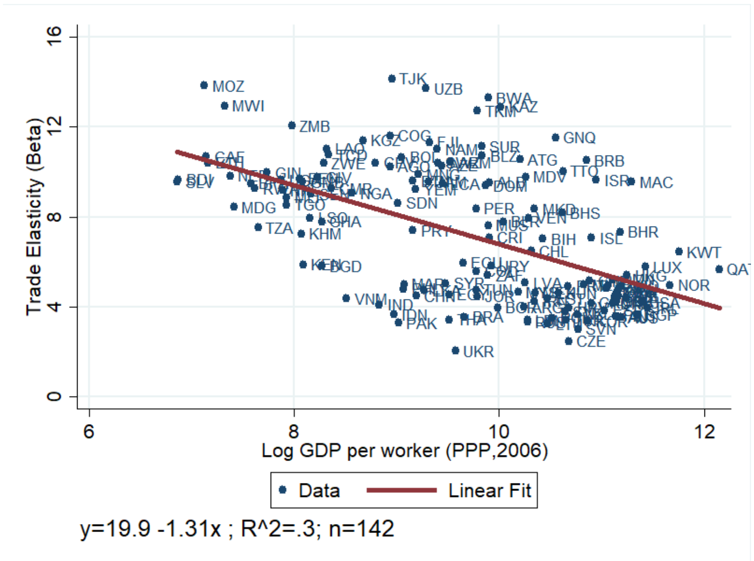
Figure 11 shows that elasticities covary systematically with output per worker. Low-elasticity exporters tend to be advanced countries, whereas high-elasticity exporters tend to be developing economies. In particular, OECD countries are overrepresented in the cluster of points with elasticities between 4 and 6. This result reconciles my numbers with the recent estimates in the gravity literature, which are based on data for developed countries. One concern is that cross-country differences in industry composition within the manufacturing sector is driving the relationship between aggregate productivity and trade elasticity. I address this issue in Appendix C, and I find little evidence supporting this alternative explanation.

With values of $\{\gamma_i, \beta_i\}_{i=1}^N$ in hand, I choose the model's dispersion of TFPQ such that trade elasticities in the model match the empirical elasticities. More specifically, I invert equation (27) to get:

$$\theta_i = \frac{\beta_i(\sigma - 1 - \sigma\gamma_i)}{\sigma - 1} + \gamma_i \tag{38}$$

An alternative to this strategy would be to use the empirical dispersion of TFPQ and TFPR as additional moments and choose $\{\theta_i\}_{i=1}^N$ to minimize an appropriate criterion function. I did not follow that route for two reasons. First, the magnitude of the trade channel (see equation (31)) depends on the model's value for β_i and $\frac{\partial \beta_i}{\partial \gamma_i}$. Since this paper is concerned with the magnitude of this mechanism, it is more important to match these last moments exactly. Second, the Pareto parameters that correspond to the empirical dispersion of TFPQ are too low. Lower θ values are more likely to violate the regularity condition (20) and to inflate the aggregate losses from distortions.

Figure 11: Trade Elasticity and Aggregate Productivity



Note: Output per worker is measure in PPP exchange rates from PWT 8.0. Sample size=142 countries.
Source: Author's calculation based on data from COMTRADE, WITS, CEPII, and PWT 8.0.

4.3 Technology and Trade Costs

This subsection completes the calibration of the model. I supplement the dataset on manufacturing production and bilateral trade described in section 2 with data on endowments of physical and human capital from the PWT 8.0, and data on the costs of starting a business from the World Bank's *Doing Business Survey* (WBDB). The final sample contains a rich description of macroeconomic development and microeconomic efficiency for 77 countries that correspond to more than 90% of the world output and trade.[34] The basic idea of this part of the calibration is to find a sequence of technologies and trade costs $\{A_i, d_{ji}, f_{ji}\}_{i=1}^N$ such that the model's trade shares $\{s_{ji}\}_{i,j=1}^N$ match the empirical shares.[35]

The first step is finding nominal wages $\{w_i\}_{i=1}^N$ such that the empirical trade matrix is a world balanced trade equilibrium. With nominal wages in hand, I only need values of μ and α to calculate total spending of the tradable sector $\{\frac{(1-\mu)w_iL_i}{(1-\alpha)}\}_{i=1}^N = \{Z_i\}_{i=1}^N$ and model-consistent trade flows $\{s_{ji}Z_j\}_{i,j=1}^N$. The parameter μ controls the share of labor employed in the service sector and α is the capital share of income. Common values in the literature are $\mu = .72$ and $\alpha = 1/3$ (see Alvarez and Lucas [2007]). Using model-consistent trade flows, one can write the gravity equation as:

$$X_{ji} = T_i(V_j)^{\beta_i} D_{ji} \tag{39}$$

where I have defined $V_j \equiv Z_j^{\frac{1}{\sigma-1}} P_j$ and $D_{ji} \equiv d_{ji}^{-\beta_i} f_{ji}^{\left(1-\frac{\beta_i}{\sigma-1}\right)}$. Applying the balanced trade condition and normalizing $D_{ii} = 1$ for all i, I find a unique sequence $\{T_i\}_{i=1}^N$ and $\{D_{ji}\}_{i,j=1}^N$ that solves the system of equations above.[36] At this point, T_i is a function of known variables and the unknown parameter A_i. This last parameter is then calculated by inverting the expression for T_i. The term D_{ji}, however, depends both on the trade elasticity and two unknown parameters: d_{ji} and f_{ji}.

I address this indeterminacy following the strategy in Di Giovanni and Levchenko [2012]. First, I assume that bilateral variable costs depend on tariffs, distance, and an indicator of shared border through a known function parameterized such that the elasticities of costs with respect to observed trade barriers match the intensive-margin estimates in Helpman et al. [2008]. Finally, I scale this function such that the average cost matches the estimate of variable trade costs in Anderson and Van Wincoop [2004]. Once d_{ji} is defined, I recover f_{ji} by inverting the equation for D_{ji}.

[34]Distortion schedules are not available for 20 countries, all developed economies and members of the OECD. To calibrate the model, I input their γ_i using the average slope across OECD countries with available estimates. The fact that both trade elasticities and measures of dispersion of firm-level productivity among OECD members are very homogeneous reassures that this procedure is a good approximation.

[35]See appendix C for details about the construction of the empirical trade shares.

[36]See appendix A for a detailed derivation of this result.

Table 4: Model's Parameters

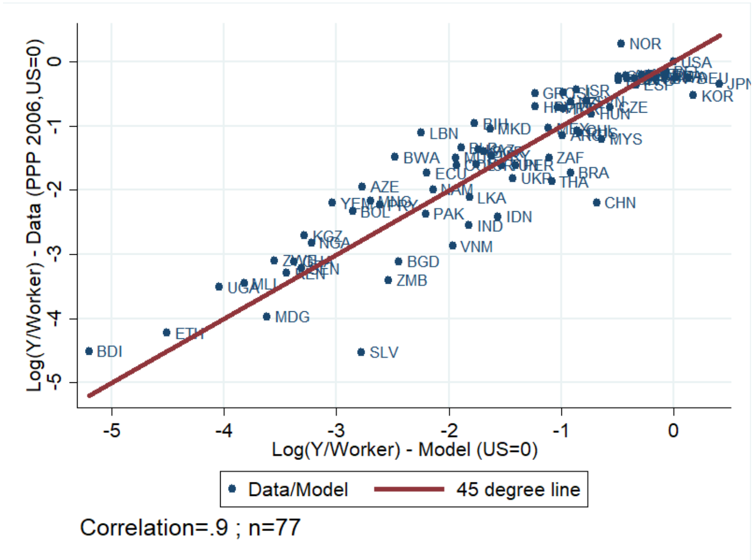
Parameter	Value	Source/Target
σ	3	EKK (2011), HK (2014)
α	.33	Capital Share
μ	.72	Labor in Services
c_{ji}	$[1, 3.4]$	Tariffs, Geography, HMR (2008)
f_{ji}	$[.17, 1.1e+33]$	Trade Shares, World Equilibrium
A_i	$[1.6e-06, .31]$	Trade Shares, World Equilibrium
γ_i	$[.09, .65]$	TFPR,TFPQ elasticity
θ_i	$[.84, 6.2]$	Structural Gravity
f_i^e	$[.002, 4.8]$	WB Doing Business Survey
κ_i	$[1.48e+3, 3.08e+5]$	PWT 8.0
h_i	$[1.28, 3.58]$	PWT 8.0
L_i	$[1.7e+5, 7.6e+8]$	PWT 8.0

Note: For technical details see appendix A. κ_i refers to physical capital per worker and h_i to average human capital per worker. **Source:** See table.

4.4 Out-of-sample Performance

Having calibrated the model to perfectly match the empirical bilateral trade shares, trade elasticities, and distortion schedules, I study its ability to predict untargeted moments. The model successfully replicates the distribution of PPP aggregate output per worker with a correlation in logs of 0.9. Figure 12 gives a visual representation of the model's performance along this dimension. Table 5 compares the model's and empirical moments of the distribution of productivity. The model slightly overestimates international inequality in productivity. One possible reason for this result is that developing countries are not as unproductive in nontradables as in tradable goods (see Hsieh and Klenow [2007]). Given the assumption of no international initial productivity differences in services, the model ends up generating more inequality than what is in the data.

Figure 12: Output per Worker: Model and Data



Note: Output per worker is measured in PPP exchange rates from PWT 8.0. Both measures are relative to the US. Year is 2006. Sample size=77 countries. **Source:** Author's calculation based on data from the simulated model and from PWT 8.0.

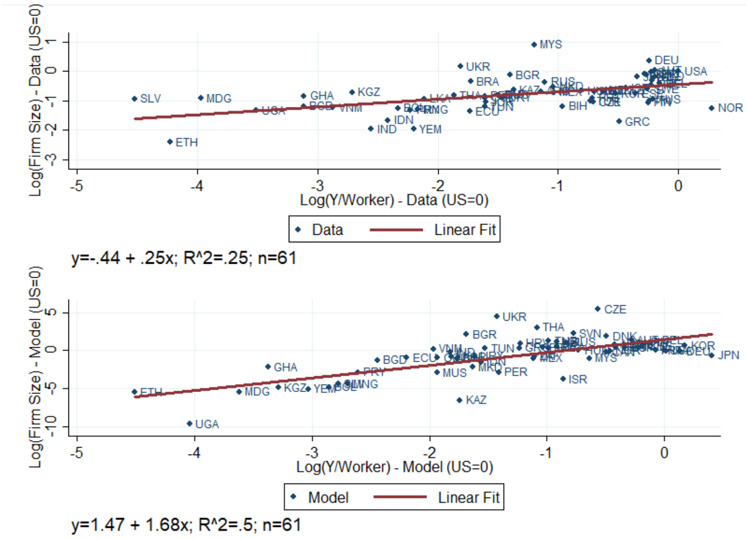
Table 5: Output per Worker: Model and Data

	Data	Model
Mean	0.359	0.357
Coef.of Variation	0.852	0.934
Var(log)	1.42	1.52
p90/p10	21.2	24.4

Note: Output per worker is measured relative to the US. Sample size=77 countries. **Source:** Author's calculation based on data from the simulated model and from PWT 8.0.

At the disaggregated level, the model overestimates the positive association between average firm size in manufacturing and output per worker. Figure 13 displays this relationship in the data and in the model. Firm size is measured as the average number of persons engaged per establishment. The elasticity is .25 in the data but 1.68 in the model. Also, variation in productivity predicts 25% of the variation in firm size in the data but 50% in the model. The stronger correlation between development and firm size in the model is due in part to the absence of shocks to firm revenue. These shocks could attenuate such a relationship, bringing the theoretical results closer to what is observed in the data. In addition, the Pareto distribution is a good approximation of the right tail of the distribution of firm size, but it could be a poor predictor of other parts of the distribution.

Figure 13: Development and Firm Size: Model and Data

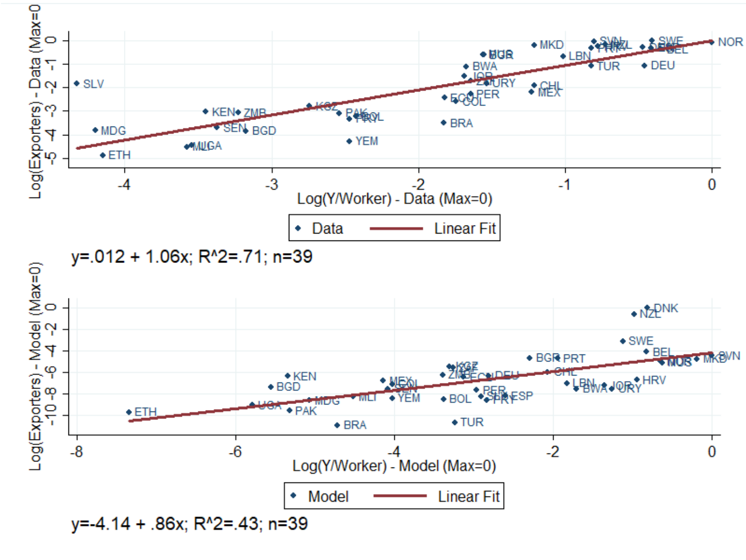


Note: Output per worker is measured in PPP exchange rates from PWT 8.0. Sample size=61 countries. **Source:** Author's calculation based on the simulated model and data from Bento and Restuccia [2017] and PWT 8.0.

For a sample of 39 countries, I have information on the number of firms with positive exports sales in the period 2006-2009 from the WBED dataset. I use these data to test the model's ability to predict the covariance between development and access to export markets. In the data, there is a high positive correlation between aggregate productivity and number of exporting firms net of population size with an elasticity of 1.06. The model delivers an elasticity of .86. The model's improved performance along this dimension is related to the Pareto assumption. Since export firms tend to come mainly from the right tail of the firm size distribution, the model is much better at predicting the covariance between development and export participation than the relationship between development and average size.

