Firm-Level Distortions and Aggregate Productivity: The Trade Channel

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Abstract

At the macro level, developing countries present low TFP and trade less than their size and geography would predict. At the micro level, they are characterized by small firm size and persistent within-industry misallocation. I develop a tractable multi-country general equilibrium model of production and international trade in which heterogeneous producers face both domestic distortions to firm size and costly entry into export markets. Since larger firms engage more intensely in international trade, misallocation induced by size distortions impacts aggregate productivity by also affecting the economy's trade volumes and gains from trade. 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 the trade channel greatly multiplies the effect of size distortions on aggregate TFP. Firm selection and factor reallocation amongst surviving firms totally account for this amplification, whereas the contribution from changes in firm entry is actually dampened by trade. Moreover, I find that cross-country differences in size distortions can account for a substantial share of the international dispersion in output per worker, 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

At the aggregate level, developing countries present low Total Factor Productivity (TFP) and export less than their size and geography would predict.[1] At the disaggregate level, they are characterized by small firm size and persistent within-industry misallocation.[2] This paper aims to connect these two sets of facts. In so doing, the paper provides a tractable extension of quantitative multi-country models of international trade that incorporates cross-country differences in firm size distribution and in allocative efficiency across firms. I then use the model to assess quantitatively how misallocation stemming from distortions correlated with firm size and barriers to international trade interact to engender aggregate outcomes. In particular, are the gains from improved domestic allocative efficiency mitigated by international trade because of terms-of-trade effects - just like the gains from factor accumulation or technological progress? Or are these gains amplified by exposure to trade? From a policy perspective, does trade liberalization complement or substitute domestic reforms that improve the allocation of resources across establishments?

At the heart of my analysis is the fact that exporting is costly and, therefore, highly concentrated among large producers.[3] Even within the selective set of exporters, larger and more productive firms tend to export more of each good, and a wider variety of goods, to more and farther destinations. Under these circumstances, I argue that correlated distortions not only affect firm selection and the allocation of factors among domestic firms, but they also shrink the size of the export sector relative to costs of entering foreign markets, thereby depressing the economy's trade performance. I then show that this last effect, which I refer to as *trade channel*, is quantitatively important in reinforcing the aggregate productivity losses from misallocation induced by distortions to firm size distribution. Importantly, this amplification is absent in a trade model without endogenous firm selection, i.g, one in which all entrants produce and sell to all markets like in Krugman [1980]. In this case, a superior micro allocation is equivalent to a positive aggregate productivity shock, whose gain in an open economy is moderated by depreciation of terms of trade.

My starting point is a multi-country general equilibrium model of production and trade with heterogeneous firms, in the spirit of Chaney [2008] and Di Giovanni and Levchenko [2012], extended to incorporate key elements from the misallocation and productivity literature. Trade is balanced and labor is mobile across firms and sectors within a country but immobile across countries. Each economy has two sectors: a perfectly competitive

[1] For evidence on the relationship between TFP and output per worker, see Hall and Jones [1999] and Caselli [2005]. For evidence on export performance, trade costs, and output per worker, see Helpman et al. [2008], Waugh [2010], and Tombe [2015].

[2] See Alfaro et al. [2008], Bartelsman et al. [2013], Hsieh and Klenow [2014], Poschke [2014], Bento and Restuccia [2016] and the excellent review by Hopenhayn [2014].

[3] See Bernard et al. [2007] and Eaton et al. [2011].

service sector, which combines labor with intermediate inputs to produce a nontradable final good; and a manufacturing sector, with monopolistic competition, CES demand, and free-entry of ex-ante identical producers of intermediate inputs for domestic and foreign markets. As in Melitz [2003], after entry these producers face fixed operating costs and fixed and variable international trade costs, which yields endogenous selection into production and exporting.

Upon paying a cost to start a business, the entrepreneur discovers her physical total factor productivity (TFPQ), which comes from a known Pareto distribution. Consistent with micro evidence, I assume that both the scale and the shape parameters of this distribution are country-specific. Therefore, countries may differ in their firm size distribution simply because they are working with different technologies. Conditional on her productivity, the entrepreneur then draws an exogenous size distortion in the form of an idiosyncratic wedge on total revenues, as in Bartelsman et al. [2013] and Hsieh and Klenow [2014]. Both distortions and TFPQ determine equilibrium firm size, with firms facing higher distortions selling and employing less than in the first-best equilibrium. To the extent that resource allocation is driven by distortions rather than by productivity, there will be differences in the marginal revenue product of factors across firms.

Revenue wedges increase in TFPQ according to a country-specific distortion schedule, whose slope controls the severity of distortions to firm size. A steeper slope implies that the gap between actual and first-best firm size increases faster in firm productivity, representing a business environment less conducive to firm growth. This modeling device serves as a simple and abstract representation of a myriad of market and policy-related domestic frictions that effectively penalize large, more productive establishments relative to small, less productive ones. Examples of detailed mechanisms that would map into this distortion schedule include: (i) quality of the managerial delegation environment (Akcigit et al. [2016]); (ii) factor market frictions (Hopenhayn and Rogerson [1993] and Midrigan and Xu [2014]); (iii) rent-seeking and unequal regulation enforcement (Aterido et al. [2007]); and (iv) size-dependent policies (Guner et al. [2008] and Garicano et al. [2016]). After learning her idiosyncratic factors, the manufacturer makes production and export decisions.

I use this framework first to study the effects of correlated distortions on key economic outcomes in a closed-economy setting. First, a steeper distortion schedule decreases the expected value of entry, reducing the creation of manufacturing firms and the measure of intermediate inputs available for the service sector. Second, a steeper schedule hinders the expansion of the most efficient firms, which in equilibrium weakens the competitive pressure on less efficient firms, reducing average firm size and worsening the selection of producers in the market. Finally, a steeper schedule increases the dispersion of idiosyncratic distortions, aggravating the misallocation of factors among surviving producers. These three elements result in low aggregate TFP and output per worker.

What are the additional consequences of correlated distortions when the economy opens to international trade? The building block to answering this question is the gravity equation that describes bilateral trade flows in the model. According to this equation, for *any given selection of exporting firms*, distortions affect aggregate exports through changes in the number and in the volume of exported varieties. This impact is akin to the one from changes in the aggregate state of technology in the gravity model of Eaton and Kortum [2002]. More importantly, correlated distortions also affect the *selection of firms* into export markets as well as the relative size of marginal and infra-marginal exporting firms. These latter effects introduce a relationship between domestic distortions and the extensive-margin elasticity of aggregate exports with respect to trade costs. Since distortions grow in firm size and only the largest firms select into exporting, a steeper schedule makes aggregate exports more sensitive to trade barriers. In this sense, the same trade barrier (i.g, geography) will represent a larger impediment to exporting for more distorted economies.

If the aggregate losses from correlated distortions are larger or smaller in an open economy will depend on two factors. First, since large establishments benefit from trade liberalization the most, correlated distortions reduce the reallocation gains from trade for *any given level of trade openness*. The second factor is the effect of distortions on trade openness itself. On the one hand, distortions increase the price of domestic goods - an appreciation of terms of trade. This creates an incentive for domestic buyers to substitute away from these goods, *increasing* imports and trade openness. In this case trade could help alleviate the losses from distortions. On the other hand, correlated distortions disproportionately harm large firms, precisely those that are more likely to access export markets. This force works in the opposite direction, i.e, to *decrease* trade openness and the gains from trade. Therefore, if trade amplifies or dampens the effects of distortions is ultimately an empirical matter.

To take the model to the data, I 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 divide the calibration of the model into three steps. The first step estimates the country-specific distortion schedules in the manufacturing sector. The microdata come from the latest version of the *World Bank Enterprise Survey* (2016). Earlier versions of this dataset have been used by other studies in the misallocation literature (see Asker et al. [2014] and Bento and Restuccia [2016]). As in Hsieh and Klenow [2009], the model predicts that establishment-level revenue productivity (TFPR) is proportional to the marginal revenue product of factors, and thus identifies the idiosyncratic distortions faced by establishments.[4] Additionally, by imposing the model's demand structure on establishment revenues I am able to iden-

[4]This relationship only applies to the revenue productivity of variable factors of production. In my data, it is not possible to disentangle variable from fixed costs. Given this limitation, my procedure is valid under the assumption that in the data all measured costs are variable, and the fixed operating cost represents the entrepreneur's opportunity cost as in Lucas [1978].

tify establishment-level TFPQ. I then estimate the slope of the distortion schedule as the within-sector elasticity between TFPR and TFPQ.[5] The estimates reveal that these slopes decline sharply with development. Whereas in OECD countries a doubling of establishment efficiency is associated with a 10-25 percent increase in average distortions, in developing economies it leads to an increment of 35-60 percent.

The second step recovers trade elasticities through the estimation of the structural gravity equation. This specification differs from the usual estimators in the gravity literature in two crucial aspects. First, the trade elasticity with respect to trade costs varies across exporters. Second, the interaction between importer's fixed effect and exporter's firm size distribution makes the loglinearized version of the gravity equation nonlinear in parameters. To deal with the computational burden of estimating a nonlinear model with hundreds of parameters, I use the method in De la Roca and Puga [2017] which estimates a nonlinear model through an iterative sequence of linear estimators.

In contrast to the common assumption in the quantitative gravity literature, I find a considerable dispersion in manufacturing trade elasticities across origin countries. Whereas OECD economies present trade elasticities between 4 and 5,[6] developing economies display much higher elasticities, ranging between 7 and 12. As predicted by the theory, steeper distortion schedules at the micro level are associated with higher trade elasticities at the macro level. Armed with the outcomes from steps one and two, I calibrate the dispersion of TFPQ in each country such that the model matches the empirical trade elasticities.

The final step calibrates trade costs and technology parameters such that the model perfectly matches the empirical world matrix of bilateral trade. The calibrated model successfully reproduces salient features of the cross-country data at both aggregate and disaggregate levels. First, it correctly predicts the large international differences in productivity per worker - the correlation between real output per worker in the model and in the data is .84. Second, it reproduces 60% of the empirical relationship between average manufacturing firm size and aggregate output per worker. Third, it replicates 92% of the observed elasticity between the share of manufacturing firms that export and aggregate productivity. Finally, the model reproduces 38% of the cross-country variation in the within-sector dispersion in TFPR, and 21% of the variation in TFPQ.

[5] The benchmark estimation is based on a sample that includes only firms whose domestic sales correspond to at least 95% of total revenues. The results are insensitive to restricting the sample to purely domestic firms. I exclude exporters from the sample for three reasons: first, the distortion schedule is meant to capture domestic distortions that do not respond to trade liberalization; second, the existence of fixed export costs can introduce a positive correlation between TFPQ and TFPR even in the absence of domestic distortions; third, in the model, the formulas that link unobservables like TFPQ and TFPR and observables like revenues, value added and input use only hold for domestic sales.

[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].

With the calibrated model in hand, I study the general equilibrium effects of correlated distortions on aggregate outcomes. I first quantify the output losses from distortions when the economy is able to trade at the estimated trade costs. This exercise consists of endowing each country in the sample - one at a time - with the "US efficiency" and then computing the new trade equilibrium. The US slope is a crucial benchmark in this context because even an undistorted economy can look distorted because of overhead costs, adjustment costs, or model misspecification.[7]

I find a cross-country average gain in output per worker of 27%. The bulk of this effect comes from the selection and reallocation channels - 24 percentage points - whereas the entry channel plays a minor role. I then perform a similar exercise in the closed-economy case, in which the world economy becomes just a set of isolated domestic economies. The average gain from eliminating distortions significantly drops to 14%. Selection and reallocation channels totally account for this reduction, with their contribution to output increase falling from 24 to 11 percentage points. Therefore, the trade channel greatly reinforces the selection and reallocation mechanisms through which micro distortions affect aggregate productivity.

I further find that on average 63% of the trade channel comes from the increase in the reallocation gains from trade given the initial level of trade openness, and 37% from expansion of the trade openness itself. Intuitively, a less distorted economy is better able to scale up the production of its most efficient firms - and force the exit of its least efficient producers - after trade liberalization comes into effect. Likewise, the reduction of correlated distortions increases firm size relative to export entry costs, thereby promoting export sales. This last effect helps to reduce the gap in trade openness in manufactures between developed and developing economies observed in the data. Furthermore, it suggests that domestic policies and institutions that distort the firm size distribution can have significant unintended consequences for trade performance.

My last counterfactual exercise addresses the following question: in a world economy integrated through trade, what does the international distribution of productivity look like when *all countries* have converged to the "US efficiency"? In this counterfactual scenario, two factors affect each country's output per worker: (i) the direct impact examined earlier, and (ii) the indirect "trade-transmitted" impact stemming from improvements in allocative efficiency in the rest of the world. I find that the international inequality

[7]Bartelsman et al. [2013] emphasize that if data on input use include overhead costs, then average productivity does not identify marginal productivity anymore. In this case, we could observe within-sector dispersion in TFPR *and* equalization of marginal products across establishments. Moreover, the presence of overhead costs introduce a positive covariance between establishment TFPQ and TFPR even in the absence of distortions. Asker et al. [2014] show that in the presence of adjustment costs, high time-series volatility in TFPQ can generate high cross-section dispersion in TFPR. In this case as well, TFPQ is positively correlated with TFPR even in the absence of distortions. Finally, dispersion in markups can generate a positive relationship between TFPQ and TFPR as shown by Bernard et al. [2003] and Peters [2013].

in output per worker decreases substantially - the variance of log productivity decreases by 49%, and the 90^{th} to 10^{th} percentile ratio decreases by 48%. This convergence effect becomes negligible when international trade is shut down. Therefore, misallocation induced by distortions to firm size potentially contributes to a significant share of cross-country differences in standards of living, and international trade is instrumental for this contribution.

Related Literature

This paper mainly relates to a recent research agenda on the relationship between micro-level heterogeneity and aggregate industry outcomes. The working hypothesis of this literature is that market imperfections and/or policy-related frictions may prevent productive factors from flowing to the most efficient firms in the industry, thereby reducing aggregate productivity. One branch of this research agenda has studied the impact of frictions in input and in output markets on aggregate productivity in closed-economy models - see Buera et al. [2011] and Moll [2014] for financial frictions, Lagos [2006] for labor market frictions, and Peters [2013] for imperfect competition in output markets. Another strain of work, based on the seminal contributions of Melitz [2003] and Bernard et al. [2003], has investigated how international trade affects industry performance by inducing reallocations across heterogeneous producers.

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 quantitative relevant amplifier of the aggregate effects from domestic micro distortions. This result is important because the quantitative results found in the closed-economy literature, despite being large in absolute terms, still fall short at explaining the immense observed cross-country differences in output per worker.[8] Second, I show that micro distortions quantitatively matter for assessing the reallocation gains from trade.[9]

This paper also relates to the literature on gains from trade and firm heterogeneity. Arkolakis et al. [2012] (ACR) highlight that the new trade models with firm heterogeneity deliver the same gains from trade as traditional models with representative firms. This equivalence rests on two results. First, the same equation describes gains from trade in the two classes of models, and this equation depends on two sufficient statistics: the level of trade openness (which is observed) and the trade elasticity. Second, the estimation of the trade elasticity is not model-specific because both models deliver the

[8]See Hopenhayn [2014].

[9]Some few papers have studied the interaction between trade and misallocation. Manova [2013] studies the effect of capital misallocation among heterogeneous producers and export performance. Her exercise does not fully solve for and estimate the structural parameters of the model though, which prevents it from assessing the general equilibrium effects of financial frictions on aggregate productivity and trade. 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. Finally, Tombe [2015] and Swikecki [2017] introduce frictions at the sector level into quantitative trade models.

same estimating gravity equation.[10] My contribution is to show that if the distribution of firm size varies across countries, then the second result no longer holds true. In this case, the estimation of trade elasticities - which are now origin-country-specific - and the magnitude of gains from trade will differ across models.