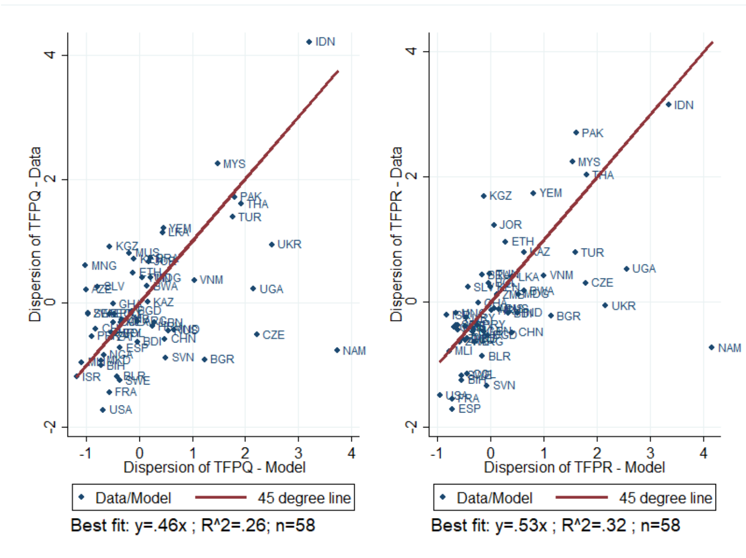
Finally, I test the model's ability to predict cross-country variation in the dispersion of establishment-level productivity. In the model, the parameter θ_i is inversely related to the dispersion of TFPQ and is one determinant of the dispersion of TFPR. Since this parameter was chosen to match i's trade elasticity β_i, we can use the correlation between dispersion of TFPQ (TFPR) in the model and in the data as an out-of-sample test. According to figure 15, the model has a fair predictive power along this dimension. An increase of one standard deviation of dispersion of TFPQ in the model leads to an increase of .46 standard deviation in the data. Moreover, the model reproduces 24% of the observed variation. The model's performance is even stronger in the dispersion of TFPR. The theoretical variation explains 37% of the empirical variation, and the slope of a regression of the standardized measure of empirical dispersion on model's dispersion is .53.

Figure 14: Development and Export Participation: Model and Data



Note: Output per worker is measured in PPP exchange rates from PWT 8.0. Export participation is number of exporting firms net of population size. Sample size=39 countries. **Source:** Author's calculation based on the simulated model and data from the WBED and PWT 8.0.

Figure 15: Dispersion of TFPQ and TFPR: Model and Data



Note: Dispersion of TFPQ (TFPR) is the z-score of the standard deviation of the logarithm of TFPQ (TFPR) net of the sectoral average. Sample size=58 countries. **Source:** Author's calculation based on the simulated model and data from the WBES.

4.5 Trade Elasticities, Exporter Sales Distribution, and Distortions

In this subsection, I test the main hypothesis of the theoretical model. Basically, the theory predicts that cross-country differences in trade elasticities estimated with aggregate data should reflect differences in characteristics of the underlying firm size distribution. Proposition (1) predicts that low-elasticity countries should have export sales distributions that are both more dispersed and more skewed towards large firms. Proposition (3) states that countries with smaller dispersion of TFPQ and more severe SDD should have higher trade elasticities.

I test Proposition (1) using moments of the distribution of firm-level exports from the WBED. Data on export sales are available at three different levels of aggregation: origin, origin-destination, and origin-destination-sector. Consistent with the theory, low-elasticity countries tend to have sales distributions that are both more dispersed and more skewed towards the largest firms. Table 6 shows that a twofold increase in the trade elasticity is associated with a 53% lower dispersion in export sales and a 6.4 percentage points smaller participation of top 1% exporters in total exports. Table 7 shows that these correlations persist at the origin-destination level. For instance, given a twofold increase in trade elasticity, the sales share of the top 1% firms in every destination is expected to decrease by 6 percentage points. Finally, Table 8 presents regressions with sector fixed effects. Even within sectors, lower trade elasticities are associated with more dispersed and more skewed distributions of export sales.

The results for other moments are less clear-cut. Higher elasticities are associated with lower number of exporting firms in tables 6 and 7 but not in table 8. The coefficients of mean sales regressions also change sign according to the level of aggregation. Finally, although trade elasticities are negatively correlated with the share of the top 5% largest exporting firms, the coefficients are not statistically significant.

Table 6: Trade Elasticity and Exporter Size Distribution: Origin Level

VARIABLES	(1) Number of Exporters	(2) Mean Sales	(3) Sales Dispersion	(4) Share of Top 1%	(5) Share of Top 5%
Trade Elasticity (β)	-2.352***	-0.582***	-0.566***	-0.0635***	-0.0129
	(0.151)	(0.0857)	(0.0547)	(0.0170)	(0.00969)
Observations	472	472	472	472	472
R-squared	0.369	0.152	0.176	0.036	0.012

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The coefficients are from regressions of moments of export-sales distribution on the log of trade elasticities. Moments are computed with data at the origin-year level. The sample includes only observations from distributions calculated with at least 100 firms. Year fixed effects are included. Number of exporters is log of exporting firms minus log of population. Mean sales is also in logs. Sales dispersion is calculated as the log of the coefficient of variation of sales. Share of top x% is the share of total export sales controlled by the x% largest exporting firms. **Source:** Author's calculation based on data from the WBED.

Table 7: Trade Elasticity and Exporter Size Distribution: Origin-Destination Level

VARIABLES	(1) Number of Exporters	(2) Mean Sales	(3) Sales Dispersion	(4) Share of Top 1%	(5) Share of Top 5%
Trade Elasticity (β)	-0.108**	0.384***	-0.243***	-0.0615***	-0.00280
	(0.0550)	(0.0380)	(0.0204)	(0.00733)	(0.00596)
Observations	10,201	10,201	10,201	10,201	10,201
R-squared	0.376	0.510	0.174	0.134	0.162

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The coefficients are from regressions of moments of export-sales distribution on the log of trade elasticities. Moments are computed with data at the origin-destination-year level. The sample includes only observations from distributions with at least 100 firms. Year and importer fixed effects are included. Additional controls include: log of geographic distance, indicator of shared border and indicator of common official language. Number of exporters is log of exporting firms minus log of population. Mean sales is also in logs. Sales dispersion is calculated as the log of the coefficient of variation of sales. Share of top x% is the share of total export sales controlled by the x% largest exporting firms. **Source:** Author's calculation based on data from the WBED.

Table 8: Trade Elasticity and Exporter Size Distribution: Origin-Destination-Sector Level

VARIABLES	(1) Number of Exporters	(2) Mean Sales	(3) Sales Dispersion	(4) Share of Top 1%	(5) Share of Top 5%
Trade Elasticity (β)	0.937***	-0.394***	-0.117***	-0.0201***	-0.00328
	(0.0342)	(0.0488)	(0.0156)	(0.00663)	(0.00558)
Observations	26,779	26,779	26,779	26,779	26,779
R-squared	0.583	0.609	0.359	0.269	0.412

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The coefficients are from regressions of moments of export-sales distribution on the log of trade elasticities. Moments are computed with data at the origin-destination-sector-year level. The sample includes only observations from distributions with at least 100 firms. Year, importer and sector fixed effects are included. Additional controls include: log of geographic distance, indicator of shared border and indicator of common official language. Number of exporters is log of exporting firms minus log of population. Mean sales is also in logs. Sales dispersion is calculated as the log of the coefficient of variation of sales. Share of top x% is the share of total export sales controlled by the x% largest exporting firms. Sectors are defined as 97 2-digit sections of the Harmonized System (HS) 2002. **Source:** Author's calculation based on data from the WBED.

Before proceeding, it is useful to state the new expression for $Sd(log(TFPR)_i)$ consistent with the stochastic schedule (32):

$$Sd(log(TFPR)_i) = \gamma_i Sd(log(TFPQ)_i) + \sigma_{u,i} \tag{40}$$

According to equation (40), the dispersion of revenue productivity in the data captures both SDD, dispersion of physical productivity, and uncorrelated revenue shocks. In

Table 9, I present the results of regressions of trade elasticities on moments from the distribution of establishment-level productivity.

Table 9: Trade Elasticity, Dispersion of Firm-Level Productivity, and Distortions

VARIABLES	(1) Trade Elasticity (β)	(2) Trade Elasticity (β)	(3) Trade Elasticity (β)	(4) Trade Elasticity (β)	(5) Trade Elasticity (β)	(6) Trade Elasticity (β)
Dispersion TFPR	0.143			0.354	-0.225*	
	(0.115)			(0.280)	(0.133)	
Dispersion TFPQ		0.0763		-0.242		-0.216
		(0.120)		(0.293)		(0.136)
SDD (γ)			0.393***		0.547***	0.515***
			(0.0920)		(0.125)	(0.106)
Observations	71	71	71	71	71	71
R-squared	0.023	0.006	0.172	0.037	0.203	0.208

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: The coefficients are from regressions of trade elasticities on micro moments. β refers to trade elasticities. SDD refers to γ. All variables are normalized so that a unit increment represents a one standard deviation increase. Micro moments are based on the full set of firms - domestic and exporters. Similar results apply when the sample is restricted to purely domestic firms. Results remain the same if US and Spain are excluded from the sample. **Source:** Author's calculations based on estimates presented earlier.

According to column **1**, the raw correlation between β and dispersion of TFPR is low and not statistically different from zero. There are two forces behind this result. First, larger dispersion of TFPR could reflect higher γ and higher dispersion of TFPQ. According to proposition (3), the former should increase β, but the latter should reduce it. Second, variation in uncorrelated distortions changes the dispersion of TFPR without affecting trade elasticities. A similar logic applies to column **2**. Variation in dispersion of TFPQ is correlated with variation of dispersion of TFPR, yielding ambiguous effects on the trade elasticity. Therefore, the slope coefficient of these univariate regressions tends to be biased towards zero. On the other hand, column **3** shows that higher SDD is consistently associated with larger trade elasticities, corroborating one prediction from proposition (3). Compared with the former specifications, the R^2 increases from virtually zero to 17.2%.

The results in column **4** attests to the importance of taking into account both measures of dispersion. Controlling for dispersion of TFPQ, the effect of dispersion of TFPR is positive although not statistically significant. On the other hand, controlling for dispersion in TFPR, the partial effect of dispersion of TFPQ is negative but not statistically significant. Note that the R^2 decreases to 3.7%. This is consistent with the fact that the partial variation in dispersion of TFPR captures both variation in γ and in σ_u (see equation (40)). Since the former is structurally related to β but the latter is not, the regression fit is negatively affected.

In column **5**, SDD continues to have a positive impact on β, but now the sign of the coefficient of dispersion of TFPR is negative. Intuitively, controlling for γ, larger dispersion of TFPR corresponds to large dispersion of TFPQ, which tends to decrease elasticities. Column **6** provides even stronger support for proposition (3). In this specification, both the coefficients of SDD and dispersion of TFPQ have the predicted signs. A one standard deviation increase in γ increases β by .51 standard deviation, whereas the same increase in dispersion of TFPQ reduces β by approximately .21 standard deviation. In addition, the effect of SDD on elasticities are significantly larger when dispersion of TFPQ is controlled for (.5 compared to .39 in specification **(3)**).

4.6 Trade Elasticities, Asymmetric Trade Costs, and Distortions

The goal of this subsection is to illustrate the relationship between SDD and asymmetric trade costs. I show that the export fixed effect proposed in Waugh [2010] strongly correlates to trade elasticities and SDD. In this sense, cross-country differences in size-dependent distortions offer a plausible microfoundation for the trade asymmetries identified in the recent gravity literature. One can write aggregative gravity models as:

$$log\left(\frac{s_{ij}}{s_{ii}}\right) = S_j - S_i - \theta log(c_{ij}) \tag{41}$$

where θ is the trade elasticity and c_{ij} represents bilateral trade costs between j and i. The structural interpretation of the term S varies across models. The asymmetry in trade costs is modeled as:

$$log(c_{ij}) = ex_j + \beta' d_{ij} + \epsilon_{ij} \tag{42}$$

where d_{ij} is a vector of symmetric geographic variables and ex_j represents the exporter fixed effect. By combining equations (41) and (42) one can estimate $\hat{ex_j}$. Through the lens of the model, a higher $\hat{ex_j}$ implies that country j faces higher costs to export its goods than its geography would predict. Table 10 presents the coefficients of regressions of $\hat{ex_j}$ on trade elasticities and its components. Variation in trade elasticities captures 41% of the variation in export costs, and a one standard deviation increase in the former lead to a .64 standard deviation rise in the latter. Importantly, this correlation is mainly driven by the positive association between distortion schedules and exports costs. A one standard deviation increase in SDD increases export costs by .42 standard deviation. Finally, I do not find a significant correlation between export costs and dispersion of TFPQ, as measured by the shape parameter of the Pareto distribution of micro technologies.

Table 10: Correlation with Waugh's Trade Costs

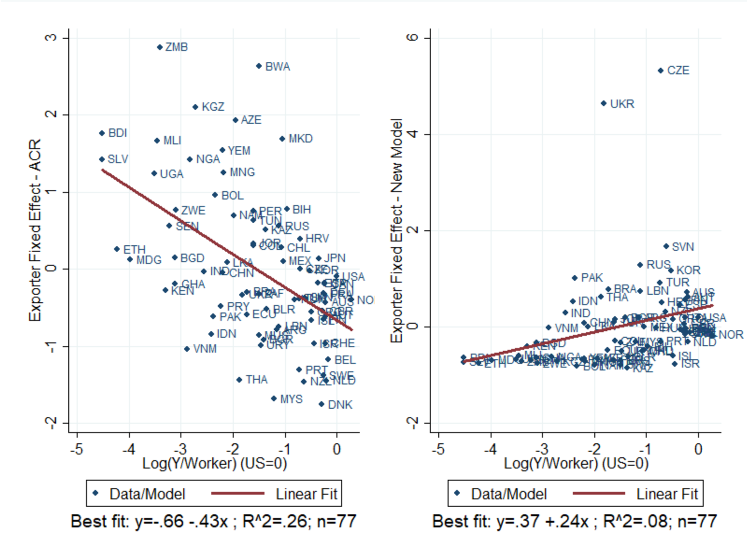
VARIABLES	(1) Export Cost	(2) Export Cost	(3) Export Cost
Trade Elasticity (β)	0.644***		
	(0.116)		
Distortion Schedule (γ)		0.417***	
		(0.117)	
Pareto Shape (θ)			0.149
			(0.0957)
Observations	77	77	77
R-squared	0.415	0.174	0.022

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: All variables are in z-scores. Export cost refers to the exporter fixed effect of Waugh [2010] gravity estimator. **Source:** Author's calculation based on data presented earlier.

The second exercise estimates an alternative version of the benchmark model assuming that firm size distribution does not vary across countries. I then compute the exporter fixed effect of trade costs from this model and compare it with the exporter fixed effects from the benchmark trade costs. Figure 16 presents the results. With constant firm size distribution, export costs need to decrease with development so the model matches the superior export performance of rich countries in the data. However, once the differences in firm size are taken into account, the association between development and export costs becomes much flatter.

Figure 16: Development and Export Costs



Note: The left-hand side panel plots the export fixed effect of trade costs when these are estimated under the assumption that firm size distribution is constant across countries. The right-hand side panel plots the exporter fixed effect of trade costs in the benchmark model. Sample size=77 countries. **Source:** Author's calculation based on data presented earlier.

5 Counterfactuals

5.1 SDD and Aggregate TFP in Open Economies

The goal of this subsection is to quantify the effect of SDD on aggregate TFP in open economies. To accomplish this I endow countries with the "US efficiency" ($\gamma_{US} = .09$) and then compute the new general equilibrium. The US benchmark is useful because part of the observed positive correlation between firm-level revenue and physical productivity might be due to overhead or adjustment costs and not due to policy or market frictions.[37] Also, a positive correlation might arise if more productive firms charge higher markups (as emphasized by Peters [2013]). Markup dispersion is another distortion, of course, but in this case firms are restricting production to maximize profits, and not because of size constraints. Therefore, my experiment assumes that the difference $\gamma_i - \gamma_{US}$ exclusively reflects allocative distortions and not cross-country differences in the domestic competitive environment.

I impose a few restrictions to ensure a valid measurement. I include only countries that satisfy the following two conditions: (i) have observed - as opposed to inferred - SDD, and (ii) satisfy the stability condition (20) at $\gamma_i = \gamma_{US}$. Of 77 countries, 45 satisfy the two requirements.[38] Further, I separately compute the counterfactual equilibrium

[37] Bartelsman et al. [2013] and Asker et al. [2014] emphasize this point.

[38] 20 OECD economies fail to satisfy the first condition. Given my focus on developing countries and

for each of the 45 economies to avoid including the effect of international spillovers on aggregate TFP.

Table 11 presents the cross-country average productivity effects from removing SDD. The average gain in TFP is 29.2% in the open-economy case and 17.9% in autarky. Therefore, accounting for the impact on trade volumes and gains from trade increases the effect of domestic allocative distortions on aggregate TFP by 63%. The open-economy gain represents approximately one third of the TFP gap between the US and the average country in the sample. In contrast, a model that ignores the interaction between domestic distortions and international trade would have attributed just one fourth of the gap to domestic allocative frictions.

Table 11: Average Gain in Aggregate TFP

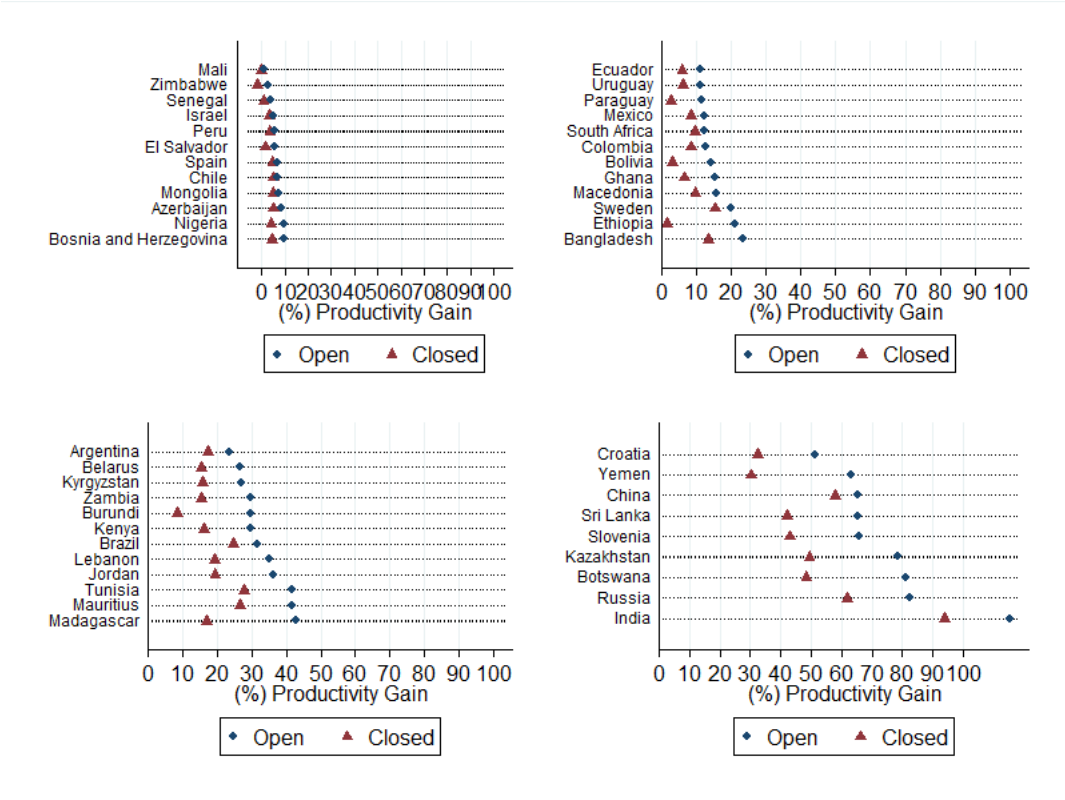
	Total Effect	Entry	Selection + Reallocation
Closed	17.9	3.33	14.6
Open	29.2	3.16	26

Note: First column presents the cross-country average gain (%) in aggregate TFP from converging to the US distortion schedule. Second and third columns decomposes this effect into the contributions of entry (firm creation) and selection/reallocation channels. **Source:** Author's calculation based on model simulation.

Figure 17 presents the complete list of gains. The effect is particularly large for big emerging economies and former socialist countries. For instance, the gains in aggregate productivity are 31% in Brazil, 65% in China, 82% in Russia, 115% in India, 51% in Croatia, and 65% in Slovenia. The results for other developing countries are mixed. They can be as high as 81% (Botswana) and as low as 2.6% (Zimbabwe). Finally, the gains are low for relatively low distorted economies - 5% in Israel, 6.5% in Spain, and 6.7% in Chile.

that there is no considerable variation in SDD and dispersion of firm-level productivity within the group of OECD countries with available microdata, this exclusion is not an important drawback. Countries that do not attend the second condition are Bulgaria, Czech Republic, Indonesia, Malaysia, Namibia, Pakistan, Thailand, Turkey, Uganda, Ukraine, and Vietnam.

Figure 17: Gains in Aggregate TFP

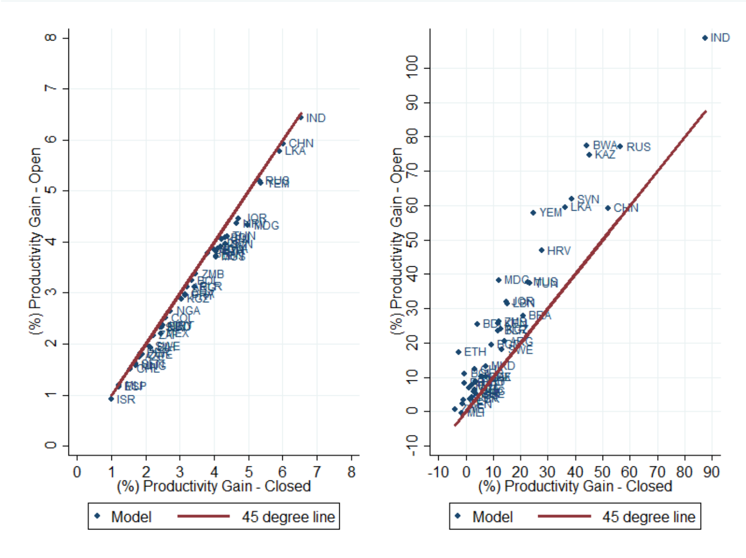


Note: Gains in aggregate TFP from converging to the US distortion schedule with and without international trade. Sample size=45 countries. **Source:** Author's calculation based on model simulation.

More than 80% of the effect of SDD on productivity is due to the selection and reallocation channels. Moreover, these channels are much stronger for open economies, whereas the entry channel is slightly weaker. Figure 18 reports these results for the 45 countries considered. The left-hand side panel compares the entry channel with trade (on the horizontal axis) and without trade (on the vertical axis). The dots tend to cluster slightly below the 45° line. The reason is that domestic output becomes relatively cheaper given an increase in the number of entrants. Therefore, part of the productivity gains associated with the entry channel is transferred to foreigners in the form of depreciated terms of trade.

At the same time, in the right-hand side panel, the dots are all significantly above the 45° line. In this case, international trade reinforces the positive effects of the selection and reallocation channels. Intuitively, the possibility to expand to export markets renders high-productivity firms to leverage the benefit of the reduction of SDD. With a larger market to explore, these producers grow ever more than in the closed-economy case, which ends up intensifying the movement of factors from low to highly efficient firms, and contributing to weed out low productivity entrepreneurs from the domestic market.

Figure 18: Gain in Aggregate TFP: Channels



Note: Gain in aggregate TFP from converging to the US distortion schedule. The horizontal axis measures the gain in a closed economy. The vertical axis represents the gain in an open economy. The left panel captures the entry channel. The right panel captures the selection and reallocation channels through which SDD affect aggregate TFP. Sample size=45 countries. **Source:** Author's calculation based on model simulation.

Using equation (31) I decompose the trade channel of domestic distortions into the allocation and trade creation subcomponents. While the former reflects the change in gains from trade from reducing distortions but keeping the initial level of trade openness constant, the latter represents the increase in gains from trade because the economy starts trading more relative to its spending.

Table 12: Decomposition of the Trade Channel

	Home Share	Trade Elasticity	Average Welfare Change
Factual	47.4	7.26	3.61
Partial	47.4	3.55	7.85
Counterfactual	29.1	3.55	13.5

Note: Home share and welfare gains are in %. First column presents the cross-country average home share. The second column presents the trade elasticities and the third column the average welfare gain from moving from autarky to the trade equilibrium. The first row refers to the factual gains from trade, in which distortions are at the estimated level. The second row presents the effects on gains from trade from moving to the counterfactual trade elasticity, but keeping the home shares at the factual level. Finally, the third row presents the full counterfactual equilibrium, in which gains from trade are a function of counterfactual trade elasticities and counterfactual home shares. **Source:** Author's calculation based on model simulation.

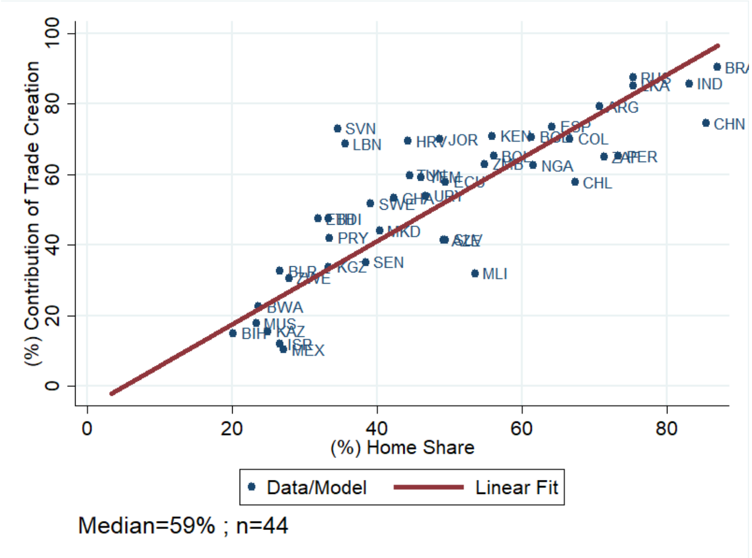
Table 12 presents the cross-country average results of the decomposition. First, when SDD converge to the US level, the average trade elasticity in developing countries gets closer to the OECD levels of approximately 4. Holding home shares constant, that change alone increases the gains from trade from 3.6% to almost 8%. Second, once we allow for the home shares to adjust, gains from trade increase even further - to 13.5%. Approximately 60% of the average total change in the gains from trade comes through this trade creation effect. Figure 19 illustrates these two channels and their respective effects on the gains from trade.

Furthermore, the contribution of the trade creation channel increases with initial home shares. Intuitively, if countries trade little in the distorted equilibrium, then the reduction in the domestic distortions by itself contributes little to increase their gains from trade. In this case, the changes in these gains stem mainly from changes in trade openness. Figure 20 illustrates this point. Therefore, even for economies that are relatively closed in the distorted equilibrium, the trade channel of the reduction of SDD boosts aggregate TFP through the expansion of trade volumes.

Figure 19: Decomposition of the Trade Channel

Note: In the upper left panel, the horizontal axis measures the estimated trade elasticity and the vertical axis, the counterfactual elasticity when countries converge to the US SDD. The upper right panel captures the changes in the gains from trade associated with this convergence. In the lower left panel, the horizontal axis measures the factual home shares, and the vertical axis, the counterfactual home shares. The lower right panel compares the counterfactual gains from trade - when both channels are taken into account - with the gains from trade in the initial distorted equilibrium. Sample size=45 countries. **Source:** Author's calculation based on model simulation.

Figure 20: Contribution of Trade Creation Channel and Initial Trade Openness



Note: Horizontal axis measures the initial home shares. The vertical axis measures the contribution of the trade-creation channel to the full trade channel. Sample size=44 countries (Madagascar is dropped because its home share actually *increases* after the reduction of SDD). **Source:** Author's calculation based on model simulation.