Methodologically, my contribution is closer to Simonovska and Waugh [2014b], who show that models with micro heterogeneity imply different estimates of trade elasticities, and therefore different gains from trade, than representative-firm models. 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 Pareto distribution, the selection effects highlighted by the new trade models matter in the aggregate exactly because they interact with the distribution of firm size, which is a country-specific object.

Related, this paper extends the workhorse quantitative multi-country trade model to allow for country-specific distributions of firm size. I develop a novel numerical method to compute the general equilibrium in this highly nonlinear environment.[11] I also prove that, under mild assumptions, the general equilibrium exists and is unique. Spearot [2016] also introduces this rich kind of cross-country heterogeneity in a multi-country gravity model. My paper differs from his study in two crucial methodological aspects. First, I solve and estimate the model in levels instead of in differences. My strategy is more costly because it requires the calibration of all structural parameters of the model, but it allows me to perform a broader set of counterfactual exercises in general equilibrium, beyond those based on changes of trade costs. Second, I show empirically that the cross-country variation in macro-level trade elasticities reflects differences in firm-level distortions observed in the microdata.

Finally, this paper offers a potential mechanism to rationalize the results in Helpman et al. [2008] and Waugh [2010]. These papers find that trade costs have to be systematically asymmetric in order for a standard gravity model to fit the data on trade flows between developed and developing countries. In particular, export costs need to be systematically higher for poor countries. I show empirically that this asymmetry in trade costs in part captures differences in domestic distortions to firm size distribution, which have been extensively documented by the empirical development literature.[12] Separating differences in trade costs from differences in trade elasticities does not affect the fit

[10] 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 micro heterogeneity, it captures the dispersion of micro-level productivity. For estimation methods of trade elasticities, see Mayer [2014] and Caliendo and Parro [2014].

[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 10 countries.

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

of the trade model in hand, but is fundamental for assessing the gains from trade. Moreover, this distinction is crucial from a policy perspective. On the one hand, if high trade costs are the main restrictions on 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 trade costs, reforms of financial and labor markets are a better alternative.

Road Map

Section (2), which follows, documents the basic facts that motivate my investigation. Section (3) provides the theoretical framework. 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. The appendix (A) contains proofs, monte carlo simulations, additional results and details of data construction.

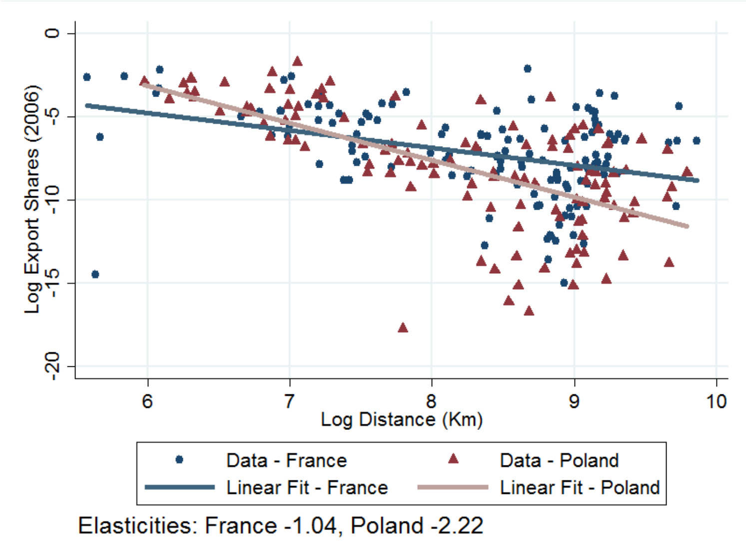
2 Basic Facts

I divide the empirical regularities that motivate my study into two categories: aggregate and disaggregate. The aggregate facts correspond to cross-country correlations between measures of trade performance and labor productivity at the industry level. The disaggregate facts involve cross-country differences in firm size distribution and in within-industry allocative efficiency. Some of these facts have been documented by previous work, so I purposely keep their description brief. Since the bulk of international trade is in manufactured goods, my analysis focuses on the manufacturing sector. Unless otherwise noted, the data are for the year 2006.

Trade-Distance Elasticity and Labor Productivity

Helpman et al. [2008], Waugh [2010] and Tombe [2015] show that bilateral trade costs inferred from bilateral trade flows are systematically asymmetric, with poor countries facing larger costs to export relative to rich countries. In this paper I explore an alternative hypothesis: that the same trade cost represents a larger trade barrier for less productive origin countries. I do that by allowing for the elasticity of trade flows with respect to trade barriers to vary according to exporter's labor productivity. Figure (1) shows a scatterplot of French and Polish foreign sales of Chemical Products (ISIC 242) against geographic distance to the destination. Comparing these two exporters is illustrative because despite having relatively similar geographic access to foreign markets, they differ considerably in labor productivity - in 2006, value added per worker in the French chemical sector was three times higher than in Poland. The difference in elasticities is large and significant. Whereas a 10% increase in distance decreases Polish sales by 22.2%, it reduces French sales by only 10.4%.

Figure 1: Trade-Distance Elasticity



Note: The horizontal axis measures the logarithm of distance to destination in Kilometers (Km). The vertical axis measures the logarithm of sales to a destination as a share of total sales. Data for 2006. Sector 242 in ISIC Rev. 2. Labor productivity in France is US$ 136,000, and in Poland US$ 45,000 (Dollars of 2006). Sources: COMTRADE, UNIDO and CEPII.

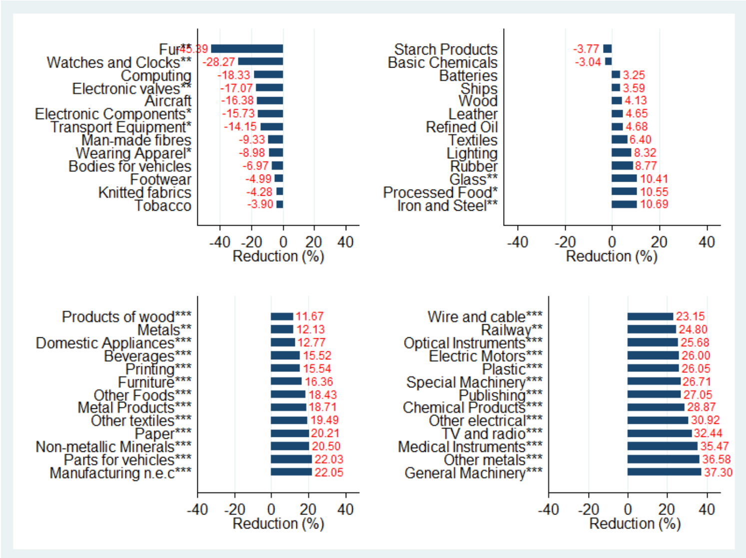
To study this hypothesis more systematically, I combine data on bilateral trade flows, bilateral trade barriers, and value added per worker for 77 countries in 52 manufacturing industries (3 digit ISIC Rev. 2). I estimate

$$log(X^k_{ji}) = \alpha^k_j + \kappa^k_i + (\beta^k_1 + \beta^k_2 y^k_i) log(d_{ji}) + \theta^k Z_{ji} + \epsilon^k_{ji} \tag{1}$$

where X^k_{ji} represents sales from country i to country j in sector k, α^k_j and κ^k_i are importer and exporter fixed effects, d_{ji} is geographic distance between countries i and j, y^k_i is labor productivity (standardized across origin countries), Z_{ji} is a vector including indicators of common language and shared border, and ϵ^k_{ji} is the regression error. When $\beta^k_1 < 0$, a positive β^k_2 means that exports decrease slower in distance for more productive exporters. Figure (2) reports the parameters $\left\{\frac{-2\beta^k_2}{\beta^k_1}\right\}^{52}_{k=1}$, which measure the percentage decrease in elasticity caused by an increase of two standard deviations in labor productivity.[13]

[13] Labor productivity is measured as value added per worker in dollars of 2006. The conversion uses the average period exchange rates as given in the International Monetary Fund International Financial Statistics (IFS).

Figure 2: Trade-Distance Elasticity and Labor Productivity



Note: The bars measure the percentage decrease in trade-distance elasticity from increasing labor productivity by two standard deviations. Robust standard errors, with *** meaning significant at 1%; **, significant at 5%; *, significant at 10%. The sample only includes strictly positive trade flows. Sources: COMTRADE, UNIDO and CEPII.

In 37 out of 52 sectors, more productive exporters have lower (in absolute terms) trade-distance elasticities. Among the 15 sectors with the opposite sign, only 6 present coefficients statistically different from zero. Within the set of sectors with positive and significant coefficients, the reduction in elasticities varies between 10% (Glass Products) and 37% (General Machinery). In summary, these results demonstrate that sales from more productive country-industry pairs are not only larger in levels but also decrease less rapidly in geographic barriers. The latter fact does not easily conform to the standard quantitative gravity model.

Why do more productive origin countries present lower trade-distance elasticities? Is it the case of their average sales per firm being less sensitive to trade costs? Is it the case of their number of exporting firms decreasing less rapidly in trade costs? Or is it a combination of intensive and extensive margin effects? To shed light on these questions, one needs data that decomposes bilateral trade flows into number of exporters and average sale per exporter. I use the World Bank's *Exporter Dynamics Database* (EDD),[14] which contains this decomposition for 38 origin countries and 159 destinations in the period 1997-2011. To increase country coverage, I use a version of the EDD that consolidates sectoral trade flows into a single manufacturing category.

[14] Fernandes et al. [2016] describes this dataset in detail.

Table (1) presents the estimates of specification (1) applied to the two measures of export performance. Whereas distance negatively affects both measures (especially the number of exporters), its interaction with labor productivity is only significant in the first regression. These results suggest that the extensive margin is the main driver of the above relationship, i.e, exports from less productive countries fall more rapidly in distance because less firms are able to access more distant markets.[15]

Table 1: Trade-Distance Elasticity and Labor Productivity: Decomposition

VARIABLES	(1) Number of Exporters	(2) Average Export
Distance	-1.318***	-0.268***
	(0.0727)	(0.0800)
Distance*(Labor Productivity)	0.0567***	-0.00475
	(0.00705)	(0.00752)
Observations	10,736	10,736
R-squared	0.794	0.693

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

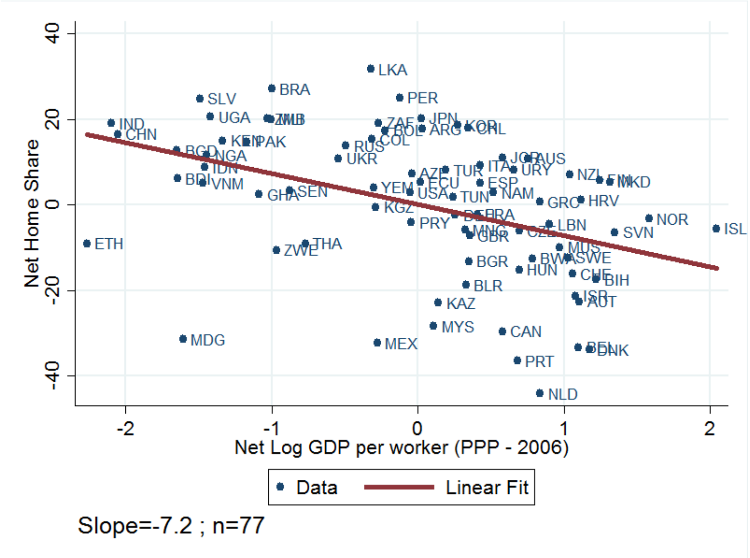
Note: The dependent variables, distance and productivity are in logarithms. Data are for manufacturing trade. Labor productivity refers to aggregate output per worker in PPP dollars of 2006. Controls include time, importer and exporter fixed effects, and indicators for common language and for shared border. Sources: CEPII, EDD and Penn World Tables 8.0.

Trade Openness and Labor Productivity

The second aggregate fact is the positive relationship between trade openness and aggregate labor productivity. Fieler [2011] and Caron et al. [2014] document this fact using the ratio of aggregate trade to GDP as a measure of trade openness. I show that this pattern still holds when we restrict the analysis to trade in manufactures. Figure (3) presents a scatterplot of home trade shares (share of total manufacturing expenditure devoted to domestic goods) against labor productivity. Doubling labor productivity is associated with a decrease of 7.2 percentage points in manufacturing home bias - the cross-country average home bias is 47%.

[15] Fernandes et al. [2015] show that the extensive margin explains 40-60% of the variation in bilateral trade.

Figure 3: Trade-Openness and Labor Productivity



Note: The horizontal axis measures labor productivity. The vertical axis measures home bias in the manufacturing sector. Home bias is measured as the share of manufacturing expenditures devoted to domestic goods. Domestic expenditure = Gross Domestic Production - Total Exports + Total Imports. Both variables are partialled out of variation in country size. Sources: COMTRADE, UNIDO and Penn World Tables 8.0.

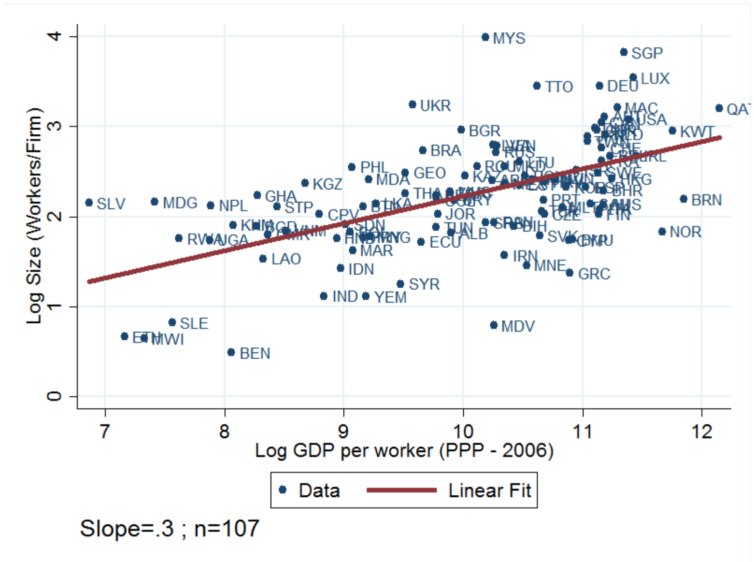
Average Firm Size and Labor Productivity

One of the most robust findings in the empirical development literature is that small production units carry out a great 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 poor countries. Lagakos [2016] documents stark cross-country differences in the composition of the retail sector. Whereas developing economies concentrate employment in traditional, small-scale shops, modern big-box stores dominate employment and value added in developed countries.

A similar pattern applies to manufacturing. Figure (4) presents a strong correlation between average manufacturing firm size, measured as the number of persons engaged per establishment, and aggregate labor productivity. The data on firm size are from Bento and Restuccia [2016] and are based on national census, representative survey and registry datasets. This dataset is particularly suitable for cross-country analysis for two reasons. First, it covers both registered and unregistered establishments. This is important because informal establishments are both smaller and more prevalent in developing economies. In fact, previous cross-country studies have found a negative association between firm size and development in part because its samples only include formal businesses. Second, the dataset includes in its definition of employment both paid and unpaid workers, which is particularly relevant in developing countries, where many establishments are family owned and operated.

The positive association between firm size and aggregate productivity also holds in time-series data. Poschke [2014] documents this association for the US during the twentieth century. Buera and Fattal-Jaef [2014] also show that growth in average firm size and in aggregate productivity followed structural reforms in Japan, South Korea, Singapore and Chile.

Figure 4: Average Firm Size and Labor Productivity



Note: The horizontal axis represents the logarithm of labor productivity measured as GDP per worker in 2006 PPP dollars. The vertical axis represents the logarithm of average firm size measured as the number of engaged persons per establishment. Data on firm size were collected during the period 2000-2012. Sources: Bento and Restuccia [2016] and Penn World Tables 8.0.