5.2 SDD, Trade, and International Productivity Differences

What is the contribution of SDD to cross-country differences in output per worker? How does it interact with international trade? To answer these questions, I compute the general equilibrium in a world where *all countries* have converged to the "US efficiency". I perform this exercise both in the baseline scenario, in which countries are allowed to trade at the calibrated trade costs, and in the autarky case, in which the world is just a set of isolated economies.[39] The difference between this exercise and the one carried out in the last section is that now any country can benefit from institutional improvements elsewhere through international trade linkages, whereas previously this possibility was ruled out.

Table 13 presents the results. First, a move from the observed trade equilibrium to a world without trade would leave the international dispersion of productivity virtually unchanged - the variance of log of output per worker goes from 1.52 to 1.5. Furthermore, this movement would reduce the cross-country average productivity by only 5.5%. These results are similar to the findings in Waugh [2010]. Second, the convergence in allocative efficiency also does little to reduce the international productivity differences when the

[39] I include in these computations all the 77 economies. I do not change the distortion schedules of countries that do not satisfy the regularity condition at the US schedule - this set comprises Bulgaria Czech Republic, Indonesia, Malaysia, Namibia, Pakistan, Thailand, Turkey, Uganda, Ukraine, and Vietnam.

economies are closed to international trade. In this case, the variance of log of output per worker actually increases by 1.8%. On the other hand, once we allow for international trade, the reduction in international productivity differences reaches approximately 40%. Therefore, the convergence in domestic efficiency benefits poor countries relatively more mainly because it helps them (i) to reap larger unrealized gains from trade and (ii) trade more.

Table 13: SDD, Trade, and International Productivity Distribution

	Mean	Var(log)	p90/p10
Baseline-Trade	7.23	1.52	24.4
Counterfactual-Trade	10.9	0.919	12.8
Change (%)	50.6	-39.4	-47.8
Baseline-Closed	6.9	1.5	23.9
Counterfactual-Closed	7.64	1.52	24.5
Change (%)	10.8	1.82	2.23

Note: First row presents the moments of the distribution of output per worker in the calibrated model. Second row shows moments of the distribution when all countries have converged to the US distortion schedule. The fourth row shows the moments of the productivity distribution in a world economy without trade and with the baseline distortion schedules. Finally, the fifth row shows the moments of this distribution when countries have converged to the US distortion schedule. The sample includes all 77 countries. **Source:** Author's calculation based on model simulation.

To put these magnitudes in perspective, I compute the effect of eliminating bilateral trade frictions on the international productivity distribution. Following Waugh [2010], I define bilateral trade friction as the difference between the calibrated bilateral cost for a given pair of countries and the minimum calibrated trade cost of the pair. The idea is that any cost above the minimum reflects trade barriers that are not geographic and, therefore, could disappear under trade liberalization policies.

Table 14: SDD, Bilateral Trade Frictions, and International Productivity Distribution

	Mean	Var(log)	p90/p10
Baseline-Trade	7.23	1.52	24.4
Counterfactual-Trade	10.9	0.919	12.8
Change (%)	50.6	-39.4	-47.8
Symmetric Trade Costs	8.16	1.12	16.1
Change (%)	12.8	-26.1	-33.9

Note: First row presents the moments of the distribution of output per worker in the calibrated model. Second row shows moments of the distribution when all countries have converged to the US distortion schedule. The fourth row shows the moments of the productivity distribution in a world economy with symmetric bilateral trade costs. Symmetric trade costs: $\hat{f}_{ji} = min\{f_{ji}, f_{ij}\}$ and $\hat{c}_{ji} = min\{c_{ji}, c_{ij}\}$. The sample includes all 77 countries. **Source:** Author's calculation based on model simulation.

According to table 14, eliminating this asymmetry in bilateral trade costs increases average income by 12.8% and reduces income dispersion by 26%. These estimates are less than the 24.2% and 31% found in Waugh [2010], suggesting that part of the asymmetry in trade costs captured by gravity models is due to differences in firm size distribution. Therefore, my results suggest that the convergence in domestic institutions at the current trade costs is quantitatively more important to reducing the international productivity gaps than the reduction in trade frictions.

6 Conclusion

Recent literature has highlighted that resource allocation across firms can have a significant impact on aggregate productivity. In this paper, I have combined two branches of this literature by analyzing the joint effect of domestic allocative distortions and international trade barriers on aggregate outcomes. I found that the aggregate effect of misallocation where large establishments are harmed disproportionately more than small establishments is greatly magnified when there is endogenous firm selection into production and export markets. I also found that cross-country variation in this distortion contributes to explaining facts about the differences in trade performance across economies. In particular, these distortions explain the thin export flows from developing economies to more distant and smaller markets, asymmetric trade patterns, and the negative correlation between trade openness and development. Finally, I found that the interaction between domestic allocative distortions and international trade is potentially relevant to explaining cross-country differences in output per worker.

On the methodological side, this paper developed theoretical and numerical tools to solve and estimate the standard multi-country trade model when the firm size distribution varies across countries. Accordingly, the paper shows that cross-country variation in firm size alters the macro predictions of standard trade models with heterogeneous firms. These new predictions are no longer equivalent to those of representative-firm models.

My results come with some caveats. First, I have recovered establishment-level TFPQ using the model's CES demand system. Forthcoming datasets that decompose establishment revenues into quantity and prices could help perform a more robust estimation of physical productivity. Second, for tractability reasons, my analysis is restricted to manufacturing, broadly defined. It would be interesting to study the connection between firm-level distortions and international trade in richer environments, such as multisectoral models with multiple input-output linkages. Finally, I work with firm-level distortions that are abstract and not tightly related to any policy or market imperfection. A natural topic for future research is examining the joint consequences of specific reforms, like liberalization of labor and financial markets, or reforms like privatization and delicensing, to aggregate productivity and export performance.

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A Mathematical Appendix

A.1 Solving the Model

To compute the general equilibrium, I follow the strategy proposed by Allen et al. [2015], and break up the system into three more manageable blocks. The first block solves for the mass of entry given vectors of prices and wages. The second block takes the vector of wages and the solution from the first block as given and calculates prices. Due to the high non-linearity of the price system, the usual iterative fixed-point procedure is unable to find the solution. I overcome this problem by applying a bisection algorithm to this system. The third block finds the set of wages that equalizes exports and imports in every country. The framework developed here can be easily adapted to analyze other trade questions in which cross-country heterogeneity is salient. A few examples are (i) the role of multinational or superstar firms in shaping aggregate trade flows and (ii) the impact on trade flows of non-neutral technological change.

Mass of Firms

Defining aggregate after-tax revenues as S_i, one can show that

$$S_i = \sum_{j=1}^{N} \frac{M_i \theta_i A_i^{\sigma-1}}{(\chi_i + \gamma_i)} (\tilde{\sigma} \bar{c}_i d_{ji})^{1-\sigma} Z_j P_j^{\sigma-1} (\omega_{ji}^*)^{-\chi_i - \gamma_i} \tag{43}$$

Using equation (43), one can express the free-entry condition as

$$\Pi_i = \frac{S_i}{\sigma} - \frac{S_i(\theta_i - \epsilon_i)}{\sigma\theta_i} - M_i w_i f_i^e = 0 \tag{44}$$

Assuming balanced trade, one can show that the equilibrium in the tradable sector implies

$$\frac{S_i}{m} + \frac{S_i(\theta_i - \epsilon_i)}{\sigma\theta_i} + M_i w_i f_i^e = (1-\mu)Y_i \tag{45}$$

Finally, the FOC that determines demand for capital is

$$r_i = \frac{\alpha}{(1-\alpha)}\frac{w_i}{\kappa_i} \tag{46}$$

where $\kappa_i \equiv \frac{K_i}{L_i}$. By combining the three equations above, one can show that

$$S_i = \frac{(1-\mu)}{(1-\alpha)} w_i L_i \tag{47}$$

and

$$M_i = \frac{(\sigma - 1 - \sigma\gamma_i)}{\sigma\theta_i f_i^e}\frac{(1-\mu)}{(1-\alpha)} L_i \tag{48}$$

Price Index

Given the values of $\{M_i, w_i\}_{i=1}^N$, the next step finds N prices that solve the following system of N independent equations for any strictly positive vector of nominal wages:

$$P_j^{1-\sigma} = \sum_{i=1}^N T_i Z_j^{\frac{\chi_i}{\epsilon_i}} P_j^{(\sigma-1)\frac{\chi_i}{\epsilon_i}} d_{ji}^{(1-\sigma)\left(1+\frac{\chi_i}{\epsilon_i}\right)} f_{ji}^{-\frac{\chi_i}{\epsilon_i}} \tag{49}$$

Naturally, the price level in one country depends on the number of firms that enter the market, which itself is a function of prices. However, this last relationship is controlled by the shape of the exporter's firm size distribution. Since there are differences in the distribution of firm size across exporters, the price equation becomes highly non-linear. It turns out that the following proof of existence and uniqueness of the price vector embeds a computational strategy to solve the problem.

Proposition 4. *If conditions (18) and (20) hold, then the price equation has a unique solution for any strictly positive vector of nominal wages. This solution can be computed by a bisection algorithm.*

Proof. Define the function $\Phi(P_j) \equiv P_j^{1-\sigma} - \sum_{i=1}^N T_i Z_j^{\frac{\chi_i}{\epsilon_i}} P_j^{(\sigma-1)\frac{\chi_i}{\epsilon_i}} d_{ji}^{(1-\sigma)\left(\frac{\chi_i}{\epsilon_i}+1\right)} f_{ji}^{-\frac{\chi_i}{\epsilon_i}}$. $\Phi(.)$ is defined over the domain $(0,\infty)$. Since (i) $\Phi'(P_j) < 0$, (ii) $\underset{P_j \to 0}{lim}\,\Phi(P_j) = \infty$, (iii) $\underset{P_j \to \infty}{lim}\,\Phi(P_j) < 0$, and the function $\Phi(.)$ is continuous, there exists a unique P^* such that $\Phi(P^*) = 0$. □

Balanced Trade and Wages

Finally, defining $s_{ji} = \frac{X_{ji}}{Z_j}$ as the share of country j's expenditures on tradable goods that is devoted to i's goods, the following balanced trade condition pins down wages:

$$w_i L_i = \sum_{j=1}^{N} s_{ji} w_j L_j \tag{50}$$

I find the equilibrium vector of wages $\{w_i\}_{i=1}^{N}$ by applying the algorithm of Alvarez and Lucas [2007].

A.2 Existence and Uniqueness

In this subsection, I prove the existence and uniqueness of the general equilibrium defined earlier. I start by defining the excess aggregate demand $\tilde{Z}_i(w)$ as

$$\tilde{Z}_i(w) = \frac{1}{w_i}\left(\sum_{j=1}^{N}(s_{ji} w_j L_j) - w_i L_i\right) \tag{51}$$

which is defined $\forall\ w \in \mathbf{R}^N_{++}$. Defining $\tilde{Z}(w) = (\tilde{Z}_1(w), ..., \tilde{Z}_N(w))$, the next proposition demonstrates the existence of an equilibrium.

Proposition 5. *If conditions (18) and (20) hold, then there is a $w \in \mathbf{R}^N_{++}$ such that $\tilde{Z}(w) = 0$.*

Proof. I verify that $\tilde{Z}(w)$ satisfies the following properties:
(i) $\tilde{Z}(w)$ is continuous
(ii) $\tilde{Z}(w)$ is homogeneous of degree zero
(iii) $w\tilde{Z}(w) = 0\ \forall\ w \in \mathbf{R}^N_{++}$ (Walras' Law)
(iv) For $k = max_j L_j > 0$, $\tilde{Z}_i(w) > -k$ for all $i = 1, ..., n$ and $\forall\ w \in \mathbf{R}^N_{++}$
(v) If $w^m \to w^0$, where $w^0 \neq 0$ and $w^0_i = 0$ for some i, then

$$max_j \tilde{Z}_j(w^m) \to \infty \tag{52}$$

Then the result follows from Proposition 17.C.1 of Mas-Colell et al. [1995].
(i) Given prices, $s_{ji}(w)$ is a function of continuous functions of w and, therefore, continuous. Defining $\forall\ j\ P_j(w)$ as the implicit function derived from the solution of equation (49), it is straightforward to show that $\frac{\partial P_j(w)}{\partial w_i}$ exists $\forall\ i$. Therefore, $\forall\ j\ P_j(w)$ is also continuous is w. These two results imply that $\tilde{Z}(w)$ is continuous is w.
(ii) I first show that $P_j(w)$ is homogeneous of degree one in w. For notational convenience define $D_{ji} \equiv d_{ji}^{-\beta_i} f_{ji}^{\left(1-\frac{\beta_i}{\sigma-1}\right)}$ and $\tilde{T}_i \equiv \frac{T_i(w)}{w_i^{\left(1-\sigma-\sigma\frac{X_i}{\epsilon_i}\right)}}$. $P_j(w)$ is determined by the

implicit solution of

$$0 = 1 - \sum_{i=1}^{N} \tilde{T}_i w_i^{1-\sigma-\sigma\frac{\chi_i}{\epsilon_i}} w_j^{\frac{\chi_i}{\epsilon_i}} L_j^{\frac{\chi_i}{\epsilon_i}} P_j(w)^{\beta_i} D_{ji} \tag{53}$$

For any $t > 0$, $P_j(tw)$ is given by the implicit solution of

$$0 = 1 - \sum_{i=1}^{N} \tilde{T}_i w_i^{1-\sigma-\sigma\frac{\chi_i}{\epsilon_i}} w_j^{\frac{\chi_i}{\epsilon_i}} L_j^{\frac{\chi_i}{\epsilon_i}} (t^{-1}P_j(tw))^{\beta_i} D_{ji} \tag{54}$$

Since $P_j(w)$ and $P_j(tw)$ are unique, we can combine the two equations above to get $P_j(tw) = tP_j(w)$. Using this result, one can show that:

$$s_{ji}(tw) = \frac{t^{1-\sigma} T_i(w)(Z_j(w)P_j(w)^{\sigma-1})^{\left(\frac{\beta_i}{\sigma-1}-1\right)} D_{ji}}{t^{1-\sigma}\sum_{k=1}^{N} T_k(w)(Z_j(w)P_j(w)^{\sigma-1})^{\left(\frac{\beta_k}{\sigma-1}-1\right)} D_{jk}} = s_{ji}(w) \tag{55}$$

Thus, $s_{ji}(w)$ and, consequentially, $\tilde{Z}(w)$, is homogeneous of degree 0 in w.
(iii) For all $w \in \mathbf{R}^N_{++}$ one can write $w\tilde{Z}(w)$ as

$$\sum_{i=1}^{N} w_i \tilde{Z}_i(w) = \sum_j w_j L_j \sum_{i=1}^{N} s_{ji} - \sum_{i=1}^{N} w_i L_i \tag{56}$$

Since $\forall\ j\ \sum_{i=1}^{N} s_{ji} = 1$, we have: $w\tilde{Z}(w) = \sum_j w_j L_j - \sum_i w_i L_i = 0$.
(iv) For all $w \in \mathbf{R}^N_{++}$, $\tilde{Z}_i(w) = \frac{1}{w_i}\sum_{j=1}^{N} s_{ji} w_j L_j - L_i > -L_i > -K$.
(iv) Assume that $w_h^0 = 0$ and $w_k^0 = c > 0$. The sequence $\{s_{kh}^m \frac{w_k^m}{w_h^m}\}$ converges to ∞ because it is a product of a bounded sequence and a sequence that converges to ∞. Therefore, $\{\sum_{j=1}^{N} s_{jh}^m \frac{w_j^m}{w_h^m}\} \to \infty$ and, consequentially, $\{max_k\{\sum_{j=1}^{N} s_{jk}^m \frac{w_j^m}{w_k^m}\}\} \to \infty$. □

Having proved the existence, the next step is to show that the solution is unique (up to scale).
Proposition 6. *If conditions (18) and (20) hold, then there is exactly one $w \in \mathbf{R}^N_{++}$ such that $\tilde{Z}(w) = 0$ and $\sum_{i=1}^{N} w_i = 1$.*

Proof. To establish this result it is sufficient to demonstrate that the function $\tilde{Z}(w)$ satisfies the gross substitution property, i.e., that $\forall\ i,k$ with $i \neq k$ and $\forall\ w \in \mathbf{R}^N_{++}$, $\frac{\partial \tilde{Z}_i(w)}{\partial w_k} > 0$. Then the result will follow from Proposition 17.F.3 of Mas-Colell et al. [1995]. I start by determining $\frac{dP_j(w)}{dw_h}$ for $j \neq h$. Differentiating equation (49) with respect to P_j and w_h we get:

$$\frac{dP_j(w)}{dw_h} = \frac{\frac{\partial T_h}{\partial w_h} Z_j^{\frac{\chi_h}{\epsilon_h}} P_j(w)^{(\sigma-1)\frac{\chi_h}{\epsilon_h}} D_{jh}}{\left((1-\sigma)P_j(w)^{-\sigma} - \sum_{i=1}^{N} T_i Z_j^{\frac{\chi_i}{\epsilon_i}} D_{ji}(\sigma-1)\frac{\chi_i}{\epsilon_i} P_j(w)^{(\sigma-1)\frac{\chi_i}{\epsilon_i}-1}\right)} \tag{57}$$

Since $\frac{\partial T_h}{\partial w_h} < 0$, $\frac{dP_j(w)}{dw_h} > 0 \; \forall j \neq h$. For $j = h$, the derivative is

$$\frac{dP_j(w)}{dw_j} = \frac{(\sigma-1)\left(1+\frac{\chi_j}{\epsilon_j}\right) w_j^{-1} T_j Z_j^{\frac{\chi_j}{\epsilon_j}} P_j(w)^{(\sigma-1)\frac{\chi_j}{\epsilon_j}} D_{jj}}{(\sigma-1)\left(P_j(w)^{-\sigma} + \sum_{i=1}^N T_i Z_j^{\frac{\chi_i}{\epsilon_i}} P_j(w)^{\left((\sigma-1)\frac{\chi_i}{\epsilon_i}-1\right)} D_{ji}\frac{\chi_i}{\epsilon_i}\right)} > 0 \tag{58}$$

The next step is to sign the derivative $\frac{\partial s_{ji}}{\partial w_h}$ for all cases with $h \neq i$. Let's first consider the case where $h \neq j$. We have:

$$\begin{aligned}
\frac{\partial s_{ji}}{\partial w_h} \;=\; & \left(\sum_{k=1}^N T_k (Z_j P_j(w)^{\sigma-1})^{\left(\frac{\beta_k}{\sigma-1}-1\right)} D_{jk}\right)^{-1} \\
& \left(T_i (Z_j)^{\left(\frac{\beta_i}{\sigma-1}-1\right)} (\beta_i + 1 - \sigma) P_j(w)^{\beta_i - \sigma} \frac{dP_j(w)}{dw_h} D_{ji}\right) \\
& - \left(T_i (Z_j P_j(w)^{\sigma-1})^{\left(\frac{\beta_i}{\sigma-1}-1\right)} D_{ji}\right)\left(\sum_{k=1}^N T_k (Z_j P_j(w)^{\sigma-1})^{\left(\frac{\beta_k}{\sigma-1}-1\right)} D_{jk}\right)^{-2} \\
& \left(Z_j^{\left(\frac{\beta_h}{\sigma-1}-1\right)} D_{jh} T_h\right) \\
& \left((P_j(w)^{\sigma-1})^{\left(\frac{\beta_h}{\sigma-1}-1\right)}\left(1-\sigma-\sigma\left(\frac{\chi_h}{\epsilon_h}\right)\right) w_h^{-1} + (\beta_h + 1 - \sigma) P_j(w)^{\beta_h - \sigma} \frac{dP_j(w)}{dw_h}\right)
\end{aligned}$$

Since $\beta_i + 1 - \sigma > 0$ for all i, if the last line of the expression above is negative, then $\frac{\partial s_{ji}}{\partial w_h} > 0$. Call the term in the last line Q_{jh}. Using the equation for $\frac{dP_j(w)}{dw_h}$, one can show that

$$Q_{jh} = P_j(w)^{\beta_h - \sigma - 1}\left(1 - \sigma - \sigma\frac{\chi_h}{\epsilon_h}\right) w_n^{-1}\left(1 - \frac{T_h Z_j^{\frac{\chi_h}{\epsilon_h}} P_j(w)^{(\sigma-1)\frac{\chi_h}{\epsilon_h}} D_{jh}}{P_j^{1-\sigma} + \sum_{k=1}^N T_k Z_j^{\frac{\chi_k}{\epsilon_k}} P_j(w)^{(\sigma-1)\frac{\chi_k}{\epsilon_k}} D_{jk}}\right) \tag{59}$$

Using the expression above it is straightforward to verify that $Q_{jh} < 0$. Therefore,

$\frac{\partial s_{ji}}{\partial w_h} > 0$ for $h \neq j$. The next step is to sign the term $\frac{\partial s_{ji}}{\partial w_j}$.

$$\begin{aligned}
\frac{\partial s_{ji}}{\partial w_j} &= \left(\sum_{k=1}^{N} T_k (Z_j P_j(w)^{\sigma-1})^{\left(\frac{\beta_k}{\sigma-1}-1\right)} D_{jk}\right)^{-1} \\
&\left(T_i D_{ji}\left(\frac{\beta_i}{\sigma-1}-1\right)(Z_j P_j(w)^{\sigma-1})^{\left(\frac{\beta_i}{\sigma-1}-2\right)}\left(L_j P_j(w)^{\sigma-1} + Z_j(\sigma-1)P_j(w)^{\sigma-2}\frac{dP_j(w)}{dw_j}\right)\right) \\
&-\left(T_i (Z_j P_j(w)^{\sigma-1})^{\left(\frac{\beta_i}{\sigma-1}-1\right)} D_{ji}\right)\left(\sum_{k=1}^{N} T_k (Z_j P_j(w)^{\sigma-1})^{\left(\frac{\beta_k}{\sigma-1}-1\right)} D_{jk}\right)^{-2} \\
&(\frac{\partial T_j}{\partial w_j}(Z_j P_j(w)^{\sigma-1})^{\left(\frac{\beta_j}{\sigma-1}-1\right)} D_{jj} \\
&+T_j\left(\frac{\beta_j}{\sigma-1}-1\right)(Z_j P_j(w)^{\sigma-2})^{\left(\frac{\beta_j}{\sigma-1}-1\right)} D_{jj}\left(L_j P_j(w)^{\sigma-1} + Z_j(\sigma-1)P_j(w)^{\sigma-2}\frac{dP_j(w)}{dw_j}\right))
\end{aligned}$$

As before, if the last term of the equation above is negative, then $\frac{\partial s_{ji}}{\partial w_j} > 0$. Call this term $\tilde{V}_j$. Using the expression for $\frac{dP_j(w)}{dw_j}$, one can show that:

$$\tilde{V}_j = T_j (Z_j P_j^{\sigma-1})^{\left(\frac{\beta_j}{\sigma-1}-1\right)} D_{jj} w_j^{-1} \beta_j \left(\frac{T_j (Z_j P_j(w)^{\sigma-1})^{\frac{\chi_j}{\epsilon_j}} \frac{\chi_j}{\epsilon_j} D_{jj}}{P_j^{1-\sigma} + \sum_{k=1}^{N} T_k (Z_j P_j(w)^{\sigma-1})^{\frac{\chi_k}{\epsilon_k}} \frac{\chi_k}{\epsilon_k} D_{jk}} - 1\right) \tag{60}$$

Since $\tilde{V}_j < 0$ we have $\frac{\partial s_{ji}}{\partial w_j} > 0$. Finally, for $i \neq k$ we have:

$$\frac{\partial \tilde{Z}_i(w)}{\partial w_k} = \sum_{j \neq i,k}\left(\frac{\partial s_{ji}}{\partial w_k}\frac{w_j}{w_i}L_j\right) + \frac{\partial s_{ki}}{\partial w_k}\frac{w_k}{w_i}L_k + s_{ki}\frac{L_k}{w_i} \tag{61}$$

Thus $\frac{\partial \tilde{Z}_i(w)}{\partial w_k} > 0 \ \forall i \neq k$ and $\forall w \in \mathbf{R}^N_{++}$. $\square$

A.3 ACR Formula

In this section, I prove that the model satisfies a modified version of the ACR equation, i.e., it posits that the effect of international shocks on domestic welfare can be summarized by two sufficient statistics: (i) the change in the home trade shares, and (ii) the trade elasticity. For notational convenience, and without loss of generality, I assume $\alpha = 0$ and $\gamma_i = 0 \ \forall i$. When labor in country j is the numeraire, any change in country j's welfare is given by:

$$dln(C_j) = -(1-\mu)dln(P_j) \tag{62}$$

By total differentiating the price equation and solving for $dln(P_j)$ we find:

$$dln(P_j) = \left(\sum_{i=1}^{N}\theta_i s_{ji}\right)^{-1}\sum_{i=1}^{N} s_{ji}\left(\theta_i dln(d_{ji}) + \left(\frac{\theta_i - 1 - \sigma}{\sigma - 1}\right)dln(f_{ji}) - dln(T_i)\right) \tag{63}$$

Using the trade share equation, take the log of the ratio $\frac{s_{ji}}{s_{jj}}$ and total differentiate it (but not with respect to T_j) to find:

$$dln(s_{ji})-dln(s_{jj}) = dln(T_i)+(\theta_i-\theta_j)dln(P_j)-\theta_i dln(d_{ji})+\left(\frac{\sigma-1-\theta_i}{\sigma-1}\right)dln(f_{ji}) \quad (64)$$

Using the equation above, one can show that:

$$dln(P_j) = \left(\sum_{i=1}^{N}\theta_i s_{ji}\right)^{-1}\sum_{i=1}^{N}s_{ji}\left((\theta_i-\theta_j)dln(P_j)+dln(s_{jj})-\frac{ds_{ji}}{s_{ji}}\right) \quad (65)$$

Since $\sum_{i=1}^{N}s_{ji}=1$ and $\sum_{i=1}^{N}d_{ji}=0$, we have:

$$dln(P_j) = \frac{1}{\theta_j}dln(s_{jj}) \quad (66)$$

Integrating both sides of the expression above, we find the ACR formula:

$$\hat{C}_j = (\hat{s}_{jj})^{\frac{-(1-\mu)}{\theta_j}} \quad (67)$$

A.4 Details of Calibration

Rewrite the gravity equation as

$$X_{ji} = T_i(V_j)^{\beta_i}D_{ji} \quad (68)$$

where I have defined $V_j \equiv Z_j^{\frac{1}{\sigma-1}}P_j$ and $D_{ji} \equiv d_{ji}^{-\beta_i}f_{ji}^{\left(1-\frac{\beta_i}{\sigma-1}\right)}$. The balanced trade condition implies that i's total exports equals i's imports:

$$Z_i = \sum_{j=1}^{N}X_{ji} = T_i\sum_{j=1}^{N}(V_j)^{\beta_i}D_{ji} \quad (69)$$

Solving the equation above for T_i and plugging the solution into the gravity equation we have:

$$X_{ji} = \frac{Z_i}{\sum_{j=1}^{N}(V_j)^{\beta_i}D_{ji}}(V_j^{\beta_i}D_{ji}) \quad (70)$$

Defining $\hat{D}_{ji} = V_j^{\beta_i}D_{ji}$, I rewrite the equations above in the form of the following system of equations to solve for $\hat{D}_i \equiv (\hat{D}_{11},...,\hat{D}_{N1})$:

$$\hat{D}_i = E_i\hat{D}_i \quad (71)$$

where I have defined the matrix E_i as:

$$E_i = \begin{pmatrix} \frac{X_{1i}}{Z_i} & \cdots & \frac{X_{1i}}{Z_i} \\ \frac{X_{2i}}{Z_i} & \cdots & \frac{X_{2i}}{Z_i} \\ \vdots & \ddots & \vdots \\ \frac{X_{Ni}}{Z_i} & \cdots & \frac{X_{Ni}}{Z_i} \end{pmatrix} \quad (72)$$

Note that we have all the elements to calculate $\{E_i\}_{i=1}^N$. Thus, $\hat{D}_i$ is just the eigenvector associated with the maximum eigenvalue (which is one) of matrix E_i's and T_i is calculated using equation (69) - see Allen et al. [2014]. Finally, given $(L_i, K_i, h_i, f_i^e, \gamma_i, \theta_i)$, the inversion of expression for T_i recovers A_i. Assuming $D_{jj} = 1$ one can show that:

$$D_{ji} = \left(\frac{X_{ji}}{T_i}\right)\left(\frac{T_j}{X_{jj}}\right)^{\frac{\beta_i}{\beta_j}} \tag{73}$$

Note that all the elements on the right-hand side are known, so we can compute D_{ji}. However, D_{ji} is a composite of the structural variable trade costs and fixed trade costs. Without additional data on firms' average sales there is no theory-based way to separately identify those two types of trade costs. I follow the strategy of Di Giovanni and Levchenko [2012] and assume a functional form for variable trade costs. I then recover fixed trade costs as residuals. Consider the following specification for variable trade costs

$$d_{ji} = (1 + t_{ji}) + \alpha_1 (dist_{ji})^{\alpha_2} exp(\alpha_3 border_{ji}) \tag{74}$$

where t_{ji} is the ad-valorem import tariff, $dist_{ji}$ is the geographic distance between j and i, and $border_{ji}$ is an indicator of shared border. I use the estimates from the intensive-margin gravity equations in Helpman et al. [2008] for α_2 and α_3. I then calibrate α_1 such that the average bilateral variable trade cost matches the estimate of the average variable cost of moving goods across borders in Anderson and Van Wincoop [2004]. Finally, I recover bilateral fixed trade costs from the expression for D_{ji}.