A Glance at Correlated Distortions

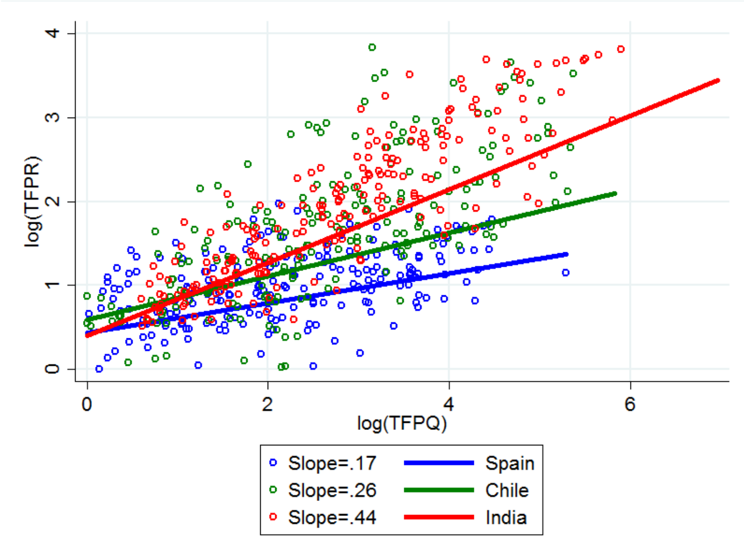
Recent work in economic growth and development has highlighted the interplay between firm-level heterogeneity and the business environment as an important determinant of cross-country differences in firm size distribution and in aggregate productivity. The working hypothesis of this literature is that small firm size and low aggregate productivity is in part due to frictions that prevent the more efficient entrepreneurs of the economy from expanding and from driving out of the market low productive producers. Given their dependence on firm size, these frictions are conventionally called *correlated distortions*. The recent development of micro-level datasets that are comparable across countries has allowed for the empirical assessment of this hypothesis - see Bartelsman et al. [2009], Hsieh and Klenow [2009], Bartelsman et al. [2013] and Bento and Restuccia

[2016].

I postpone a detailed discussion of the dataset and strategy to identify correlated distortions for the empirical section (4). In this subsection I briefly describe the methodology and present a illustrative result. Following Hsieh and Klenow [2009], I combine firm-level data with the structure of the model to recover firm-level TFPQ and TFPR. Through the lens of the model, TFPR is proportional to firm's marginal productivity. Therefore, a high TFPR in the data is interpreted by the model as a high idiosyncratic distortion. I then compute the within-sector elasticity between TFPQ and TFPR to measure how fast firm-level distortions grow in firm productivity. This elasticity is zero in a first-best economy. Higher slopes are then interpreted as representing business environments less conducive to firm expansion. Due to its tractability and relatively low data requirements, this formulation has become common in the macro development literature - see Buera and Fattal-Jaef [2014], Poschke [2014], Hsieh and Klenow [2014] and Bento and Restuccia [2016].

Figure (5) shows scatterplots of firm-level TFPQ and TFPR for three countries: Spain, a high income country; Chile, a middle income country that has experienced major structural reforms in the last decades; and India, a low income economy. There is a clear relationship between correlated distortions and development. A two-fold growth in TFPQ increases revenue productivity by 17% in Spain, by 26% in Chile, and by 44% in India. Through the lens of the model, these results imply that larger firms in India face more obstructions to growth than in Chile, whose firms, by their turn, face more distortions than in Spain. In the rest of the paper, I will argue that this cross-country variation in correlated distortions allows us to connect all the facts described above in a parsimonious fashion.

Figure 5: Correlated Distortions: Spain, Chile and India



Note: Logarithm of TFPQ and TFPR are measured in deviations from sectoral averages (ISIC 2-digit Rev. 2). Relative TFPQ is recovered assuming a demand elasticity of 3. Only firms whose domestic revenues comprise at least 95% of total sales are included. The empirical section explains in detail the computation of establishment-level measures.

3 Theoretical Framework

This section describes the quantitative model used in the paper. The minimalist framework to study the effects of correlated distortions on international trade and on aggregate productivity must include: (i) distributions of firm-level productivity that capture cross-country differences in technology; (ii) distortion schedules 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 into domestic and export markets. It is fundamental that the inclusion of these features do not compromise the amenability of the model to quantitative analysis.

Service Sector

Consider a world economy comprising N countries indexed by i. There is a mass of L_i workers in country i. Labor is the only factor of production and is freely mobile within a country but immobile between countries. The representative consumer's utility is linear in the nontradable final good (C_i) and her budget constraint is $Y_i = w_i L_i + \Pi_i + R_i$. The consumer spends her entire income, which is the sum of total wages ($w_i L_i$), distributed profits (Π_i), and net government transfers (R_i). The service sector is perfectly competitive and produces the final good according to the following Cobb-Douglas production function

$$C_i = (L_i^s)^\alpha (I_i)^{1-\alpha} \tag{2}$$

where L_i^s is labor employed in the service sector and I_i is a bundle of intermediate inputs. The parameter α controls the share of total labor employed in the service sector. The input bundle is a CES aggregator of intermediate varieties as follows

$$I_i = \left(\int_{\Omega_i} q(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}} \tag{3}$$

where $q(\omega)$ is the quantity of variety ω and $\sigma > 1$. The set Ω_i is determined endogenously and includes both domestic and imported varieties. The expenditure on variety ω is

$$x_i(\omega) = \left(\frac{p_i(\omega)}{P_i} \right)^{1-\sigma} Z_i \tag{4}$$

where Z_i is the total amount spent on inputs by the service sector and P_i is the input price index $\left(P_i \equiv \left(\int_{\Omega_i} p_i(\omega)^{1-\sigma} d\omega \right)^{\frac{1}{1-\sigma}} \right)$. The perfect competition assumption implies that $Z_i = (1-\alpha)Y_i$.

Manufacturing Sector

The manufacturing sector is characterized by a steady state equilibrium of firms in monopolistic competition. In country i, a mass κ_i of ex-ante identical entrepreneurs pays an exploration cost of $w_i f_i^e$. This term captures the direct and indirect costs with taxes, regulations and permits required to start a business. Djankov et al. [2002] document that the amount of time, the monetary cost and the number of procedures necessary just to start a business vary widely across countries. Importantly, these measures are strongly negatively correlated with output per worker. According to the World Bank's *Doing Business Survey*, in 2006 the regulatory cost to open a firm, measured as a share of income per capita, was 0.7% in the US and 51% in Ecuador. After the payment, the producer access a TFPQ draw (ω) from the following Pareto distribution

$$G_i(\omega) = 1 - A_i^{\theta_i} \omega^{-\theta_i} \tag{5}$$

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

Two parameters characterize country i's technology. The scale parameter (A_i) controls average TFPQ and reflects factors that equally affect all firms (independently of size). In other words, growth of A_i improves aggregate productivity while keeping the relative productivity between any pair of firms constant. This parameter is a catch-all variable capturing elements such as the state of technology and stocks of human and physical capital, which are not explicitly modeled in my framework.

The shape parameter (θ_i) controls the dispersion of TFPQ. The assumption that this dispersion is country-specific gives the model more flexibility to match the cross-country differences in firm size distribution. It also prevents the theory from attributing all those differences to variation in distortions. Even in the absence of frictions, countries will differ in their size distribution because of technological reasons. Moreover, since the aggregate gains from selection and reallocation crucially depend on the country's degree of heterogeneity of TFPQ, it is important to discipline this parameter with the microdata available for the country in question.

Manufacturing firms use labor as the sole input of a linear production function. The total cost of selling q units of product ω from origin i to destination j is:

$$c_{ji}(\omega, q) = \frac{q w_i d_{ji}}{\omega} + w_i f_{ji} \tag{6}$$

The term $d_{ji} \geq 1$ is the iceberg trade cost, which captures tariffs and transportation costs,[16] and f_{ji} is the fixed cost of serving destination j - like search and contractual costs, costs to adapt the product to local standards, regulations, and other non-tariff barriers. I assume that the fixed cost is entirely paid at the source country. For every country i, d_{ii} and f_{ii} are normalized to one. Thus, we can interpret the domestic fixed cost as the entrepreneur's opportunity cost of running a business.[17] If the variable profit from domestic sales is less than this cost, then the firm terminates its operation. Fixed and iceberg trade costs can be asymmetric, reflecting both geographic and policy barriers to international trade.

Firm ω from country i faces an idiosyncratic distortion $\tau_i(\omega)$ that works as a tax/subsidy on total revenues. The after-tax revenue from sales to destination j is

$$r_{ji}(\omega) = \tau_i(\omega) x_{ji}(\omega) \tag{7}$$

where $x_{ji}(\omega)$ is j's spending on i's variety ω as defined in equation (4). If $\tau_i(\omega) > 1$ the distortion works as a subsidy; if $\tau_i(\omega) < 1$, as a tax. The wedge distorts firm's decision both at the intensive margin - how much to sell - and at the extensive margin - how many markets to enter. Introducing idiosyncratic distortions in the model as taxes and subsidies is simply an analytical convenience. These wedges can also be taxes and subsidies, but in the context of the model they serve as a parsimonious representation of

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

[17] 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] when fixed costs are interpreted as the entrepreneur's forgone wage.

the whole set of policies and institutions that distort firm size.[18] I assume the following deterministic relationship between $\tau_i(\omega)$ and ω:

$$\tau_i(\omega) = \frac{b_i}{\omega^{\gamma_i}} \tag{8}$$

This distortion schedule depends on two parameters: level (b_i) and slope (γ_i). I adjust b_i such that $E(\tau_i(\omega)) = 1 \ \forall \ \gamma_i$.[19] Without this adjustment, a higher slope would mechanically increase the average tax rate, thereby affecting the relative price of the input bundle and the economy's terms of trade. Therefore, such correction allows me to isolate the consequences of changes in micro distortions from the more conventional effects produced by distortions to macro prices. The first part of the firm's problem is to determine the optimal price and quantity in each potential destination by maximizing after-tax profit $\pi_{ji}(\omega)$:

$$\begin{aligned} \max_{q_{ji},p_{ji}} \quad & \tau_i(\omega)p_{ji}(\omega)q_{ji}(\omega) - c_{ji}(\omega, q_{ji}(\omega)) \\ \text{s.t.} \quad & q_{ji}(\omega) = Z_j p_{ji}(\omega)^{-\sigma} P_j^{\sigma-1} \end{aligned}$$

Defining $m \equiv \frac{\sigma}{\sigma-1}$ as the undistorted markup, the optimal price is just the product of markup and marginal cost: $p_{ji}(\omega) = \left(\frac{m\omega^{\gamma_i}}{b_i}\right)\left(\frac{w_i d_{ji}}{\omega}\right)$. Note that when $\gamma_i \neq 0$ there is markup dispersion across active producers. After-tax revenue, which is proportional to after-tax profit, is

$$r_{ji}(\omega) = b_i^{\sigma}(m w_i d_{ji})^{1-\sigma}(Z_j P_j^{\sigma-1})\omega^{\sigma-1-\sigma\gamma_i} \tag{9}$$

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 $\forall i$ the following **non-ranking reversal** condition is true:

$$\epsilon_i \equiv \sigma - 1 - \sigma\gamma_i > 0 \tag{10}$$

Intuitively, condition (10) assures that, despite heavier distortions, more productive firms still make higher after-tax profits and, therefore, sell more and access more markets than less productive firms. I show in the empirical section that the estimates of $\{\gamma_i\}_{i=1}^N$ satisfy this condition for the values of σ usually used in the trade and macro literatures. The second part of the firm's problem is choosing which destinations - domestic market included - to serve. Firm ω activates market j if and only if $\pi_{ji}(\omega) \geq 0$. For each pair (j, i) there is a threshold productivity ω^*_{ji} such that $\pi_{ji}(\omega^*_{ji}) = 0$.

Aggregation and Equilibrium

[18] 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].

[19] More specifically: $b_i = \frac{(\theta_i+\gamma_i)}{\theta_i}A_i^{\gamma_i}$.

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

$$P_j^{1-\sigma} = \sum_{i=1}^{N} \kappa_i \int_{\omega_{ji}^*}^{\infty} p_{ji}(\omega)^{1-\sigma} dG_i(\omega) \tag{11}$$

where P_j affects the right-hand side through the selection of foreign sellers (ω_{ji}^*). The integrals converge if, and only if, $\forall i$ the following **regularity condition** is satisfied

$$\chi_i \equiv \theta_i + (\sigma - 1)(\gamma_i - 1) > 0 \tag{12}$$

Condition (12) subsumes 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 (12), all the aggregate objects in the model are well defined. For instance, the aggregate sale from country i to country j is finite and given by $X_{ji} = \kappa_i \int_{\omega_{ji}^*}^{\infty} x_{ji}(\omega) dG_i(\omega)$; distributed profit is $\Pi_i = \kappa_i \left(\sum_{j=1}^{N} \int_{\omega_{ji}^*}^{\infty} \pi_{ji}(\omega) dG_i(\omega) - w_i f_i^e \right)$; and net government transfer to consumers is $R_i = \kappa_i \left(\sum_{j=1}^{N} \int_{\omega_{ji}^*}^{\infty} x_{ji}(\omega) dG_i(\omega) - \sum_{j=1}^{N} \int_{\omega_{ji}^*}^{\infty} r_{ji}(\omega) dG_i(\omega) \right)$.

I now have all the elements necessary to define the general equilibrium. I demonstrate in the appendix that for parameters $\{\sigma, \alpha\}$, $\{A_i, L_i, \gamma_i, \theta_i, f_i^e\}_{i=1}^{N}$ that satisfy conditions (10) and (12) and trade costs $(f_{ji}, d_{ji})_{i,j=1}^{N}$, there exists a unique (up to scale) vector $\{w_i, P_i, \kappa_i, R_i\}_{i=1}^{N}$ such that:

- Consumers and firms behave optimally
- Goods and labor markets clear
- **Balanced Trade** $\forall i$ $Y_i = \sum_{j=1}^{N} X_{ji}$
- **Free Entry** $\forall i$ $\Pi_i = 0$
- $\forall i$ P_i satisfies equation (11)

Correlated Distortions and Aggregate Productivity in a Closed Economy

To gain intuition about how correlated distortions and trade costs interact to determine aggregate productivity in the model, it is illustrative to begin by studying the effects of distortions in a closed economy. In this environment, distortions affect output per worker through three channels, namely, firm entry, resource allocation and firm selection. It is useful to describe each of these channels separately before analyzing their combined effect. Starting with the entry channel it can be shown that balanced trade, labor market equilibrium and free entry in the manufacturing sector imply that

$$\kappa_i = \frac{(\sigma - 1 - \sigma\gamma_i)}{\sigma\theta_i f_i^e}(1-\alpha)L_i \tag{13}$$

Therefore, a steeper distortion schedule reduces the creation of manufacturing firms. Intuitively, more severe correlated distortions disproportionately decrease profits from higher draws of TFPQ, which makes entry less appealing. This impact is similar to the one caused by higher entry costs and affects aggregate productivity by reducing the measure of inputs available for the service sector - see equation (3). Equation (13) also reveals a complementarity between policies that reduce costs to start a firm and policies that improve allocative efficiency among existing firms. For example, the effect on firm creation of reforms in credit markets is larger when entry barriers are lower.

The second channel is the misallocation of labor across active manufacturing producers. In the model, producer ω's marginal before-tax revenue product of labor is

$$MRPL_i(\omega) \equiv \frac{\partial x_i(\omega)}{\partial l_i(\omega)} = \frac{m w_i \omega^{\gamma_i}}{b_i} \tag{14}$$

It is straightforward to show that $TFPR_i(\omega) \equiv \frac{x_i(\omega)}{l_i(\omega)} = MRPL_i(\omega)$, which just states that in the model average and marginal products of labor are equivalent. When $\gamma_i = 0$ the monopoly distortion implies that the marginal product of labor is greater than the marginal cost of labor, but all firms in the same industry still present a common marginal product and revenue productivity. When $\gamma_i \neq 0$ marginal products are no longer equalized across firms. In the empirically relevant case of $\gamma_i > 0$, more efficient firms present higher revenue productivity and, therefore, are operating below their optimal size. Moreover, if $0 < 2\gamma_i < \theta_i$ one can show that the coefficient of variation of MRPL for active producers is

$$CV_i(MRPL) = \frac{\gamma_i}{\sqrt{\theta_i(\theta_i - 2\gamma_i)}} \tag{15}$$

In this case, a greater γ_i leads to more dispersion of marginal products across producers and, therefore, to larger losses in aggregate productivity. Finally, correlated distortions affect aggregates through the selection of firms into production. The endogenous threshold below which firms leave the domestic market is

$$\omega_{ii}^* = \left(\frac{w_i^\sigma \sigma m^{\sigma-1}}{b_i^\sigma Z_i P_i^{\sigma-1}}\right)^{\frac{1}{\epsilon_i}} \tag{16}$$

The threshold productivity depends on the equilibrium wage rate, prices and aggregate spending, which are simultaneously determined in equilibrium. Intuitively, higher wages, lower prices and small market size contribute to the exit of the least productive firms by reducing their variable profits. Correlated distortions affect selection in equilibrium by maintaining in the market producers who would not survive otherwise, or by pushing out of production firms that would be profitable in the first-best equilibrium.

Now we are in a position to study how these three channels combine to determine aggregate output. Without loss of generality, one can normalize $L_i = 1$ and $A_i = 1$,[20] and assume that labor is the numeraire good to express aggregate output as

$$C_i = \bar{K}\left(\kappa_i \frac{(\theta_i+\gamma_i)^{\sigma-1}}{\chi_i \theta_i^{\sigma-2}} \bar{\omega}_{ii}^*\right)^{\frac{1-\alpha}{\sigma-1}} \tag{17}$$

where $\bar{K} \equiv \alpha^\alpha(1-\alpha)^{1-\alpha} m^{\alpha-1}$ and $\bar{\omega}_{ii}^* \equiv (\omega_{ii}^*)^{\chi_i}$. Keeping the selection term constant, correlated distortions affect output through the entry and allocation channels. The latter channel is captured by the term $\frac{(\theta_i+\gamma_i)^{\sigma-1}}{\chi_i}$. When $\gamma_i > 0$, assumptions (10) and (12) imply that this term is decreasing in γ_i.[21] In this case, a higher γ_i unambiguously leads to lower aggregate productivity. The analysis is not so straightforward when we allow for selection effects. In this scenario, the final impact of correlated distortions will depend on the sign of $\frac{\partial \bar{\omega}_{ii}^*}{\partial \gamma_i}$. If $\frac{\partial \bar{\omega}_{ii}^*}{\partial \gamma_i} < 0$ - the case in which heavier distortions on large firms end up in equilibrium coddling the least efficient producers in the economy - the selection effect reinforces the negative impact from the entry and misallocation channels. In the more extreme case with $\frac{\partial \bar{\omega}_{ii}^*}{\partial \gamma_i} > 0$, a steeper distortion schedule could even lead to higher aggregate productivity if the positive selection effect is greater than the misallocation and entry effects combined.[22]

Correlated Distortions and Aggregate Productivity in an Open Economy

Does international trade amplify or alleviate the aggregate productivity losses from correlated distortions? The answer to this question lies on the interplay between gains from trade and domestic misallocation. On the one hand, trade liberalization could help alleviate these losses by allowing consumers to adjust their spending towards cheaper/superior imported goods. On the other hand, distortions could reduce the economy's potential to reap the reallocation gains from trade and adversely affect the selection of firms into export markets, in which case the losses could be even larger in an economy open to trade. My goal in this section is to use the model above to shed light on these potential outcomes. The threshold productivity above which firms from country i export to destination j is

$$\omega_{ji}^* = \left(\frac{w_i^\sigma \sigma f_{ji} d_{ji}^{\sigma-1}}{b_i^\sigma Z_j P_j^{\sigma-1} m^{1-\sigma}}\right)^{\frac{1}{\epsilon_i}} \tag{18}$$

[20] Given that $b_i = \frac{(\theta_i+\gamma_i)}{\theta_i} A_i^{\gamma_i}$, γ_i could affect b_i through A_i when $A_i \neq 1$. By redefining the micro-level production function as $y_i(\omega) = A_i \omega l_i$, with ω being distributed Pareto on the domain $[1,\infty)$, we would have $b_i = \frac{(\theta_i+\gamma_i)}{\theta_i}$ and we would arrive at the same result as in the case with $A_i = 1$.

[21] $\frac{\partial\left(\frac{(\theta_i+\gamma_i)^{\sigma-1}}{\chi_i}\right)}{\partial \gamma_i} = \frac{(\sigma-1)(\gamma_i-1)-\gamma_i}{\chi_i(\theta_i+\gamma_i)} < 0.$

[22] Although theoretically possible, this last outcome is quite infrequent in the numerical experiments based on the calibrated model.

Using equation (11), I express aggregate exports from country i to country j as

$$X_{ji} = s_{ji} Z_j = \left(\frac{\bar{T}_i d_{ji}^{1-\sigma} (\omega_{ji}^*)^{-\chi_i}}{\sum_{k=1}^{N} \bar{T}_k d_{jk}^{1-\sigma} (\omega_{jk}^*)^{-\chi_k}} \right) Z_j \tag{19}$$

where s_{ji} is the share of j's spending on manufactures that is devoted to goods from i. The term $\bar{T}_i$ is country i's *intensive-margin competitiveness* and is given by

$$\bar{T}_i = \kappa_i (m w_i)^{1-\sigma} \frac{(\theta_i + \gamma_i)^{\sigma-1}}{\chi_i} \frac{A_i^{\theta_i + (\sigma-1)\gamma_i}}{\theta_i^{\sigma-2}} \tag{20}$$

Keeping the selection term constant ($(\omega_{ji}^*)^{-\chi_i}$), γ_i only affects aggregate exports through its effect on $\bar{T}_i$. According to equation (20), any change in $\bar{T}_i$ caused by variation in γ_i can be replicated by a correspondent change in A_i. In other words, in the absence of endogenous firm selection into production and exporting, micro distortions and aggregate technology are isomorphic. Therefore, the same way international trade reduces the local gains from domestic technological progress through depreciation of terms of trade, it will also moderate the gains from a superior micro allocation. In order for trade to interact more meaningfully with misallocation we must take the extensive margin seriously. Substituting expression (18) into equation (19) we have

$$X_{ji} = \left(\frac{T_i (Z_j P_j^{\sigma-1})^{\left(\frac{\beta_i}{\sigma-1} - 1\right)} d_{ji}^{-\beta_i} f_{ji}^{\left(1 - \frac{\beta_i}{\sigma-1}\right)}}{\sum_{k=1}^{N} T_k (Z_j P_j^{\sigma-1})^{\left(\frac{\beta_k}{\sigma-1} - 1\right)} d_{jk}^{-\beta_k} f_{jk}^{\left(1 - \frac{\beta_k}{\sigma-1}\right)}} \right) Z_j \tag{21}$$

where T_i captures country i's competitiveness at the extensive and intensive margins,[23] and β_i controls the sensitivity of country i's aggregate exports to trade barriers and to importer's demand shifters according to the following equation:

$$\beta_i \equiv (\sigma - 1) \left(1 + \frac{\chi_i}{\epsilon_i} \right) = (\sigma - 1) \left(1 + \frac{\theta_i + (\sigma-1)(\gamma_i - 1)}{\sigma - 1 - \sigma\gamma_i} \right) > \sigma - 1 \tag{22}$$

The gravity equation (21) differs from the standard formulation featuring Pareto distributions of firm-level productivity in a number of aspects. First, the effect of trade costs on trade flows varies across origin countries. According to expression (22) trade elasticities are lower for exporters with more dispersed technologies (lower θ_i) and less steep correlated distortions (lower γ_i). Given an increase in trade costs, more distorted economies experiment a larger drop in exports because (i) the proportion of exporting firms that exit the market is higher $\left(\frac{\partial(1/\epsilon_i)}{\partial\gamma_i} > 0\right)$, and (ii) the sales from these marginal firms represent a larger share of aggregate exports $\left(\frac{\partial\chi_i}{\partial\gamma_i} > 0\right)$. To this extent, a reduction in γ_i will work just like a reduction in export costs.

[23] $T_i \equiv \bar{T}_i \left(\frac{b_i^\sigma m^{1-\sigma}}{w_i^\sigma \sigma} \right)^{\frac{\chi_i}{\epsilon_i}}$.

Second, the trade elasticity with respect to variable trade costs reflects both extensive and intensive margin effects. Although trade models with heterogeneous firms generically exhibit this characteristic, the assumption of Pareto (or Frechet) heterogeneity usually entails trade elasticities that are independent from intensive-margin parameters - see 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 correlated distortions. Finally, the variation in firm size distribution across exporters implies that trade shares depend on importer's spending level, yielding nonhomothetic aggregate demands.

Without loss of generality, we can assume $w_i = 1$ and use expression (21) to write country i's equilibrium output per worker as[24]

$$c_i \equiv \frac{C_i}{L_i} = \bar{K} \quad \underbrace{s_{ii}^{\frac{-(1-\alpha)}{\beta_i}}}_{\text{Gains from Trade}} \quad \underbrace{M(\gamma_i, \theta_i, f_i^e) A_i^{1-\alpha}}_{\text{Closed-Economy TFP}} L_i^{\frac{1-\alpha}{\sigma-1}} \tag{23}$$

where $\bar{K}$ is a constant that does not influence international productivity differences.[25] Equation (23) offers a rich description of the aggregate TFP in an open economy. As in Arkolakis et al. [2012], the contribution of trade depends on only three sufficient statistics: (i) the size of the tradable sector $(1-\alpha)$, (ii) the trade elasticity with respect to variable trade costs (β_i), and (iii) the share of expenditure on domestic goods (s_{ii}), which is an inverse measure of trade openness. The closed-economy component of TFP comprises the state of technology (A_i) and the function $M(\gamma_i, \theta_i, f_i^e)$, which encapsulates the closed-economy effects of the entry, selection and allocation channels discussed earlier.[26] Using the equation above I decompose the total effect of correlated distortions on output per worker as follows:

$$\underbrace{\frac{\partial log(c_i)}{\partial \gamma_i}}_{\text{Total Effect}} = \underbrace{\left(log(s_{ii}) \frac{(1-\alpha)}{\beta_i^2} \frac{\partial \beta_i}{\partial \gamma_i} - \frac{(1-\alpha)}{\beta_i} \frac{\partial log(s_{ii})}{\partial \gamma_i} \right)}_{\text{Trade Channel}} + \underbrace{\frac{\partial log(M(\gamma_i, \theta_i, f_i^e))}{\partial \gamma_i}}_{\text{Closed-Economy Effect}} \tag{24}$$

According to equation (24), correlated distortions affect the gains from trade through two components. The first term captures the fact that a less distorted economy is better at reaping the reallocation gains from trade or, equivalently, at converting trade into welfare $\left(\frac{\partial \beta_i}{\partial \gamma_i} > 0 \right)$. Therefore, the gains from trade increase after a reduction in domestic distortions even if trade openness is unchanged.

[24] The mathematical appendix contains a detailed derivation of this result.

[25] $K \equiv \alpha^{\alpha} (1-\alpha)^{(1-\alpha)} (1-\alpha)^{\frac{1-\alpha}{\sigma-1}} \left(\frac{1}{\sigma m^{(\sigma-1)}} \right)^{\frac{(1-\alpha)}{\sigma-1}}$

[26] $M(\gamma_i, \theta_i, f_i^e) \equiv \left(\frac{\epsilon_i}{\chi_i f_i^e} \right)^{\frac{1-\alpha}{\beta_i}} \left(\frac{\theta_i + \gamma_i}{\theta_i} \right)^{\frac{(1-\alpha)(\sigma(\theta_i - 1)+1)}{(\sigma-1)(\theta_i - \gamma_i)}}$.

The second component represents the effect of distortions on trade openness itself. Differently from the first term, its sign is not determined analytically. On the one hand, the reduction in distortions is to some extent equivalent to a positive technological shock, which reduces the economy's terms of trade and increases the demand for the domestic product, thereby reducing 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 firm size relative to export costs, which in equilibrium tends to increase trade openness $\left(\frac{\partial log(s_{ii})}{\partial \gamma_i} > 0\right)$. Therefore, the contribution of the trade channel to the aggregate losses from correlated distortions will ultimately depend on the equilibrium reaction of trade openness to changes in distortions.

To gain intuition about the interplay between distortions to firm size, selection, and trade costs, it is instructive to analyze the trade channel in a model without fixed costs. In this model the trade elasticity is constant across exporters ($\beta_i = \sigma - 1$) and the gains from trade no longer stem from factor reallocations across domestic firms. Since all firms sell to all markets, steeper correlated distortions does not play a role at reducing access to exporting. In this scenario, a superior micro allocation is isomorphic to a better aggregate technology, whose gains in an open economy are moderated by the depreciation of terms of trade.

4 Taking the Model to the Data

I divide the calibration of the model into three sequential steps. In the first part, I estimate distortions schedules ($\{\gamma_i\}_{i=1}^N$) for a large cross-section of countries using establishment-level data for the manufacturing sector. The next step recovers the dispersion of TFPQ ($\{\theta_i\}_{i=1}^N$) from estimates of exporter-specific trade elasticities ($\{\beta_i\}_{i=1}^N$) according to equation (22). The third part combines data on labor force, entry costs and geography 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 as: (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 Distortion Schedule

The establishment-level data come from the World Bank's Enterprise Survey (WBES) version 2016. The WBES is an ongoing research project to collect establishment-level data 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 in 52 ISIC 2-digit sectors, with a larger coverage of manufacturing industries. The dataset spans the whole spectrum of the world income distribution, including OECD countries (Spain, Israel, Sweden and Ireland), big emerging economies (Brazil, Russia, India, China and Indonesia) and developing countries (Nigeria, Cambodia and Bolivia). A well-known feature of this dataset is that it tends to oversample large firms. Despite being a disadvantage in other contexts, this characteristic is actually a strength for the purposes of this study, which focus on the constraints faced by large producers.

The dataset contains standardized establishment-level information on: total sales, spending on raw materials and intermediate goods, net book value of assets (machinery, vehicles, land and buildings) and total cost of labor (including wages, salaries, bonuses and social security payments).[27] To focus on domestic distortions, the benchmark estimation only includes firms whose domestic sales comprise at least 95% of total sales. Appendix (A) describes in detail the data and the construction of the final sample.

To estimate distortion schedules I first need to calculate establishment-level measures of physical and marginal productivity as in Hsieh and Klenow [2009]. I define physical productivity of firm i in sector s as

$$TFPQ_{si} \equiv \omega_{si} = \frac{Y_{si}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}} \tag{25}$$

where the country index has been suppressed for notational simplicity. Although labor is the sole factor of production in the theoretical model, I include physical capital in the empirical analysis in order to get more precise estimates of establishment productivity. Combining the production function above with the optimality condition of a non-exporting firm we have

$$\frac{(P_{si}Y_{si})^{\frac{\sigma}{\sigma-1}}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}} = P_s^{\frac{\sigma}{\sigma-1}} Y_s^{\frac{1}{\sigma-1}} \omega_{si} \tag{26}$$

where P_s and Y_s are the price and output CES aggregators of industry s. Therefore, with establishment-level data and values for σ and α_s, we can identify establishment i's TFPQ up to a sectoral constant.[28] $P_{si}Y_{si}$ is measured as value added (sales minus spending with intermediate inputs and raw materials); L_{si} is total wage bill - using wages instead of number of workers provides an implicit control for cross-establishment differences in

[27] Recent papers have used WBES to infer measures of productivity dispersion and distortions. See Asker et al. [2014] and Bento and Restuccia [2016].