B Monte Carlo Experiment

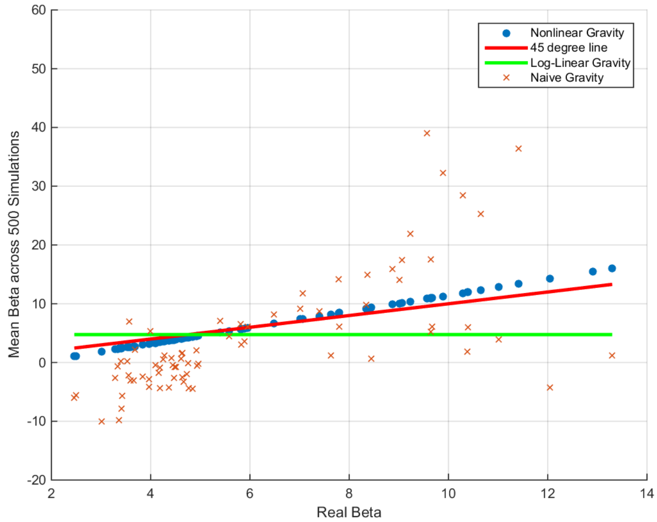
In this section, I analyze the performance of the nonlinear gravity estimator in a Monte Carlo experiment. Spearot [2016] studies numerically the conditions under which this estimator is identified. My goal here is a bit different. Assuming that the identification condition holds (sufficient variation in bilateral variable trade costs), I investigate whether my numerical algorithm is able to recover the original parameters with precision. My first step is to project the matrix of calibrated bilateral fixed costs $\{f_{ji}\}_{i,j=1}^N$ onto bilateral geographic distance, exporter fixed effects, and importer fixed effects. I then feed these projections into the model and calculate the equilibrium trade flows.

My second step is to simulate a sequence of 500 trade matrices. Each matrix is the sum of the equilibrium trade flow calculated above and a matrix of random shocks, whose variance is calibrated such that the average ratio between the variation in residuals and variation in observed flows matches the empirical one. The final step is to estimate the following nonlinear gravity equation with the simulated data

$$\tilde{X}_{ji} = \Pi_i + \xi_j + \beta_i \zeta_j - \beta_i log(c_{ji}) + \mathbf{z}'_{ji}\delta_i + \epsilon_{ji} \tag{75}$$

where $\{c_{ji}\}_{i,j=1}^N$ represents the calibrated variable trade costs. I compare the performance of the nonlinear estimator with two alternative estimators: the standard log-linear gravity estimator advocated by Arkolakis et al. [2012], and the naive linear estimator, which interacts cost shifters with exporter fixed effects but does not taken into account the nonlinear term. Figure 21 presents the results. The nonlinear gravity estimator has great performance, with the average elasticity across simulation very close to the original parameter value. On the other hand, the naive estimator performs poorly, delivering negative average elasticities for a considerable amount of exporters. Finally, the log-linear gravity estimator delivers a trade elasticity of 4.75, which is close to the median structural trade elasticity (see table 15).

Figure 21: Nonlinear Gravity Estimator: Monte Carlo Experiment



Note: The vertical axis measures the average trade elasticity across 500 simulations. Naive gravity refers to the gravity estimators in which cost-shifters interact with exporter fixed effects but the nonlinear term is not taken into account. The log-linear gravity represents the standard gravity estimator advocated by Arkolakis et al. [2012]. **Source:** Author's calculation.

Table 15: Nonlinear Gravity Estimator: Monte Carlo Experiment

	Min	Max	Mean	Median	S.e	Corr.
Original Beta	2.46	13.3	6.13	4.77	2.77	1
Nonlinear Gravity	1.08	16	6.15	4.3	3.81	1
Naive Gravity	-10.1	54.1	4.7	1.17	11.4	0.701
Log-Linear Gravity	4.75	4.75	4.75	4.75	7.15e-15	0

Note: Estimates are the average across 500 simulations. The last column displays the correlation between the row variable and the original structural trade elasticities. **Source:** Author's calculation.

C Data Construction

C.1 Establishment-Level Data

In constructing the establishment-level dataset, I first compute the measures TFPR and TFPQ, and then eliminate outliers, defined as firms above the 95 percentile or below the 5 percentile of the productivity distribution. With the cleaned data in hand, I calculate for each country-sector-year the correspondent $\overline{TFPR}$ and $\overline{TFPQ}$. I eliminate from the sample countries with less than 90 observations. Finally, I compute the dispersion of TFPR and TFPQ and the distortion schedules using the sampling weights provided by the WBES.

To estimate the distortion schedules, regression (33) controls for time fixed effects for countries with data that span multiple years, and weights observations according to firm revenues.

C.2 Manufacturing Market Size

For most countries I use gross production data from the UNIDO Industrial Statistics Dataset to calculate manufacturing market size. I define market size of country j as:

$$MS_j = Y_j + M_j - X_j \tag{76}$$

where Y_j is total gross manufacturing production, M_j is total value imported, and X_j is total value exported. For a small share of the sample, I input gross production using the following procedure. For the countries with available production data, I estimate a model in which the log of gross manufacturing production is a function of log gross domestic product, log of labor force, log of share of total value added in manufacturing, log of share of total value added in agriculture, and a set of quadratic and cubic terms of these variables. I then use the coefficients of this regression with the information on GDP, labor forces, and sectoral shares to forecast the unobserved values of gross manufacturing production. For a similar strategy see Bertoletti et al. [2015].

D Additional Results

D.1 Distortion Schedules Under Different Sample Definitions

In the benchmark analysis, I estimate distortion schedules using establishment-level data that includes both domestic and export firms from the manufacturing and service sectors (with manufacturing firms comprising the bulk of the sample). Since fixed export costs are included in establishment expenditure, one potential concern is that the inclusion of exporters in the sample might introduce an upward bias into the estimation of schedules. In other words, larger firms would present higher TFPR in part because they are able to dilute the export fixed costs in larger sales volumes. I investigate if this is the case by computing the correlation between the benchmark distortion schedules and the schedules estimated with alternative samples.

In sample 1, I eliminate all firms that report export sales larger than 5% of total sales. In sample 2, I eliminate all firms from the service sector. Sample 3 includes only mainly domestic establishments of the manufacturing sector. Finally, sample 4 calculates distortions schedules in the original sample using the sampling weights provided by the WBES. Table 16 presents the results. The coefficients are all above .85, revealing that the cross-country variation in schedules does not change when we work with alternative samples.

Table 16: Distortion Schedules Under Different Sample Definitions

Variables	Full-sample Gamma	Sample-1 Gamma	Sample-2 Gamma	Sample-3 Gamma	Sample-4 Gamma
Full-sample Gamma	1.000				
Sample-1 Gamma	0.918	1.000			
Sample-2 Gamma	0.997	0.932	1.000		
Sample-3 Gamma	0.917	0.999	0.930	1.000	
Sample-4 Gamma	0.858	0.856	0.864	0.857	1.000

Note: Correlation table between distortion schedules estimated under different sample definitions.
Source: Author's calculation based on data from the WBES.

D.2 Benchmark Trade Elasticity and Comparative Advantage Trade Elasticity

One potential explanation for the negative correlation between trade elasticity and development is that rich countries have comparative advantage in low-elastic sector, whereas developing economies specialize in high-elastic industries. Aggregative models of interindustry trade naturally generate this pattern of specialization because high wages in rich countries are a relatively more important cost disadvantage in sectors in which trade flows are very sensitive to trade costs (see Fieler [2011] and Lashkaripour [2015]).

To test this hypothesis, I first compute for each country i its "comparative advantage trade elasticity" (CATE). This index is a weighted average of sectoral trade elasticities, with weights given by the sector's participation in total exports. Therefore, countries specialized in high elasticity sectors would present higher aggregate trade elasticities. I use the sectoral trade elasticities from Caliendo and Parro [2014] and calculate the weights with sectoral trade data for the year 2006. I consider 18 ISIC 2 digit manufacturing sectors and 160 countries.

I then compute the correlation between CATE and the nonlinear trade elasticity from this paper. Table 17 presents the results. CATE's 1, 2 and 3 are arithmetic averages, whereas CATE's 4, 5 and 6 are geometric averages. The three different CATE's within each of these two categories are based on trade elasticities that were calculated with different samples in Caliendo and Parro [2014]. The correlation between the nonlinear elasticity and CATE is very low, suggesting that sectoral composition is unlikely to be the main driver of the relationship between aggregate trade elasticities and development. These results are consistent with evidence in Spearot [2016], according to which within-sector variation is the main driver of the cross-country differences in trade elasticities.

Table 17: Benchmark Trade Elasticity and "Comparative Advantage" Trade Elasticity

Variables	Nonlinear Beta	CATE 1	CATE 2	CATE 3	CATE 4	CATE 5	CATE 6
Nonlinear Beta	1.000						
CATE 1	0.070	1.000					
CATE 2	0.088	0.998	1.000				
CATE 3	0.101	0.997	0.995	1.000			
CATE 4	0.084	0.954	0.953	0.944	1.000		
CATE 5	0.116	0.937	0.942	0.928	0.994	1.000	
CATE 6	0.141	0.937	0.936	0.937	0.988	0.986	1.000

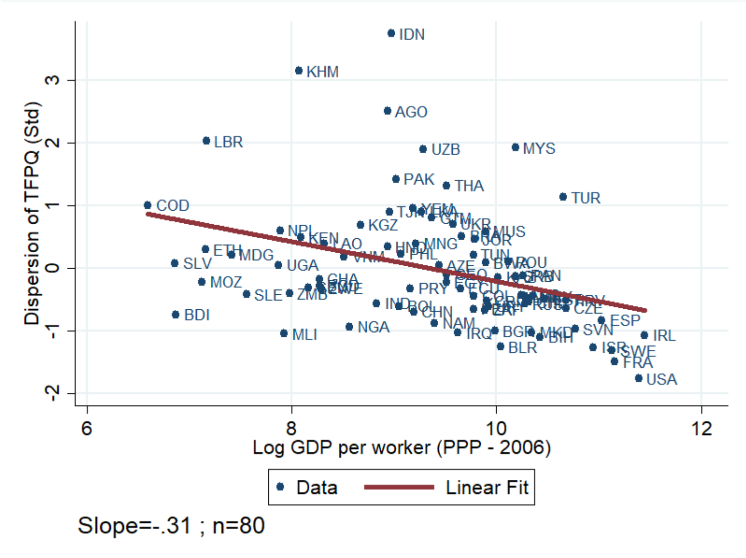
Note: Correlation table between the benchmark trade elasticity and the elasticities based on the sectoral composition of the origin country. Sample size = 160 countries. **Source:** Author's calculation based on earlier estimates, COMTRADE, and Caliendo and Parro [2014].

D.3 An Alternative Model: the Theta Model

The goal of this section is to investigate the following question: is a model without micro distortions consistent with the data? In many dimensions, the empirical content of the model developed above is similar to a framework in which $\gamma_i = 0\ \forall i$ and all the cross-country variation in β_i is due to differences in θ_i. However, this last model, which I refer to as theta model, is unable to reconcile two salient features of the data: (i) systematic negative relationship between dispersion of TFPQ and development, and (ii) negative correlation between development and trade elasticity.

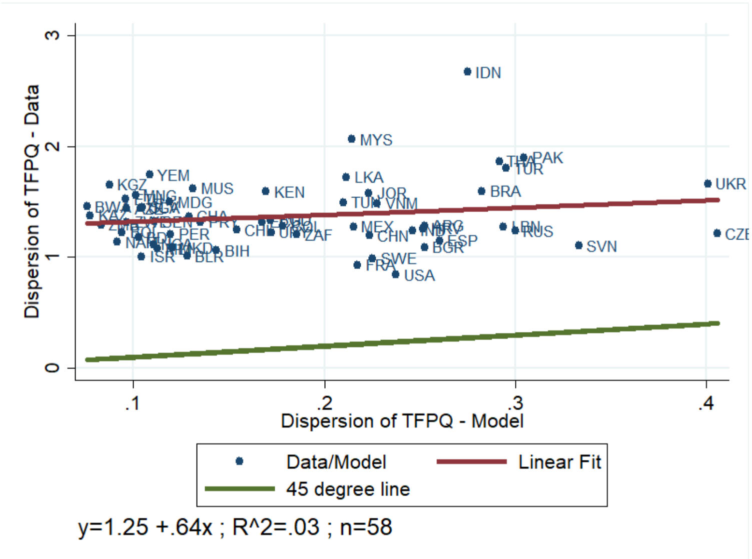
Figure 22 presents the first relationship. The within-sector dispersion of TFPQ significantly decreases with development. Since the dispersion of TFPQ in the theta model is inversely proportional to the trade elasticity ($Sd(log(TFPQ)_i)^{-1} = \beta_i = \theta_i$), that negative correlation would imply that trade elasticities should be lower, not higher, in developing economies. Therefore, the theta model is not flexible enough to deliver simultaneously high dispersion of TFPQ at the micro level and high trade elasticities at the macro level. As a result, when $\{\theta_i\}_i$ are chosen to match the trade elasticities, the theta model performs poorly at predicting the cross-country variation in the within-sector dispersion of TFPQ, as evidenced in figure 23.