[28] The advantage of this procedure is that it allows me to recover establishment physical productivity without data on establishment prices. However, since it relies on strong assumptions on demand and market structure, it is less robust to model misspecification.

human capital; and K_{si} is the net book value of assets. I assume $\sigma = 3$ and use the U.S labor shares $\{1-\alpha_s\}_{s=1}^{S}$ from the NBER Productivity Database complemented by estimates from Gollin [2002].[29] [30]

In a similar fashion, one can use establishment i's revenue productivity to recover its idiosyncratic distortion (τ_{si}) as follows:

$$TFPR_{si} \equiv \frac{P_{si}Y_{si}}{K_{si}^{\alpha_s}L_{si}^{1-\alpha_s}} = \frac{\lambda_s}{\tau_{si}} \tag{27}$$

where $\lambda_s \equiv m\left(\frac{r}{\alpha_s}\right)^{\alpha_s}\left(\frac{w}{(1-\alpha_s)}\right)^{1-\alpha_s}$. Armed with the two measures of productivity, I estimate a stochastic version of equation (8) by running for each country j the following regression:[31]

$$log\left(\frac{TFPR_{si}^{j}}{\overline{TFPR}_{s}^{j}}\right) = \beta_0^j + \gamma_j log\left(\frac{TFPQ_{si}^{j}}{\overline{TFPQ}_{s}^{j}}\right) + \epsilon_i^j \tag{28}$$

Given my focus on correlated distortions, I attribute no structural role to the error term of the regression above. Therefore, I interpret the share of the within-industry variation of TFPR not explained by variation in TFPQ simply as statistical noise. This approach differs from Hsieh and Klenow [2009] to the extent that they consider all the observed within-industry variation of TFPR as structural wedges that misallocate resources across firms.

Figure (6) illustrates the cross-country variation in the estimated distortion schedules. There is a clear negative relationship between distortions and aggregate labor productivity. Rich countries present the smallest coefficients. For instance, the US slope is .09 and the slopes of other OECD economies vary from .17 (Spain) to .25 (Sweden). The schedules in middle income countries concentrate in a range from .3 (Brazil) to .5 (Turkey). Finally, the least productive countries in the sample tend to present slopes above .5. This is the case for many economies in Sub-Saharan African and Southeast Asia. A similar negative relationship holds when aggregate TFP is used as a measure of productivity.

My estimates are close to estimates based on 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. This is reassuring that the WBES dataset is indeed providing

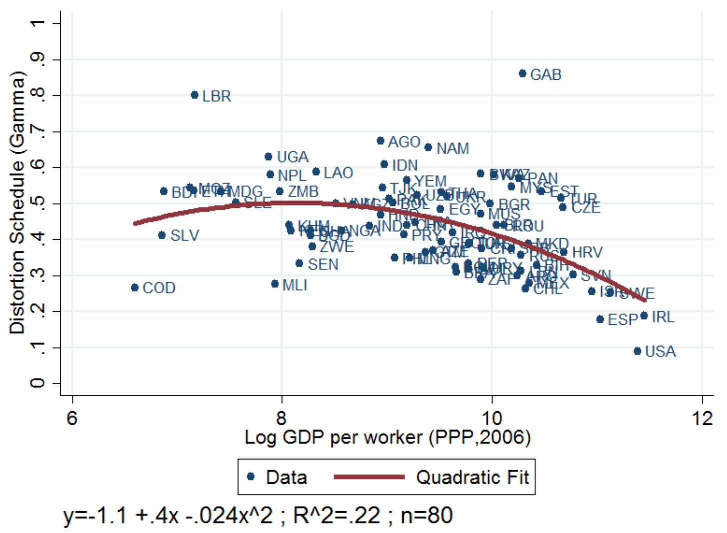
[29] The value of the elasticity of substitutions is the same used in Hsieh and Klenow [2009] and it is close to the 2.98 estimated in Eaton et al. [2011].

[30] Output-labor elasticities are equal to labor shares in an imperfectly competitive environment only under the assumption that monopoly rents are distributed to capital and labor accordingly to their output elasticities.

[31] Where I have defined $\overline{TFPQ}_s \equiv \left(\sum_i TFPQ_{si}^{(\sigma-1)}\right)^{\frac{1}{\sigma-1}}$ and $\overline{TFPR}_s$ is the weighted average of $TFPR_{si}$ with weights given by firm i's share of industry's value added.

a good approximation of firm and industry performance across countries. In Appendix (A), I show that the estimates above are robust to different sample definitions.

Figure 6: Distortion Schedule and Output per Worker



Note Estimates are the within-sector elasticity between firms' $TFPR$ and $TFPQ$. I only include countries with sample size above 90 observations after trimming outliers. The median number of observations per country is 249 and the average is 426. All regressions include time fixed effects. Observations are weighed according to establishment revenue. The estimate for the US economy comes from Hsieh and Klenow [2014].

4.2 Dispersion of TFPQ and Trade Elasticities

The second step of my calibration procedure consists of recovering the parameters that control the dispersion of TFPQ $(\{\theta_i\})_{i=1}^{N}$. I do that by first estimating the structural gravity equation (21), which yields estimates of the trade elasticity with respect to trade costs $(\{\beta_i\}_{i=1}^{N})$. I then combine these estimates with the distortion schedules from the first step to arrive at the measures of TFPQ dispersion. I use data on bilateral manufacturing trade flows in 2006 from COMTRADE. Manufactures correspond to digits 151 through 372 of ISIC Rev. 3. There are 21,942 observations, featuring 160 origin countries and 138 destination countries. Import tariff data is from UNCTAD's *Trade Analysis Information System* (TRAINS). 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 them 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 employ Mayer and Zignago [2006] data on bilateral geographic variables - geographic distance, shared borders and common official language

- as controls.

Using the price equation (11), we can rewrite the gravity equation (21) in a more convenient form:

$$X_{ji} = T_i(Z_j^{\frac{1}{\sigma-1}} P_j f_{ji}^{\frac{-1}{\sigma-1}})^{\beta_i} d_{ji}^{-\beta_i} f_{ji} \tag{29}$$

In order to estimate the equation above, I need to assume functional forms for d_{ji} and f_{ji}. Following Caliendo and Parro [2014], I model iceberg trade costs as a loglinear function of tariffs and transportation costs:

$$d_{ji} = (1 + t_{ji})exp(x_i^d + m_j^d + \mathbf{z}_{ji}'\delta^d) \tag{30}$$

where t_{ji} is the *ad-valorem* import tariff, x_i^d is the exporter's fixed effect, m_j^d is the importer's fixed effect, and z_{ji} is a vector of observed geographic trade barriers. Note that tariffs enter the model only as cost shifters on imported goods and do not generate tariff revenue.[32] In a similar vein, I model fixed trade cost as a function of exporter and importer fixed effects, geography and unobserved trade barriers as follows:

$$f_{ji} = exp(x_j^f + m_i^f + \mathbf{z}_{ji}'\delta^f + \bar{\epsilon}_{ji}) \tag{31}$$

These two specifications are very flexible. In particular, the presence of both importer and exporter fixed effects allows for a rich pattern of asymmetric bilateral trade costs. Plugging these equations into the structural gravity and taking logs we get the following estimating gravity equation

$$\tilde{X}_{ji} = \Pi_i + \xi_j + \beta_i\zeta_j - \beta_i log(1 + t_{ji}) + \mathbf{z}_{ji}'\delta_i + \epsilon_{ji} \tag{32}$$

where $\{\Pi_i, \beta_i, \delta_i\}_{i=1}^N$ 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 the error term reflecting unobserved trade barriers - which I assume is mean independent from the systematic component. The novel feature of the equation above is the nonlinear term $\beta_i\zeta_j$. It reflects the fact that the structural terms contained in the importer fixed effect ζ_j, like market size, price, and importer-specific trade costs, affect aggregate imports according to the firm size distribution of the origin country. This term, combined with variation in tariffs, will help to identify $\{\beta_i\}_{i=1}^N$. 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 iterative steps. The first step estimates a vector β *given* a vector ζ through an OLS regression - in this step 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 $\zeta^{(0)} = 0$, the bilateral variation in tariffs identifies $\beta^{(1)}$. This step also produces residuals $\hat{\epsilon}_{j,i}^{(1)}$.

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

The second step calculates $\zeta^{(1)}$ 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) $\zeta^{(2)}$ relatively to $\zeta^{(1)}$. Intuitively, if country j imports relatively more from high elastic 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 identify $\beta^{(2)}$ and so on and so forth. The estimator stops when a fixed point is achieved. I show in Appendix (A) that the algorithm recovers with precision the vector of trade elasticities in Monte Carlo experiments.

Table (2) displays the estimates of the heterogeneous model and compares them with those from the traditional model, which constrains trade elasticities to be constant across exporters. The heterogeneous estimator fits the data better than the standard model, as evidenced by the F-Test. The gain in goodness-of-fit is approximately 4%. This is a nontrivial improvement if 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 Eaton and Kortum [2002] preferred estimate - 8.28 - but way above the ballpark of estimates for manufacturing trade among developed countries found by recent research. For example, Eaton et al. [2011] and Caliendo and Parro [2014] find numbers between 4 and 5.

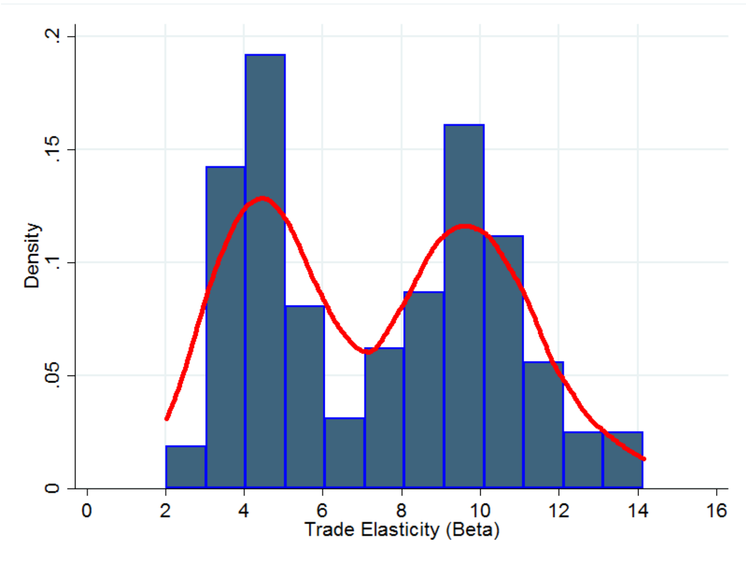
Table 2: Estimates of Trade Elasticities

	Homogeneous	Heterogeneous
Min	8.85	2.03
Max	8.85	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 robust to heteroskedaticity. The F-test rejects the hypothesis of equivalence between the two models at 1% 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.

Figure (7) starts to unveil the cause of that apparent discrepancy. The distribution of trade elasticities is bi-modal with one peak around 4 and another peak around 10. According to these results, the export side of manufacturing trade is basically characterized by two sets of countries: (i) low-elastic exporters; (ii) high-elastic exporters. This bimodality resembles the results in Fieler [2011] and Lashkaripour [2015]. However, there are two central differences between my methodology and theirs. First, these papers assume that aggregate trade flows are composed by two broad categories of goods whose trade elasticities differ because of technology or markup differences. In their framework, cross-country variation in elasticities emerge because countries select into production of different types of goods, e.g, raw materials vs manufactures. Second, the identification of differences in elasticities in their gravity models depends fundamentally on the assumption of symmetric trade costs. Under symmetry, a low volume of exports is automatically attributed to higher trade elasticity instead of higher export costs.

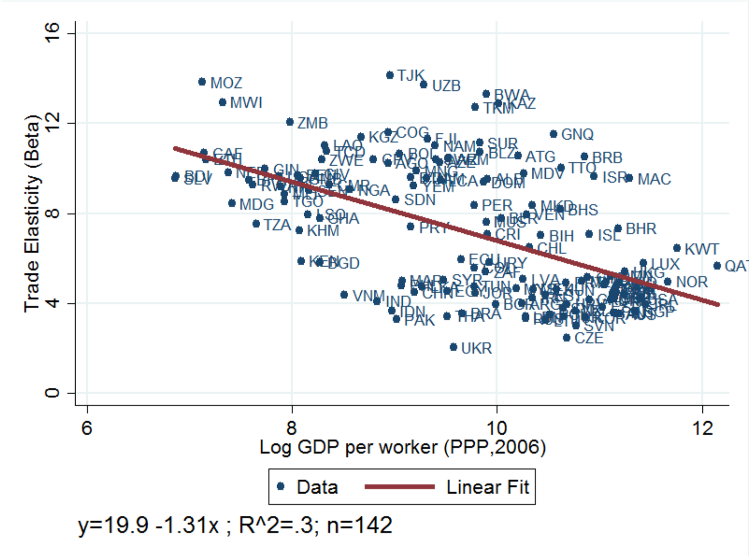
Figure 7: Distribution of Trade Elasticities



Note Blue bars represent the density on unit intervals of elasticities. The red line is the kernel density estimate. Sample size=160 countries

Figure (8) shows that elasticities covary systematically with output per worker. Low elastic exporters tend to be advanced countries, whereas high elastic 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. One natural concern is that the relationship between aggregate productivity and trade elasticity is being driven by cross-country differences in industry composition within the manufacturing sector. I address this issue in Appendix (A) and I find little evidence supporting this alternative explanation. With values of $\{\gamma_i, \beta_i\}_{i=1}^{N}$ in hand, I use equation (22) to calculate the dispersion of TFPQ $\{\theta_i\}_{i=1}^{N}$. In other words, I choose the dispersion of TFPQ such that the elasticities in the model match the empirical elasticities.

Figure 8: Trade Elasticity and Aggregate Productivity



Note Output per worker is measure in PPP exchange rates from PWT 8.0. Sample size=142 countries.

Trade Elasticities, Exporter Size Distribution, and Correlated Distortions

Before continuing with the calibration I investigate more closely the determinants of the cross-country variation in trade elasticities. According to the theoretical model, the elasticities estimated with aggregate data should reflect characteristics of the underlying firm size distribution. In particular, the model predicts that: (i) countries with low trade elasticities should have a distribution of exports more dispersed and more skewed toward large firms; (ii) countries with higher correlated distortions tend to present higher trade elasticities.

I test the first prediction by regressing moments of the empirical distribution of firm-level exports from World Bank's EDD on trade elasticities. The sales distributions are available at three different levels of aggregation: origin, origin-destination, and origin-destination-sector. Consistent with the theory, low-elastic origin countries tend to present sales distributions that are both both more dispersed and more skewed towards the largest exporting firms. Table (3) shows that a two-fold 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 (4) reveals that these correlations persist at the origin-destination level. For instance, given a two-fold 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 (5) 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 (3) and (4) but not in table (5). The coefficient for average sales also changes sign according to the level of aggregation. Finally, although trade elasticities correlate negatively with the share of top 5% largest exporting firms, the coefficient is not statistically significant.

Table 3: Trade Elasticity and Exporter Size Distribution: Origin Level

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Number of Exporters	Mean Sales	Sales Dispersion	Share of Top 1%	Share of Top 5%
Trade Elasticity	-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 Coefficients 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.

Table 4: Trade Elasticity and Exporter Size Distribution: Origin-Destination Level

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Number of Exporters	Mean Sales	Sales Dispersion	Share of Top 1%	Share of Top 5%
Trade Elasticity	-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 Coefficients 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.

Table 5: Trade Elasticity and Exporter Size Distribution: Origin-Destination-Sector Level

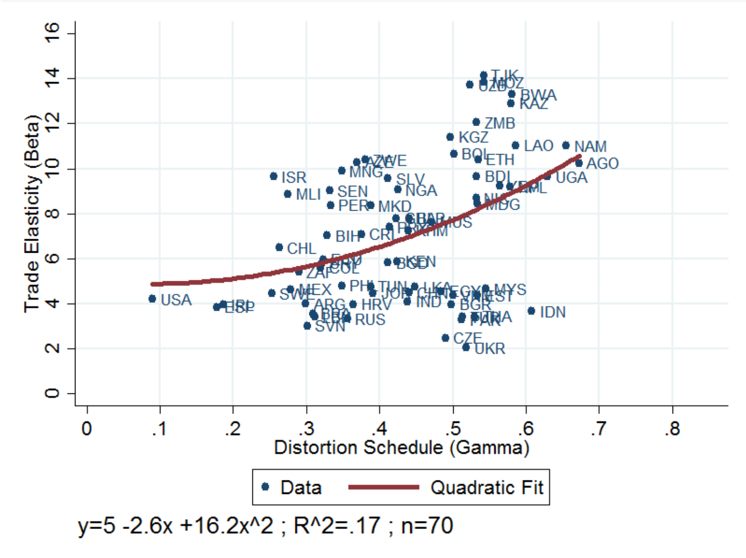
VARIABLES	(1) Number of Exporters	(2) Mean Sales	(3) Sales Dispersion	(4) Share of Top 1%	(5) Share of Top 5%
Trade Elasticity	0.937***	-0.394***	-0.117***	-0.0201***	-0.00328
	(0.0342)	(0.0488)	(0.0156)	(0.00663)	(0.00558)
Observations	26,779	26,779	26,779	26,779	26,779
R-squared	0.583	0.609	0.359	0.269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

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

Note Coefficients 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.

Figure (9) shows that the data are consistent with the model's prediction about the connection between correlated distortions and trade elasticity. Countries with steeper distortion schedules, as revealed by the firm-level data, tend to present aggregate exports that are more sensitive to trade costs. An increment of one standard deviation in the distortion schedule increases the average trade elasticity by .44 standard deviation. Controlling for variation in the dispersion of TFPQ observed in the establishment-level data practically does not affect this relationship - the coefficient drops from .44 to .41.

Figure 9: Trade Elasticity and Correlated Distortions



Note Horizontal axis measures correlated distortions from establishment-level data. Vertical axis measures trade elasticities from the nonlinear gravity equation. Sample size=70 countries.

4.3 Technology and Trade Costs

In this subsection I complete the calibration of the model. I add to the dataset described above data on gross manufacturing production from UNIDO *Industrial Statistics Database*, and data on entry costs and labor force from the World Bank's *Doing Business Survey* (WBDB) and from the World Bank's *Development Indicators* (WBDI). The final sample contains 77 countries that correspond to more than 90% of the world output and trade.[33] The basic idea of this part is to find a sequence $\{A_i, d_{ji}, f_{ji}\}_{i=1}^N$ such that the model's trade shares $(\{s_{ji}\})_{i=1}^N)$ match the empirical ones.[34]

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 a value of α to calculate total spending of the tradable sector $(\{(1-\alpha)Y_i\}_{i=1}^N)$ and model-consistent trade flows $(\{X_{ji}\}_{i,j=1}^N)$. The parameter α is the share of the labor force employed in the nontradable sector and a common choice in the literature is $\alpha = .7$. I then rewrite the gravity equation in the following form

$$X_{ji} = T_i (V_j)^{\beta_i} D_{ji} \tag{33}$$

[33]The distortion schedule is 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 distortion across the OECD countries for which I have estimates. The fact that the trade elasticities among this group are very similar reassures that this procedure is a good approximation.

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

where I have defined $V_j \equiv Z_j^{\frac{1}{\sigma-1}} P_j$ and $D_{ji} \equiv d_{ji}^{-\beta_i} f_{ji}^{\left(1-\frac{\beta_i}{\sigma-1}\right)}$. Using the balanced trade condition and normalizing $D_{ii} = 1\ \forall i$, one can find $\{T_i\}_{i=1}^N$ and $\{D_{ji}\}_{i,j=1}^N$ that solve the system of equations above.[35] At this point, T_i is a just a convolution of known variables and the unknown parameter A_i, which can then be found by a simple inversion. The term D_{ji}, however, depends on the trade elasticity and on two unknown parameters: d_{ji} and f_{ji}.

I solve this indeterminacy by 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 an known function, which is 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 known, one can recover f_{ji} by inverting the D_{ji} equation.

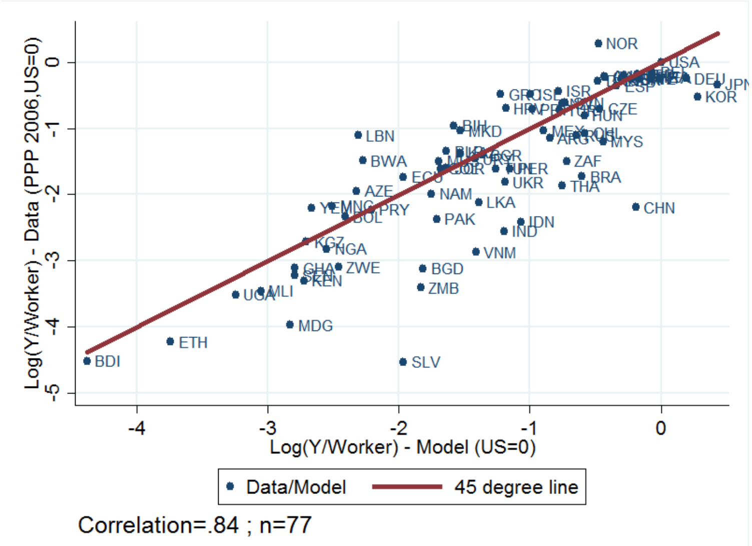
4.4 Model's Fit

Having calibrated the model to match perfectly the empirical bilateral trade shares, trade elasticities, and distortion schedules, I next study the model's ability to predict untargeted moments. The model successfully replicates the distribution of PPP aggregate output per worker, with a correlation in logs of 0.84. This goodness of fit is achieved despite the assumption of no international differences of technologies in the nontradable sector. Therefore, productivity differences in the tradable sector go a long way in explaining international differences in aggregate output per worker. Figure (10) gives a visual representation of the model's performance along this dimension. In general, the dots cluster around the 45-degree line. However, the model tends to overpredict aggregate productivity in some developing countries (for example, China). Since the parameters were chosen to match trade performance in manufactures, this discrepancy might be due to the fact that in those countries a considerable share of employment is in primary sectors with low labor productivity, like mining and agriculture.[36] This force contributes for the model to underpredict the international dispersion of productivity, as evidenced in Table (6).

[35] See the appendix for a detailed derivation of this result.

[36] See Lagakos and Waugh [2013].

Figure 10: Output per Worker: Model and Data



Note Output per worker is measure in PPP exchange rates from PWT 8.0. Both measures are relative to the US. Year 2006. Sample size=77 countries.

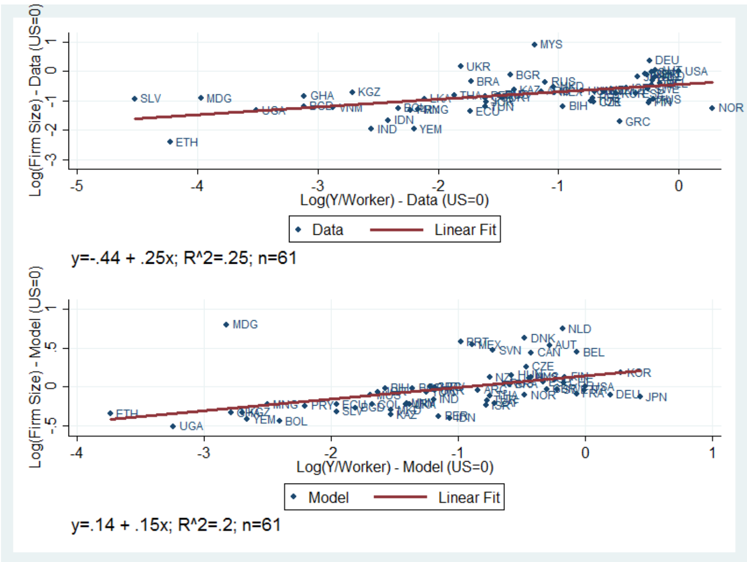
Table 6: Output per Worker: Model and Data

	Data	Model
Mean	0.358	0.409
Coef.of Variation	0.852	0.822
Var(log)	1.42	1.04
p90/p10	21.1	12.9

Note Output per worker is measured relative to US. Sample size=77 countries

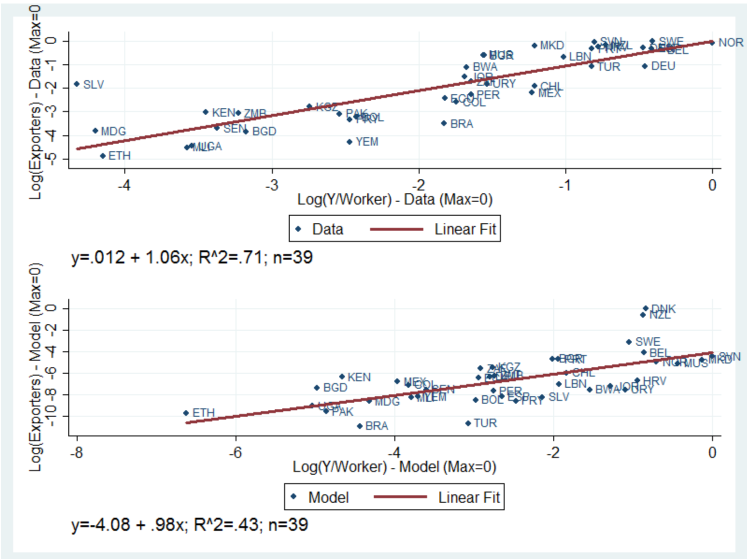
At the disaggregate level, the model correctly predicts the positive association between average firm size in manufacturing and output per worker. Figure (11) displays this relationship in the data and in the model. Firm size is measured as the average number of persons engaged per establishment. The elasticity is .25 in the data and .15 in the model. Moreover, variation in productivity predicts 25% of the variation in firm size in the data and 20% in the model. For a sample of 39 countries, I have information on the number of firms with positive exports sales in the period 2006-2009. In the data there is a strong positive correlation between aggregate productivity and number of exporting firms (net of population size), with a 10% rise in the former leading to a 10% increase in the latter. The model delivers a very similar elasticity (.98).

Figure 11: Output per Worker and Firm Size: Model and Data



Note Output per worker is measure in PPP exchange rates from PWT 8.0. Firm size is measured as number of persons engaged from Bento and Restuccia [2016]. Sample size=61 countries.

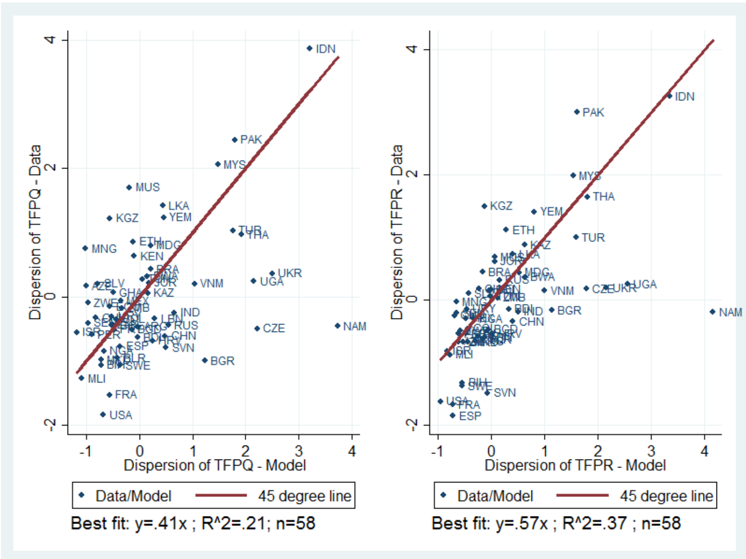
Figure 12: Output per Worker and Export Participation: Model and Data



Note Output per worker is measure in PPP exchange rates from PWT 8.0. Export participation is number of exporting firms net out of population size. Number of exporters is from World Bank's EDD. Sample size=39 countries.

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 controls the dispersion of TFPQ in country i. Since this parameter was chosen to match i's trade elasticity β_i, we can use the correlation between dispersion of TFPQ in the model and in the data as an out-of-sample test. Figure (13) shows that the model's has a fair predictive power on this dimension. An increase of one standard deviation of dispersion of TFPQ in the model is associated with a change of .41 standard deviation in the data. Moreover, the variation produced by the model captures 21% of the empirical variation. The model's performance is even stronger for the dispersion of TFPR. The theoretical variation explains 37% of the empirical one, and the slope of a regression of the standardized measure of empirical dispersion on model's dispersion is .57.

Figure 13: 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.

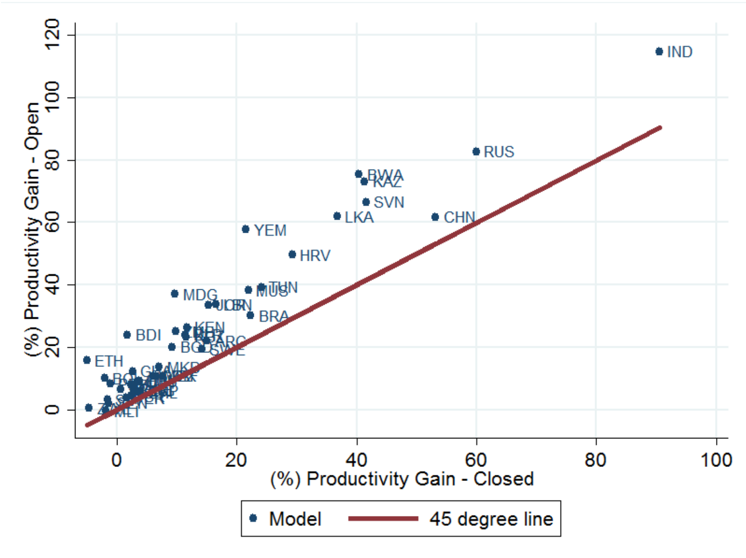
5 Counterfactuals

Correlated Distortion, International Trade, and Aggregate Productivity

The first goal of this section is to quantify the trade channel of domestic distortions, i.e, to evaluate by how much international trade influences the aggregate TFP losses stemming from correlated distortions. I perform this measurement by endowing countries with the "US efficiency" ($\gamma_{US} = .09$) and computing the new general equilibrium in two scenarios: closed economy and costly international trade. The US benchmark is a useful one because because part of the observed positive correlation between TFPQ and TFPR might be due to overhead or adjustment costs and not to policy or market failures.[37] Moreover, a positive correlation might be due to the fact that more productive firms charge higher markups as emphasized by Peters [2013]. Markup dispersion is also a distortion, of course, but in this case a positive correlation does not mean that more productive firms are facing larger constraints to growth, but that they are optimally restricting their production instead. Therefore, my experiment assumes that the difference $\gamma_i - \gamma_{US}$ exclusively reflects distortions to firm growth and not cross-country differences in the domestic competitive environment.

I only include in this exercise countries that respect the following conditions: (i) have observed - as opposed to inferred - distortion schedules, and (ii) satisfy the stability condition (12) at $\gamma_i = \gamma_{US}$. 46 out of 77 countries satisfy the two requirements.[38] Each counterfactual equilibrium is separately calculated for each of the 46 countries in order to avoid that institutional improvements in one economy affect, through trade, welfare elsewhere. Figure (14) presents the results.

Figure 14: Gain in Output per Worker: Closed vs Open Economy



Note Gain in aggregate output per worker from converging to the US distortion schedule. The horizontal axis measures the gain in a closed economy. The vertical axis represents the gain when we allow for trade. Sample size=46 countries.

[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 the fact that there is no considerable variation in distortion schedules within the group of OECD countries with available micro data, 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.

In all countries considered, the trade channel significantly multiplies the aggregate gains from converging to the US distortion schedule. The cross-country average gain is 27% in the trade equilibrium but only 14% in the closed-economy case, corresponding to an approximately two-fold amplification. A similar conclusion holds for the median impact of distortions - 18% with trade and 7% without it. The average trade channel - defined as the cross-country mean ratio between a country's gains from reducing distortions with and without trade - is 70%. The full effect of distortions on aggregate TFP is highly heterogeneous across countries. At the high end of the gain spectrum are big emerging countries like Brazil (30%), China (62%), Russia (83%) and India (114%), and transition economies like Slovenia (67%) and Croatia (50%), whereas relatively low-distorted economies like Israel (4%), Chile (5%) and Spain (6%) comprise the low end of the spectrum - see Table (18).