Figure 22: Dispersion of TFPQ and Output per Worker



Note: Dispersion of TFPQ is measured as the standard deviation of the log of establishment physical productivity net of the sectoral average. Sample size = 80 countries. **Source:** Author's calculation based on earlier estimates.

Figure 23: Dispersion of TFPQ in the Theta Model

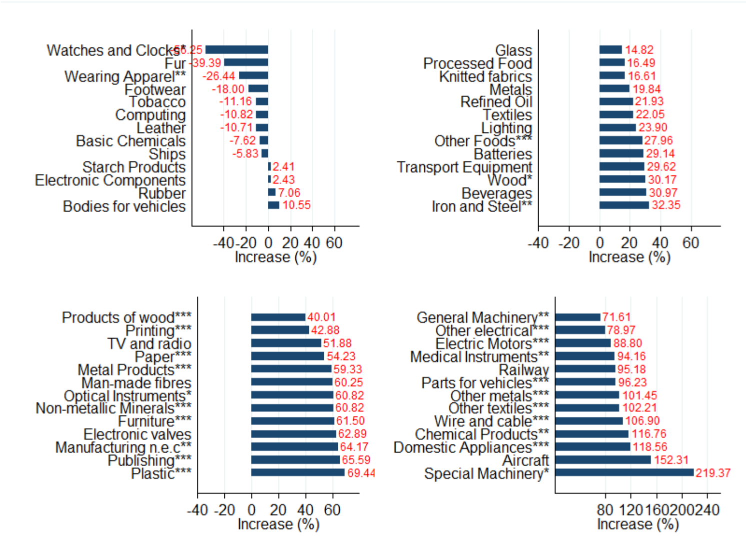


Note: Dispersion of TFPQ in the model is calculated by assuming that $\beta_i = \theta_i \; \forall i$. Sample size = 58 countries. **Source:** Author's calculation based on earlier estimates and model simulation.

D.4 Sectoral Reduced-Form Gravity

In this subsection, I estimate equation 6 at the 3 digit sectoral level. I construct a measure of manufacturing market size at this level and I measure exporter's productivity as value added per worker using data from UNIDO Industrial Statistics. Figure 24 presents the percentage difference in the absolute value of the reduced-form elasticity of trade with respect to distance between low-productivity exporters and high-productivity exporters - defined as the 5 and 95 percentile of the sectoral productivity distribution. As in the aggregate analysis, trade elasticities tend to be higher for less productive exporters in almost all sectors.

Figure 24: Sectoral Reduced-Form Gravity

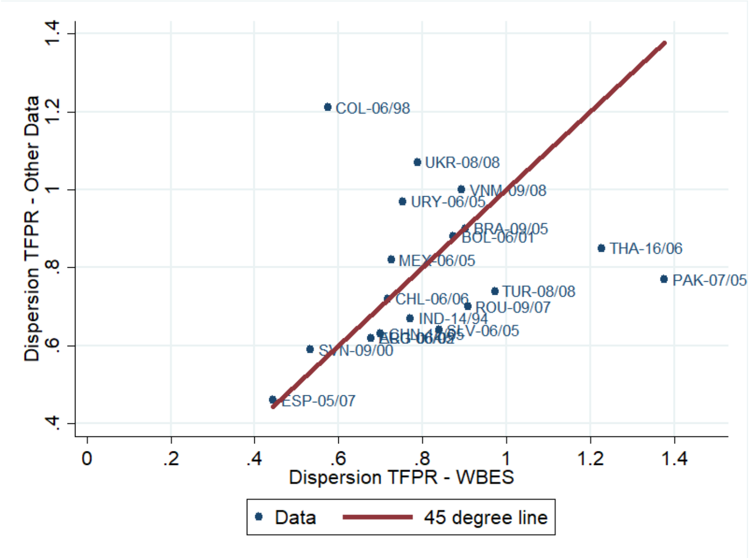


Note: Table presents the increase in the absolute value of the reduced-form trade-distance elasticity from reducing exporter's sectoral value added per worker (95 to 5 percentile of the distribution). **Source:** Author's calculation based on data from COMTRADE and CEPII.

D.5 Comparison between WBES and Other Datasets

To evaluate the accuracy of the WBES dataset, I compare the dispersion of TFPR from this dataset with estimates based on more comprehensive surveys. The alternative data include more firms, that are usually classified at finer levels of disaggregation (4 digits), and are collected by national statistical bureaus. Figure 25 presents the comparison. Overall, the estimates from WBES do a fairly good job at approximating the other estimates. The advantage of using the WBES is that it relies on a common methodology (the Global Methodology), which was particularly designed to facilitate cross-country comparisons.

Figure 25: Comparison between WBES and Other Datasets



Sources: Spain, Slovenia and Romenia (Asker et al. [2014]); India and China (Hsieh and Klenow [2009]); Mexico, Colombia, Argentina, Chile, Bolivia, Brazil, El Salvador and Uruguay (Busso et al. [2013]); Ukraine (Ryzhenkov [2016]); Pakistan (Haseeb and Chaudhry [2014]); Thailand (Dheera-Aumpon [2014]); Vietnam (Bach [2014]); Turkey (Nguyen and Yilmaz [2016]).

E Additional Tables

Table 18: List of Distortion Schedules

Country	Distortion Schedule (Gamma)	Number of Firms	Number of Sectors	Country	Distortion Schedule (Gamma)	Number of Firms	Number of Sectors
AGO	.6720221	293	16	MEX	.2740432	1800	26
ARG	.2945289	957	22	MKD	.3868529	180	20
AZE	.3683912	114	19	MLI	.2700885	273	14
BDI	.5302297	136	12	MMR	.3859082	135	15
BGD	.403202	2571	35	MNG	.3448282	177	16
BGR	.4906013	517	16	MOZ	.5364748	277	14
BIH	.3280919	133	19	MUS	.4724248	112	10
BLR	.4318199	110	18	MYS	.5464793	343	19
BOL	.5160508	254	13	NAM	.6547303	124	19
BRA	.3103082	985	21	NGA	.4226909	973	21
BWA	.5758846	159	17	NIC	.5085942	293	22
CHL	.2629523	997	20	NPL	.5802245	267	19
CHN	.436953	1398	23	PAK	.511396	256	19
COD	.2622274	366	16	PAN	.5680005	112	14
COL	.3176898	1107	19	PER	.3337835	738	17
CRI	.3721831	201	21	PHL	.3417232	1104	23
CZE	.4911349	113	22	PRY	.4118366	193	20
ECU	.3226265	329	17	ROU	.4303694	192	23
EGY	.4774229	1442	30	RUS	.3552381	754	26
ESP	.1773479	462	8	SEN	.3304761	314	14
EST	.5343354	135	19	SLV	.4125609	311	14
ETH	.5346739	326	21	SRB	.3769868	185	24
GEO	.3939069	123	16	SVN	.3004375	139	20
GHA	.4204391	397	16	SWE	.2499287	266	15
GTM	.3809011	474	22	THA	.5293427	607	20
HND	.4746613	275	18	TJK	.5425555	114	16
HRV	.3633689	333	21	TUN	.385124	284	25
IDN	.6078294	1459	25	TUR	.5180095	800	22
IND	.4381002	4724	23	UGA	.6294344	346	17
IRL	.1872938	444	8	UKR	.5179045	455	23
IRQ	.4262838	472	21	URY	.3186946	341	20
ISR	.2611017	124	23	USA	.09		
JOR	.393263	259	20	UZB	.5223429	215	19
KAZ	.5796834	174	17	VNM	.4989707	1119	24
KEN	.4211115	612	22	YEM	.5601509	165	16
KGZ	.4988502	118	17	ZAF	.3204157	652	19
KHM	.4399067	125	16	ZMB	.5306073	430	17
LAO	.5857928	476	27	ZWE	.3765668	350	22
LBN	.3110118	134	21				
LKA	.4483702	240	16				
MDG	.5302229	276	23				

Note: Sample Size = 103 countries. **Source:** Author's calculation and Hsieh and Klenow [2014].

Table 19: List of Trade Elasticities

Country	Trade Elasticity (Beta)	Standard Error	Country	Trade Elasticity (Beta)	Standard Error
AGO	10.236	1.7054	KWT	6.4475	1.1176
ALB	9.5268	1.4037	LAO	11.034	1.8643
ARE	3.0489	1.4914	LBN	3.4138	1.3636
ARG	3.9909	1.2422	LBY	8.2837	1.3128
ARM	10.43	1.6949	LCA	9.48	1.6361
ATG	10.553	1.8654	LKA	4.7328	1.1143
AUS	3.5309	1.3801	LSO	7.9502	1.1719
AUT	3.5547	1.3337	LTU	3.2353	1.3094
AZE	10.292	1.7469	LUX	5.7834	1.0593
BDI	9.6659	1.6486	LVA	5.0598	.99577
BEL	4.4156	1.0783	MAC	9.5619	1.6712
BEN	9.7114	1.5919	MAR	4.999	.99767
BFA	9.5	1.6235	MDG	8.4418	1.2091
BGD	5.8238	.93872	MDV	9.7823	1.6175
BGR	3.9724	1.2471	MEX	4.6339	1.1762
BHR	7.334	1.197	MKD	8.3418	1.1888
BHS	8.1801	1.1129	MLI	8.8743	1.411
BIH	7.0157	.94477	MLT	4.9926	.99379
BLR	7.783	1.0155	MNG	9.888	1.6367
BLZ	10.722	2.0653	MOZ	13.827	2.9371
BOL	10.648	1.783	MUS	7.6275	1.0786
BRA	3.5624	1.3854	MWI	12.945	2.5814
BRB	10.508	1.8617	MYS	4.6585	1.0873
BTN	9.6059	1.6052	NAM	11.009	1.9969
BWA	13.3	2.7993	NCL	11.305	2.1679
CAF	10.674	1.8149	NER	9.8341	1.4655
CAN	4.7685	1.1081	NGA	9.0601	1.3435
CHE	4.5036	1.0965	NIC	8.6894	1.3689
CHL	6.4896	.94338	NLD	4.9208	1.0797
CHN	4.4832	1.1576	NOR	4.9634	1.0917
CIV	9.7705	1.6628	NPL	9.1774	1.3488
CMR	9.2635	1.4656	NZL	3.6794	1.3414
COG	11.603	2.2193	OMN	5.2177	1.0799
COL	5.5845	.97533	PAK	3.2829	1.4762
CPV	10.414	1.8155	PER	8.3642	1.2648
CRI	7.0882	1.0049	PHL	4.7934	1.0823
CYP	5.1586	1.1642	PNG	11.948	2.4141
CZE	2.4619	1.639	POL	3.5122	1.3148
DEU	4.6424	1.0342	PRT	4.9308	1.1003
DMA	8.392	1.2751	PRY	7.4025	1.0762
DNK	4.1569	1.2158	PYF	12.118	2.3658
DOM	9.3966	1.4167	QAT	5.6732	1.0694
DZA	6.1716	.96981	ROM	3.4935	1.2469
ECU	5.9557	.96189	RUS	3.334	1.362
EGY	4.5457	1.1706	RWA	9.2707	1.4229
ERI	9.3941	1.4847	SAU	4.9353	1.0935
ESP	3.8413	1.3063	SDN	8.6262	1.3142
EST	4.3631	1.0848	SEN	9.0069	1.4817
ETH	10.399	1.8359	SGP	3.6275	1.3311
FIN	3.5976	1.3903	SLB	10.172	1.77
FJI	11.324	2.154	SLV	9.5624	1.5287
FRA	4.6302	1.1675	SUR	11.138	2.0389
GBR	4.2789	1.1274	SVK	3.7734	1.2799
GHA	7.7954	1.0792	SVN	3.0156	1.4885
GIN	9.9702	1.7478	SWE	4.4504	1.0714
GMB	9.5613	1.5632	SWZ	10.414	1.727
GNQ	11.526	2.2191	SYC	9.9284	1.7035
GRC	4.1852	1.2291	SYR	5.0572	1.0121
GRD	8.5436	1.3559	TCD	10.754	1.9352
GUY	12.141	2.3958	TGO	8.5476	1.3078
HKG	5.3973	1.0388	THA	3.4315	1.3119
HRV	3.9639	1.2128	TJK	14.146	3.0874
HTI	10.663	1.904	TKM	12.71	2.5133
HUN	4.6091	1.1578	TON	8.5295	1.3403
IDN	3.6596	1.2836	TTO	10.042	1.8034
IND	4.0936	1.2054	TUN	4.751	1.0994
IRL	3.9436	1.2786	TUR	3.404	1.3824
IRN	4.2633	1.2045	TZA	7.5297	1.0462
ISL	7.063	1.0966	UGA	9.639	1.5109
ISR	9.6432	1.5791	UKR	2.0268	1.7777
ITA	4.2483	1.1566	URY	5.8117	.99194
JAM	9.5609	1.4725	USA	4.1924	1.1302
JOR	4.476	1.1181	UZB	13.712	2.8601
JPN	4.8412	1.1449	VEN	7.9536	1.2059
KAZ	12.905	2.6316	VNM	4.3682	1.1667
KEN	5.8858	1.0432	YEM	9.2288	1.5111
KGZ	11.413	2.1439	ZAF	5.3984	1.0713
KHM	7.2397	.9796	ZAR	10.492	1.835
KNA	9.5903	1.651	ZMB	12.042	2.1999
KOR	3.3626	1.3963	ZWE	10.385	1.7231

Note: Sample Size = 160 countries. Standard errors are multi-clustered at the level of importer and exporter. **Source:** Author's calculation.