It is informative to compare my estimates with some quantitative results from the literature. In the closed-economy case, I find productivity gains of 53% for China and 90% for India. Hsieh and Klenow [2009] calculate gains between 30% and 50% in China and 40% and 60% in India. While my numbers are greater than theirs, a priori it is not evident that that must be the case. On the one hand, they consider the TFP effects from eliminating *all idiosyncratic wedges*, including both correlated and uncorrelated distortions, while my analysis is restricted to the correlated case. On the other hand, my model includes entry and selection mechanisms, while theirs only examines reallocation effects.

Closer to my closed-economy model is Bartelsman et al. [2013], who also quantify the entry, selection and reallocation effects of correlated distortions. They calculate welfare gains from converging to the "US efficiency" of 7% for the United Kingdom, 3% for Germany, 4% for France, and 3% for Netherlands. In my framework the counterparts of those estimates are: 8%, 5%, 7%, and 3%.[39]

Table (7) decomposes the full effect of correlated distortions into two channels: entry (firm creation) and selection/reallocation. The rise in the creation of firms explains 25% of the average effect in the closed-economy case, and only 13% in the trade equilibrium. In addition to its relatively minor quantitative importance, the entry channel virtually does not interact with international trade. The panel on the left-hand side of figure (15) illustrates this point. In fact, trade slightly lessens the productivity gains from a larger mass of domestic firms. Intuitively, in a open economy part of these gains is transferred to foreigners through depreciation of terms of trade.

Superior firm selection and improved labor allocation among surviving firms explain the bulk of the total gains. Moreover, as indicated in the right-hand-side panel of figure (15), these two mechanisms totally account for the amplification effect due to trade - see also Table (18).

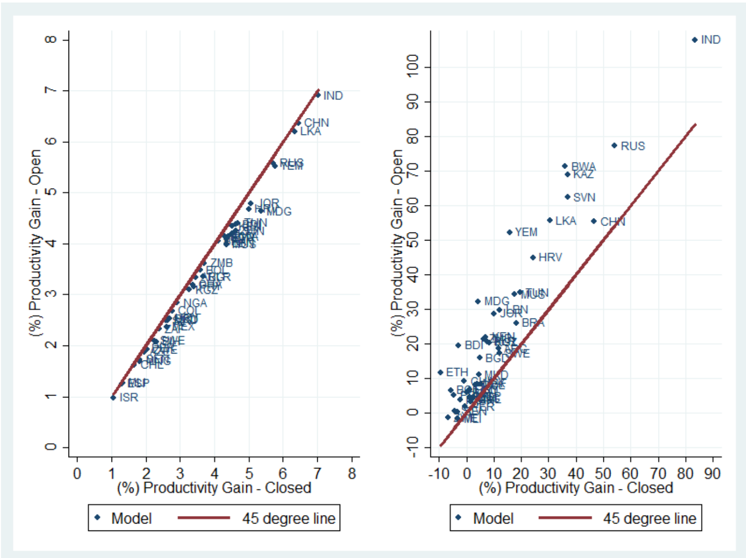
[39] These countries are not included in my baseline exercise because their distortion schedules are based on the average schedule of the OECD group with available micro data.

Table 7: Average Gain in Output per Worker: Decomposition

	Total Effect	Entry	Selection + Reallocation
Closed	14.4	3.57	10.9
Open	26.7	3.39	23.3

Note First column presents the cross-country average gain (%) 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.

Figure 15: Gain in Output per Worker: Decomposition

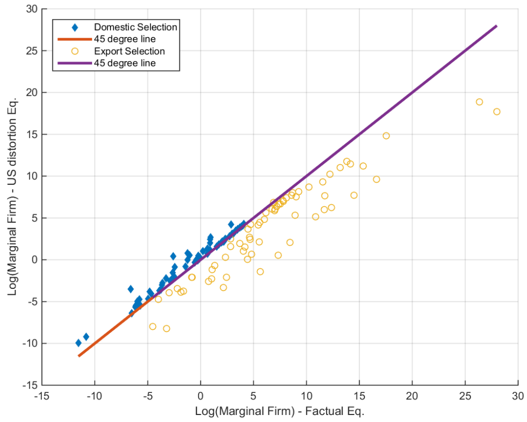


Note The left-hand side panel presents the gains in output per worker from the effect of correlated distortions on the creation of firms. The right-hand side panel shows the gains from the selection and reallocation channels from correlated distortions.

Figure (16) sheds lights on the micro-level impacts of converging to the US distortion schedule. It analyzes the marginal firms that access domestic and export markets at the distorted and at the undistorted equilibria. The blue diamonds represent the TFPQ of marginal domestic firms, and the yellow circles are the cross-destination averages of TFPQ of marginal exporting firms. The diamonds lie above the 45° degree line, which represents an improvement in domestic selection. Intuitively, some low productive firms exit the market at the new equilibrium, releasing labor to more productive producers. At the same time, the circles locate below the 45° line, meaning that new firms start exporting, thereby absorbing labor from less productive firms. Precisely for intensifying theses processes of reallocation and selection, international trade amplifies the aggregate gains from a reduction in correlated distortions.

I close this subsection by using equation (24) to further decompose the trade channel into its two subcomponents: allocation effect and trade creation. While the former reflects the growth in gains from trade caused by reducing distortions given the initial level of trade openness, the latter represents the increase in gains from trade because the economy starts trading more in proportion to its income. Table (19) presents the results. On average, the allocation effect corresponds to 63% of the trade channel. Trade creation corresponds to the remaining 37%, but its importance strongly decreases in initial trade openness.

Figure 16: US schedule equilibrium: Harder to Survive, Easier to Export



Note The horizontal axis represents the threshold productivity in the factual equilibrium. The vertical axis is the threshold productivity in the counterfactual equilibrium with the US distortion schedule. Export selection measures the simple average of threshold productivities across destinations.

Correlated Distortions, Trade and Cross-Country Income Differences

What is the contribution of correlated distortions to cross-country differences in output per worker? How does it interact with international trade? To answer these questions I compute the world equilibrium in which *all countries* have converged to the US distortion schedule. I perform this exercise both in the baseline scenario, where countries are allowed to trade at the calibrated trade costs, and in the autarky case, in which the world is formed by a set of isolated economies.[40] 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.

Table (8) presents the results. First, a move from the observed trade equilibrium to

[40] 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.

a world without trade would leave the international dispersion of productivity virtually unchanged - the variance of log of output per worker goes from 1.04 to 1.02. Second, the convergence in schedules does little to reduce the international productivity differences when the economies are closed to international trade. In this case, the 90/10 percentile ratio decreases by only 2% and the variance of log of output per worker actually increases by almost 5%. On the other hand, once we allow for international trade, the reduction in international productivity differences reaches approximately 50%. Therefore, the convergence in schedules benefits poor countries relatively more mainly because it helps them reap larger unrealized gains from trade.

Table 8: Distortions, Trade, and International Income Distribution

	Mean	Var(log)	p90/p10
Baseline-Trade	4.3	1.04	12.9
Counterfactual-Trade	6.63	0.526	6.7
Change (%)	54.3	-49.3	-47.9
Baseline-Closed	4.09	1.02	12.7
Counterfactual-Closed	4.51	1.07	12.4
Change (%)	10.3	4.76	-2.27

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.

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, can be eliminated by trade liberalization policies. According to table (9), eliminating this asymmetry in bilateral trade costs reduces income dispersion by 34%. Therefore, my results suggest that the convergence in domestic institutions is quantitatively more important to reduce the international gaps in labor productivity than the convergence in trade policies.

Table 9: Distortions, Bilateral Trade Barriers, and International Income Distribution

	Mean	Var(log)	p90/p10
Baseline-Trade	4.3	1.04	12.9
Counterfactual-Trade	6.63	0.526	6.7
Change (%)	54.3	-49.3	-47.9
Symmetric Trade Costs	4.95	0.684	8.44
Change (%)	15.1	-34.1	-34.4

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.

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 strands of this literature by analyzing the joint effect of domestic distortions to firm size and international trade barriers on aggregate outcomes. I found that the impact of a particular type of misallocation - specifically misallocation that harms large establishments - is greatly magnified when there is endogenous firm selection into production and export markets. I also found that the cross-country variation in this kind of distortion can contribute to explaining some stylized facts about the differences in export behavior across economies. In particular, correlated distortions can rationalize 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 correlated distortions and international trade is potentially important to explaining cross-country differences in output per worker.

On the methodological side, this paper has meaningfully introduced endogenous firm selection into a quantitative multicountry general equilibrium model of international trade. As highlighted by Arkolakis et al. [2012], gravity models with heterogeneous firms and invariant Pareto distribution deliver the same aggregate predictions as models without firm heterogeneity. I show that by assuming cross-country variation in the firm size distribution, the macro predictions of models with firm heterogeneity are no longer equivalent to those from aggregative models.

My results require many caveats. First, I have recovered establishment-level TFPQ using the full structure of the model. The development of datasets that decompose establishment revenues into quantity and prices can be useful for performing a more robust estimation of physical productivity. Second, for tractability reasons, my analysis is restricted to a one-sector model. It would be interesting to study the connection between domestic distortions and international trade in richer environments - i.e, multi-sectoral models with multiple input-output linkages. Finally, I work with idiosyncratic 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 consists of solving for the mass of entry and the aggregate net revenues in each country 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.

Entry and Revenues

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

$$S_i = \sum_{j=1}^{N} \frac{\kappa_i b_i \theta_i A_i^{\theta_i}}{(\chi_i + \gamma_i)} \left(\frac{m w_i d_{ji}}{b_i} \right)^{1-\sigma} Z_j P_j^{\sigma-1} (\omega_{ji}^*)^{-\chi_i - \gamma_i} \tag{34}$$

Using equation (34), one can express the free-entry condition as:

$$\Pi_i = \frac{S_i}{\sigma} - \frac{S_i(\theta_i - \epsilon_i)}{\sigma \theta_i} - \kappa_i w_i f_i^e = 0 \tag{35}$$

Assuming balanced trade, one can show that the labor market condition is:

$$\frac{S_i}{m} + \frac{S_i(\theta_i - \epsilon_i)}{\sigma \theta_i} = (1-\alpha) Y_i - \kappa_i w_i f_i^e \tag{36}$$

By combining equations (35) and (36) one can show that

$$S_i = (1-\alpha) Y_i = (1-\alpha)(w_i L_i + R_i) \tag{37}$$

Using the balanced trade condition and equation (37) we get:

$$R_i = (1-\alpha) Y_i - (1-\alpha) Y_i = 0 \tag{38}$$

Therefore, $(1-\alpha)Y_i = (1-\alpha) w_i L_i$ and the mass of entrant becomes

$$\kappa_i = \frac{(\sigma - 1 - \sigma \gamma_i)}{\sigma \theta_i f_i^e} (1-\alpha) L_i \tag{39}$$

Price Index

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

$$P_j^{1-\sigma} = \sum_{i=1}^{N} T_i Z_j^{\frac{\chi_i}{\epsilon_i}} P_j^{(\sigma-1)\frac{\chi_i}{\epsilon_i}} d_{ji}^{(1-\sigma)\left(1+\frac{\chi_i}{\epsilon_i}\right)} f_{ji}^{-\frac{\chi_i}{\epsilon_i}} \tag{40}$$

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 latter relationship is controlled by the shape of the exporter's firm size distribution. Since there are differences in the distribution of firm size among 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 1. *If conditions (10) and (12) hold, the price equation has a unique solution for any strictly positive vector of nominal wages which 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 $\Phi(P^*) = 0$. $\square$

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:

$$w_i L_i = \sum_{j=1}^{N} s_{ji} w_j L_j \tag{41}$$

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 proof the existence and uniqueness of the general equilibrium defined earlier. I start by defining the excess aggregate demand $Z_i(w)$ as

$$Z_i(w) = \frac{1}{w_i} \left(\sum_{j=1}^{N} (s_{ji} w_j L_j) - w_i L_i \right) \tag{42}$$

which is defined $\forall\ w \in \mathbf{R}_{++}^{N}$. Defining $Z(w) = (Z_1(w), ..., Z_N(w))$, the next proposition demonstrates the existence of an equilibrium.

Proposition 2. *If conditions (10) and (12) hold, then there is a $w \in \mathbf{R}_{++}^{N}$ such that $Z(w) = 0$.*

Proof. I verify that $Z(w)$ has the following properties:
(i) Z(w) is continuous
(ii) Z(w) is homogeneous of degree zero
(iii) wZ(w)=0 $\forall\ w \in \mathbf{R}_{++}^{N}$ (Walras' Law)
(iv) for $k = max_j L_j > 0$, $Z_i(w) > -k$ 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 $w_i^0 = 0$ for some i, then

$$max_j Z_j(w^m) \to \infty \tag{43}$$

Then the result will follow from Proposition 17.C.1 of Mas-Colell et al. [1995].
(i) Given prices, $s_{ji}(w)$ is a continuous function of continuous function of w and, therefore, continuous. Defining $\forall\ j\ P_j(w)$ as the implicit function derived from the solution of equation 40, 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 $Z(w)$ 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 $\tilde{T}_i(w) \equiv \bar{T}_i(w) w_i^{\sigma-1} \left(\frac{b_i^\sigma m^{1-\sigma}}{\sigma}\right)^{\frac{\chi_i}{\epsilon_i}}$. $P_j(w)$ is determined by the implicit solution of:

$$0 = 1 - \sum_{i=1}^{N} \tilde{T}_i(w) w_i^{1-\sigma-\sigma\frac{\chi_i}{\epsilon_i}} w_j^{\frac{\chi_i}{\epsilon_i}} L_j^{\frac{\chi_i}{\epsilon_i}} P_j(w)^{\beta_i} D_{ji} \tag{44}$$

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

$$0 = 1 - \sum_{i=1}^{N} \tilde{T}_i(w) w_i^{1-\sigma-\sigma\frac{\chi_i}{\epsilon_i}} w_j^{\frac{\chi_i}{\epsilon_i}} L_j^{\frac{\chi_i}{\epsilon_i}} (t^{-1} P_j(tw))^{\beta_i} D_{ji} \tag{45}$$

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:

$$s_{ji}(tw) = \frac{t^{1-\sigma} T_i(w)(Z_j(w)P_j(w)^{\sigma-1})^{\left(\frac{\beta_i}{\sigma-1}-1\right)} D_{ji}}{t^{1-\sigma}\sum_{k=1}^{N} T_k(w)(Z_j(w)P_j(w)^{\sigma-1})^{\left(\frac{\beta_k}{\sigma-1}-1\right)} D_{jk}} = s_{ji}(w) \tag{46}$$

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

$$\sum_{i=1}^{N} w_i Z_i(w) = \sum_j w_j L_j \sum_{i=1}^{N} s_{ji} - \sum_{i=1}^{N} w_i L_i \tag{47}$$

Since $\forall\ j\ \sum_{i=1}^N s_{ji} - 1$, we have: $wZ(w) = \sum_j w_j L_j - \sum_i w_i L_i = 0$.
(iv) For all $w \in \mathbf{R}^N_{++}$, $Z_i(w) = \frac{1}{w_i}\sum_{j=1}^N s_{ji} w_j L_j - L_i > -L_i > -K$.
(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, $\{max_k\{\sum_{j=1}^N s_{jk}^m \frac{w_j^m}{w_k^m}\}\} \to \infty$. $\square$

Having proved the existence, the next step is to show that the solution is unique (up to scale).
Proposition 3. *If conditions (10) and (12) hold, then there is exactly one $w \in \mathbf{R}^N_{++}$ such that $Z(w) = 0$ and $\sum_{i=1}^N w_i = 1$.*