Table 20: Effects of SDD - Country by Country Analysis

	Open Economy			Closed Economy		
Country	Total Gain (%)	Reallocation Gain (%)	Entry Gain (%)	Total Gain (%)	Reallocation Gain (%)	Entry Gain (%)
Argentina	23.565	20.4512	3.1138	17.232	14.0237	3.2083
Azerbaijan	8.1175	6.369	1.7485	5.073	3.2549	1.8181
Bangladesh	23.317	19.4608	3.8562	13.366	9.3714	3.9946
Belarus	26.764	23.637	3.127	15.314	11.8964	3.4176
Bolivia	14.293	11.0474	3.2456	2.9573	-.3813	3.3386
Bosnia and Herzegovina	9.5288	7.5924	1.9364	4.5287	2.3783	2.1504
Botswana	81.296	77.43359	3.8624	48.425	44.3169	4.1081
Brazil	31.727	27.9518	3.7752	24.656	20.8364	3.8196
Burundi	29.536	25.4519	4.0841	8.4489	4.1309	4.318
Chile	6.7619	5.25	1.5119	5.1355	3.5826	1.5529
China	65.154	59.2214	5.9326	57.914	51.9051	6.0089
Colombia	12.651	10.1451	2.5059	8.363	5.7837	2.5793
Croatia	51.164	46.8022	4.3618	32.455	27.7951	4.6599
Ecuador	10.925	8.5769	2.3481	5.8827	3.421	2.4617
El Salvador	5.7803	3.4556	2.3247	1.5348	-.8817999	2.4166
Ethiopia	21.114	17.2967	3.8173	1.4476	-2.6092	4.0568
Ghana	15.267	12.2881	2.9789	6.3619	3.2225	3.1394
India	115.19	108.7585	6.4315	93.963	87.43	6.533
Israel	5.0363	4.12312	.91318	3.3383	2.35317	.98513
Jordan	36.411	31.9472	4.4638	19.433	14.7122	4.7208
Kazakhstan	78.657	74.7448	3.9122	49.355	45.1538	4.2012
Kenya	29.692	25.6433	4.0487	16.04	11.8254	4.2146
Kyrgyzstan	26.844	23.9582	2.8858	15.864	12.818	3.046
Lebanon	35.14	31.4119	3.7281	19.233	15.1881	4.0449
Macedonia	15.601	13.2659	2.3351	9.701	7.2333	2.4677
Madagascar	42.645	38.3229	4.3221	16.96	11.9706	4.9894
Mali	.82671	-.36229	1.189	-.4189	-1.6469	1.228
Mauritius	41.486	37.7731	3.7129	26.597	22.5441	4.0529
Mexico	12.299	10.0911	2.2079	8.4604	6.031199	2.4292
Mongolia	7.4089	5.8327	1.5762	4.6739	2.9755	1.6984
Nigeria	9.4602	6.8118	2.6484	4.0769	1.3563	2.7206
Paraguay	11.296	8.347099	2.9489	2.6763	-.4860001	3.1623
Peru	5.5824	3.7634	1.819	3.4977	1.6468	1.8509
Russia	82.271	77.0727	5.1983	61.929	56.5945	5.3345
Senegal	3.7649	2.1529	1.612	.66612	-1.03798	1.7041
Slovenia	65.78	61.8194	3.9606	43.024	38.7032	4.3208
South Africa	12.329	10.1572	2.1718	9.5016	7.2763	2.2253
Spain	6.512	5.3465	1.1655	4.6487	3.4384	1.2103
Sri Lanka	65.329	59.5485	5.7805	42.126	36.2141	5.9119
Sweden	19.93	17.9761	1.9539	15.348	13.2468	2.1012
Tunisia	41.485	37.3759	4.1091	27.697	23.3265	4.3705
Uruguay	11.138	8.7731	2.3649	6.1721	3.6718	2.5003
Yemen	63.007	57.8617	5.1453	30.243	24.8707	5.3723
Zambia	29.528	26.158	3.37	15.449	11.9908	3.4582
Zimbabwe	2.581	.7849001	1.7961	-2.0839	-3.9893	1.9054

Note: Sample Size = 45 countries. **Source:** Author's calculation based on model simulation.

Table 21: Decomposition of Trade Channel

Country	Initial Home Share	Trade Channel (%)	Better Allocation (%)	Trade Creation (%)
Argentina	70.718	5.381208	20.67973	79.32027
Azerbaijan	49.197	2.868929	58.71451	41.28549
Bangladesh	61.341	8.414001	29.39779	70.60221
Belarus	26.654	9.389972	67.41806	32.58194
Bolivia	56.152	11.57617	34.76107	65.23894
Bosnia and Herzegovina	20.179	4.778131	85.07832	14.92168
Botswana	23.678	19.87194	77.59183	22.40817
Brazil	86.957	5.759496	9.584337	90.41566
Burundi	33.293	18.19868	52.59071	47.40929
Chile	67.329	1.551149	42.29565	57.70435
China	85.397	4.973332	25.48927	74.51073
Colombia	66.63	3.912714	29.89334	70.10666
Croatia	44.312	14.08622	30.60037	69.39963
Ecuador	49.477	4.723631	42.05396	57.94604
El Salvador	49.461	4.158704	58.5341	41.4659
Ethiopia	31.902	18.42895	52.63073	47.36927
Ghana	42.377	8.106891	46.68389	53.31611
India	83.063	11.41173	14.18087	85.81913
Israel	26.6	1.712587	88.17358	11.82642
Jordan	48.711	14.16331	29.98931	70.0107
Kazakhstan	24.973	19.00397	84.56551	15.43449
Kenya	55.92	11.34505	29.14243	70.85757
Kyrgyzstan	33.353	9.33615	66.18989	33.81011
Lebanon	35.629	13.52098	31.30574	68.69426
Macedonia	40.413	5.294211	56.07026	43.92974
Madagascar	3.4351	21.4844	154.6558	-54.65576
Mali	53.558	1.215441	68.07657	31.92343
Mauritius	23.37	11.64478	82.3392	17.6608
Mexico	27.147	3.521022	89.79922	10.20078
Mongolia	26.964	2.545714	107.6533	-7.653275
Nigeria	61.609	5.051887	37.43198	62.56802
Paraguay	33.464	8.192905	58.08104	41.91896
Peru	73.362	2.010968	34.75355	65.24645
Russia	75.33	12.90361	12.56332	87.43668
Senegal	38.444	3.033724	64.88421	35.11579
Slovenia	34.549	16.39358	26.94173	73.05827
South Africa	71.353	2.907305	35.12305	64.87695
Spain	64.17001	1.808865	26.37391	73.62608
Sri Lanka	75.304	16.08824	14.71102	85.28898
Sweden	39.143	3.978808	48.39159	51.60841
Tunisia	44.548	10.67307	40.23606	59.76394
Uruguay	46.799	4.623849	46.03263	53.96737
Yemen	46.06	23.60143	40.80964	59.19036
Zambia	54.878	11.51604	37.06279	62.93721
Zimbabwe	27.874	4.583946	69.45897	30.54103

Note: Sample Size = 45 countries. Trade channel refers to the percentage difference between the gains from eliminating correlated distortions in an open economy and in a closed economy. **Source:** Author's calculation based on model simulation.

Table 22: Effects of Distortions and Symmetric Costs - Global Analysis

Country	Gain, US distortion (%) - Open	Gain, Symmetric Trade Costs (%)	Gain, US distortion (%) - Closed
Argentina	52.452	4.3303	17.232
Australia	38.247	4.954	10.721
Austria	39.751	8.7401	8.974
Azerbaijan	155.51	61.438	5.073
Bangladesh	91.089	22.733	13.366
Belarus	125.73	48.532	15.314
Belgium	28.437	7.6697	5.3171
Bolivia	146.01	65.51	2.9573
Bosnia and Herzegovina	132.27	52.844	4.5287
Botswana	250.45	67.31	48.425
Brazil	38.618	.83288	24.656
Bulgaria	68.466	26.735	0
Burundi	351.68	120.9	8.4489
Canada	30.324	10.708	8.1472
Chile	42.864	15.262	5.1355
China	67.294	.66519	57.914
Colombia	78.111	24.877	8.363
Croatia	134.9	22.697	32.455
Czech Republic	26.599	9.9087	0
Denmark	53.669	16.051	11.506
Ecuador	103.68	42.726	5.8827
El Salvador	115.86	58.87	1.5348
Ethiopia	210.5	87.1	1.4476
Finland	47.704	4.3234	11.359
France	19.413	1.7935	7.4912
Germany	13.228	1.5862	5.5849
Ghana	159.08	64.178	6.3619
Greece	66.206	17.402	4.354
Hungary	44.714	15.24	3.3189
Iceland	117.19	51.793	3.4985
India	131.8	1.1917	93.963
Indonesia	28.651	4.938	0
Israel	71.928	34.798	3.3383
Italy	15.068	1.0918	4.7095
Japan	9.4567	.5655	4.4875
Jordan	152.86	42.795	19.433
Kazakhstan	181.6	49.784	49.355
Kenya	166.57	52.11	16.04
Korea, Republic of	21.338	2.2053	8.0854
Kyrgyzstan	249.82	89.391	15.864
Lebanon	193.78	36.89	19.233
Macedonia	138.85	54.141	9.701
Madagascar	180.31	58.406	16.96
Malaysia	39.382	16.888	0
Mali	168.21	73.394	-.4189
Mauritius	178.82	55.962	26.597
Mexico	33.805	11.557	8.4604
Mongolia	229.88	88.838	4.6739
Namibia	139.78	65.004	0
Netherlands	24.591	6.3763	4.2089
New Zealand	69.779	18.104	13.585
Nigeria	111.56	48.929	4.0769
Norway	54.085	16.583	5.6289
Pakistan	64.388	8.6258	0
Paraguay	136.44	62.513	2.6763
Peru	60.724	25.301	3.4977
Portugal	54.741	22.405	4.3006
Russia	96.812	2.1561	61.929
Senegal	160.11	70.734	.66612
Slovenia	125.18	15.932	43.024
South Africa	39.916	8.2926	9.5016
Spain	19.9	.86597	4.6487
Sri Lanka	143.86	17.041	42.126
Sweden	47.257	9.1791	15.348
Switzerland	35.488	11.645	5.4176
Thailand	33.264	9.2631	0
Tunisia	109.19	24.469	27.697
Turkey	23.208	1.8912	0
Uganda	184.64	73.557	0
Ukraine	36.986	6.7335	0
United Kingdom	24.285	2.6856	8.7701
United States	3.4872	.9872	0
Uruguay	100	42.947	6.1721
Vietnam	54.15	16.739	0
Yemen	235.43	76.857	30.243
Zambia	128.13	52.038	15.449
Zimbabwe	132.6	61.863	-2.0839

Note: Sample Size = 77 countries. **Source:** Author's calculation based on model simulation.

Table 23: Total Effect: Trade Liberalization and Misallocation Reduction

Country	Total Gain (%)	Trade Openness (%)	Misallocation (%)	Complementarity (%)
Argentina	26.55707	9.117931	64.88477	25.9973
Azerbaijan	10.21004	18.95613	49.71078	31.3331
Bangladesh	26.21274	8.958283	50.99331	40.04842
Belarus	32.89985	14.71243	46.55294	38.73463
Bolivia	16.02895	9.475715	18.46129	72.063
Bosnia and Herzegovina	16.71212	39.2433	27.08601	33.67068
Botswana	86.86928	3.538798	55.75003	40.71117
Brazil	33.14692	3.251967	74.3846	22.36343
Burundi	33.70876	9.556302	25.08875	65.35494
Chile	8.593098	19.96041	59.75772	20.28186
China	66.76725	1.463012	86.74626	11.79072
Colombia	14.9369	13.58504	55.99186	30.4231
Croatia	59.98222	9.725452	54.10732	36.16723
Ecuador	14.6274	22.81849	40.22934	36.95217
El Salvador	7.964789	25.92808	19.21727	54.85465
Ethiopia	24.87638	12.48766	5.806472	81.70586
Ghana	18.85338	16.50294	33.74845	49.7486
India	117.8629	1.053869	79.72179	19.22433
Israel	9.145103	42.7747	36.51011	20.7152
Jordan	42.61465	10.67184	45.60106	43.7271
Kazakhstan	84.0914	3.617267	58.69013	37.6926
Kenya	33.29467	8.343287	48.17969	43.47703
Kyrgyzstan	30.28771	8.963746	52.38037	38.65588
Lebanon	46.84644	18.49116	41.05191	40.45693
Macedonia	19.14758	16.02264	50.65222	33.32514
Madagascar	59.47916	19.8413	28.51297	51.64573
Mali	2.815505	70.05802	-14.8435	44.78548
Mauritius	49.21336	11.09773	54.0446	34.85767
Mexico	21.41799	37.91334	39.49937	22.58729
Mongolia	11.44676	32.84193	40.83588	26.32219
Nigeria	11.09305	13.44746	36.75103	49.80151
Paraguay	15.97795	26.32852	16.74651	56.92497
Peru	6.666261	15.39925	52.44302	32.15774
Russia	86.55745	2.716906	71.54229	25.7408
Senegal	6.87595	43.60372	9.678407	46.71788
Slovenia	82.52708	12.24082	52.13919	35.62
South Africa	14.29609	12.24939	66.46613	21.28448
Spain	9.976244	32.60188	46.58429	20.81384
Sri Lanka	68.0743	2.439255	61.88194	35.67881
Sweden	27.15385	22.18243	56.51888	21.29868
Tunisia	48.32643	10.00579	57.30769	32.68652
Uruguay	15.24699	24.24867	40.48224	35.26909
Yemen	66.85763	3.533246	45.22904	51.23772
Zambia	31.33575	4.453829	49.29446	46.25171
Zimbabwe	6.163257	56.66044	-33.80021	77.13976

Note: Sample Size = 45 countries. First column represents the total gain in productivity from opening the economy to trade and reducing domestic distortions. Second, third, and fourth columns inform the contribution of each channel to the total effect in column one. **Source:** Author's calculation based on model simulation.