Proof. To establish this result it is sufficient to demonstrate that the function $Z(w)$ satisfies the gross substitution property, i.e, that $\forall\ i,k$ with $i \neq k$ and $\forall\ w \in \mathbf{R}^N_{++}$, $\frac{\partial Z_i(w)}{\partial w_k} > 0$. 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 40 with respect to P_j and w_h we get:

$$\frac{dP_j(w)}{dw_h} = \frac{\frac{\partial T_h}{\partial w_h} Z_j^{\frac{\chi_h}{\epsilon_h}} P_j(w)^{(\sigma-1)\frac{\chi_h}{\epsilon_h}} D_{jh}}{\left((1-\sigma)P_j(w)^{-\sigma} - \sum_{i=1}^N T_i Z_j^{\frac{\chi_i}{\epsilon_i}} D_{ji}(\sigma-1)\frac{\chi_i}{\epsilon_i} P_j(w)^{(\sigma-1)\frac{\chi_i}{\epsilon_i}-1}\right)} \tag{48}$$

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

$$\frac{dP_j(w)}{dw_j} = \frac{(\sigma-1)\left(1+\frac{\chi_j}{\epsilon_j}\right) w_j^{-1} T_j Z_j^{\frac{\chi_j}{\epsilon_j}} P_j(w)^{(\sigma-1)\frac{\chi_j}{\epsilon_j}} D_{jj}}{(\sigma-1)\left(P_j(w)^{-\sigma} + \sum_{i=1}^N T_i Z_j^{\frac{\chi_i}{\epsilon_i}} P_j(w)^{\left((\sigma-1)\frac{\chi_i}{\epsilon_i}-1\right)} D_{ji}\frac{\chi_i}{\epsilon_i}\right)} > 0 \tag{49}$$

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 $\beta_i + 1 - \sigma > 0\ \forall i$, 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_{jih}. Using the equation for $\frac{dP_j(w)}{dw_h}$, we can show that:

$$Q_{jh} = P_j(w)^{\beta_h-\sigma-1}\left(1-\sigma-\sigma\frac{\chi_h}{\epsilon_h}\right) w_n^{-1} \left(1 - \frac{T_h Z_j^{\frac{\chi_h}{\epsilon_h}} P_j(w)^{(\sigma-1)\frac{\chi_h}{\epsilon_h}} D_{jh}}{P_j^{1-\sigma} + \sum_{k=1}^N T_k Z_j^{\frac{\chi_k}{\epsilon_k}} P_j(w)^{(\sigma-1)\frac{\chi_k}{\epsilon_k}} D_{jk}}\right) \tag{50}$$

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 V_j. Using the expression for $\frac{dP_j(w)}{dw_j}$, one can show that:

$$V_j = T_j (Z_j P_j^{\sigma-1})^{\left(\frac{\beta_j}{\sigma-1}-1\right)} D_{jj} w_j^{-1} \beta_j \left(\frac{T_j (Z_j P_j(w)^{\sigma-1})^{\frac{\chi_j}{\epsilon_j}} \frac{\chi_j}{\epsilon_j} D_{jj}}{P_j^{1-\sigma} + \sum_{k=1}^{N} T_k (Z_j P_j(w)^{\sigma-1})^{\frac{\chi_k}{\epsilon_k}} \frac{\chi_k}{\epsilon_k} D_{jk}} - 1\right) \tag{51}$$

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

$$\frac{\partial Z_i(w)}{\partial w_k} = \sum_{j \neq i,k}\left(\frac{\partial s_{ji}}{\partial w_k}\frac{w_j}{w_i}L_j\right) + \frac{\partial s_{ki}}{\partial w_k}\frac{w_k}{w_i}L_k + s_{ki}\frac{L_k}{w_i} \tag{52}$$

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

A.3 A useful representation of Output per Worker

Taking labor as the numeraire good, output per worker in economy i is:

$$C_i = P_i^{\alpha-1}\alpha^{\alpha}(1-\alpha)^{(1-\alpha)} \tag{53}$$

Using the expression of the domestic trade share, this expression becomes:

$$C_i = \alpha^{\alpha}(1-\alpha)^{(1-\alpha)}(s_{ii})^{-\frac{(1-\alpha)}{\beta_i}}(T_i((1-\alpha)L_i)^{\frac{\beta_i+1-\sigma}{\sigma-1}})^{\frac{1-\alpha}{\beta_i}} \tag{54}$$

Manipulating the expression above one can arrive at equation (23).

A.4 Details of Calibration

Rewrite the gravity equation as

$$X_{ji} = T_i (V_j)^{\beta_i} D_{ji} \tag{55}$$

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:

$$Z_i = \sum_{j=1}^{N} X_{ji} = T_i \sum_{j=1}^{N} (V_j)^{\beta_i} D_{ji} \tag{56}$$

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

$$X_{ji} = \frac{Z_i}{\sum_{j=1}^{N} (V_j)^{\beta_i} D_{ji}} (V_j^{\beta_i} D_{ji}) \tag{57}$$

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 $\hat{D}_i \equiv (\hat{D}_{11}, ..., \hat{D}_{N1})$:

$$\hat{D}_i = E_i \hat{D}_i \tag{58}$$

where I have defined the matrix E_i as:

$$E_i = \begin{pmatrix} \frac{X_{1i}}{Z_i} & \cdots & \frac{X_{1i}}{Z_i} \\ \frac{X_{2i}}{Z_i} & \cdots & \frac{X_{2i}}{Z_i} \\ \vdots & \ddots & \vdots \\ \frac{X_{Ni}}{Z_i} & \cdots & \frac{X_{Ni}}{Z_i} \end{pmatrix} \tag{59}$$

Note that we have all the elements to calculate $\{E_i\}_{i=1}^{N}$. Thus, $\hat{D}_i$ is just the eigenvector associated with eigenvalue one of matrix E_i's and T_i is calculated using equation (56). Finally, given $(L_i, f_i^e, \gamma_i, \theta_i)$, A_i is recovered by inverting the expression of T_i.

Assuming $D_{jj} = 1$ one can show that:

$$D_{ji} = \left(\frac{X_{ji}}{T_i}\right) \left(\frac{T_j}{X_{jj}}\right)^{\frac{\beta_i}{\beta_j}} \tag{60}$$

Note that all the elements on 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 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:

$$d_{ji} = (1 + t_{ji}) + \alpha_1 (dist_{ji})^{\alpha_2} exp(\alpha_3 border_{ji}) \tag{61}$$

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

B Monte Carlo Experiment

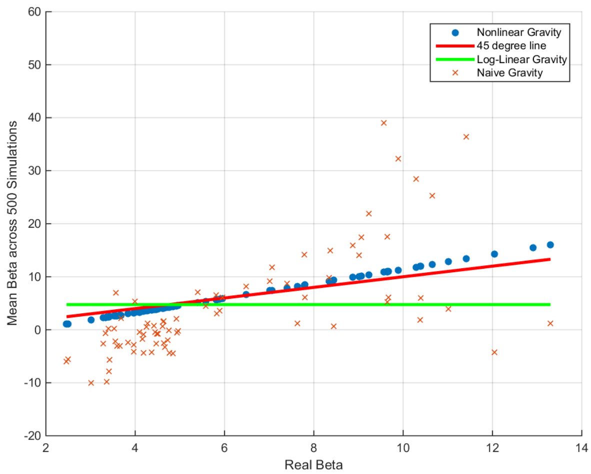
In this section I analyze the performance of the nonlinear gravity estimator in a Monte Carlo experiment. Spearot [2016] studies numerically the conditions under which this gravity estimator is identified. My goal here is a bit different. Assuming that the identification conditions hold - sufficient 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 projection into the model and calculate the equilibrium trade flows.

My second step is to simulate a sequence of 500 observed 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

$$\tilde{X}_{ji} = \Pi_i + \xi_j + \beta_i \zeta_j - \beta_i log(c_{ji}) + \mathbf{z}'_{ji}\delta_i + \epsilon_{ji} \tag{62}$$

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 of 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 17 displays the results for trade elasticities. The nonlinear gravity estimator presents 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 pretty close to median structural trade elasticity (see table 10).

Figure 17: Nonlinear Gravity Estimator: Monte Carlo Experiment



Note 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. Log-linear gravity represents the standard gravity estimator advocated by Arkolakis et al. [2012].

Table 10: 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. Last column displays the correlation between the row variable and the original structural trade elasticities.

C Data Construction

TBD

D Additional Results

Distortion Schedules Under Different Sample Definitions

In the benchmark analysis, I estimated the distortion schedules using establishment-level data comprised by firms in the manufacturing and service sectors that directly export less than 5% of their total sales, with manufactures composing 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 show whether this is the case by studying the correlation between the benchmark distortion schedules and the schedules estimated with alternative samples.

In sample 1, I eliminate all firms that report positive export sales. In sample 2, I eliminate all firms from the service sector. Finally, sample 3 comprises only purely domestic establishments in the manufacturing sector. Table (11) presents the results. The coefficients are all above .92, revealing that the schedules barely change when we work with alternative samples.

Table 11: Distortion Schedules Under Different Sample Definitions

Variables	Full-sample Gamma	Sample-1 Gamma	Sample-2 Gamma	Sample-3 Gamma
Full-sample Gamma	1.000			
Sample-1 Gamma	0.922	1.000		
Sample-2 Gamma	0.997	0.921	1.000	
Sample-3 Gamma	0.923	0.990	0.921	1.000

Note Correlation table between distortion schedules estimated under different sample definitions.

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 is 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-elastic 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 manufacturing sectors and 160 countries.

I then compute the correlation between CATE and the nonlinear trade elasticity from this paper. Table (12) presents the results. CATE's 1, 2 and 3 are weighted 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 according to different sample definitions 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 12: 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.

Trade Elasticities and Asymmetric Trade Costs

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

$$log\left(\frac{s_{ij}}{s_{ii}}\right) = S_j - S_i - \theta log(c_{ij}) \tag{63}$$

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 follows:

$$log(c_{ij}) = ex_j + \beta' d_{ij} + \epsilon_{ij} \tag{64}$$

where d_{ij} is a vector of (symmetric) geographic variables and ex_j represents the exporter fixed effect. By combining equations (63) and (64) 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 good that its geography would predict. Table (13) 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 the distortion schedule 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 13: Correlation with Waugh's Trade Costs

VARIABLES	(1) Export Cost	(2) Export Cost	(3) Export Cost
Trade Elasticity (Beta)	0.644***		
	(0.116)		
Distortion Schedule (Gamma)		0.422***	
		(0.117)	
Pareto Shape (Theta)			0.138
			(0.0971)
Observations	77	77	77
R-squared	0.415	0.178	0.019

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.

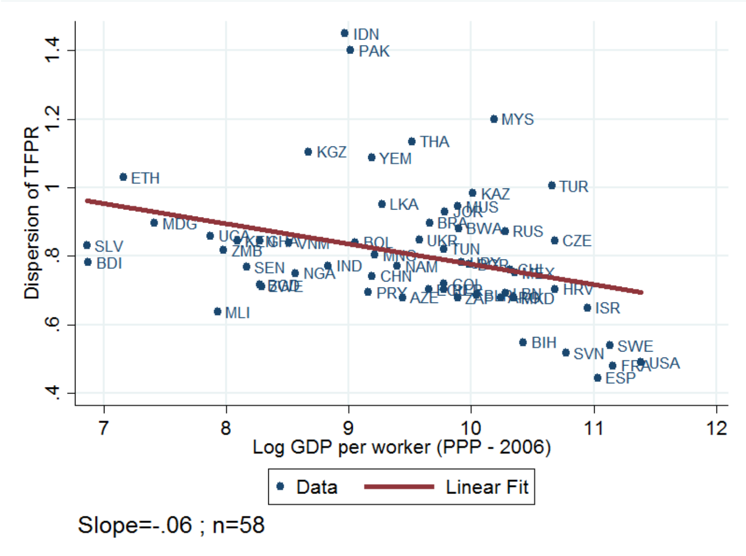
An Alternative Model: the Theta Model

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 $\theta_i = 0\ \forall i$ 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 TFPR and development, and (ii) negative correlation between development and trade elasticity.

Figure (18) presents the first relationship. The within-sector dispersion of TFPR significantly decreases with development. Since the dispersion of TFPR in the theta model is inversely proportional to the trade elasticity ($\beta_i = \theta_i$), that negative correlation would imply that trade elasticities should be lower, and not higher, in developing economies. Therefore, the theta model is not flexible enough to deliver simultaneously high dispersion of TFPQ and TFPR at the micro level and high trade elasticities at the macro level.

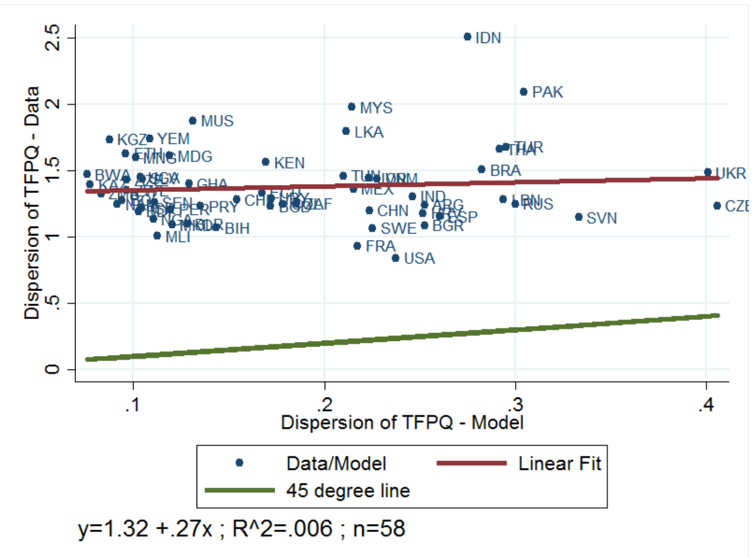
As a result, the theta model performs poorly at predicting the cross-country variation in TFPQ, as evidenced in figure (19).

Figure 18: Dispersion of TFPR and Output per Worker



Note Dispersion of TFPR is measured as the standard deviation of the log of establishment revenue productivity net of the sectoral average. Sample size = 58 countries.

Figure 19: 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.

E Additional Tables

Table 14: Calibration Table

Parameter	Value	Source/Target
σ	3	EKK (2011), HK (2014)
α	.7	Labor in Services
c_{ji}	$[1, 3.4]$	Tariffs, Geography
f_{ji}	$[.17, 1.1e + 33]$	Trade Shares, World Equilibrium
A_i	$[1.9e - 05, 29.8]$	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
L_i	$[1.7e + 5, 7.6e + 8]$	WBDI

Note I use the OECD average γ_i for the following countries: Austria, Australia, Belgium, Canada, Switzerland, Germany, Denmark, Finland, France, Great Britain, Greece, Hungary, Iceland, Italy, Japan, South Korea, Netherlands, Norway, New Zealand and Portugal. US γ_i comes from Hsieh and Klenow [2014].

Table 15: List of Parameters - Structural Model

Country	Labor Force (mil)	Beta	Theta	Gamma	Entry Cost (% GDP/capita)	Technology Level
ARG	14.53892	3.9909	2.499315	.2991337	.124	.6835
AUS	10.38522	3.5309	2.674972	.1992222	.02	1.7066
AUT	3.955203	3.5547	2.691659	.1992222	.061	4.9699
AZE	4.17627	10.292	4.959983	.3693044	.168	.016121
BDI	3.672112	9.6659	2.475569	.5326625	2.402	.000019
BEL	4.350843	4.4156	3.295294	.1992222	.111	14.324
BGD	46.27633	5.8238	2.641756	.4113453	.639	.025197
BGR	3.760754	3.9724	1.501323	.4983417	.104	.15041
BIH	.7244086	7.0157	3.88847	.3283681	.473	.41456
BLR	4.407566	7.783	3.084666	.4401456	.186	.12333
BOL	3.467567	10.648	3.143014	.5012681	1.844	.015162
BRA	91.50082	3.5624	2.220664	.3088995	.131	.56718
BWA	.9468527	13.3	2.281056	.5814746	.104	.030445
CAN	16.45672	4.7685	3.542735	.1992222	.006	1.4496
CHE	4.326287	4.5036	3.356997	.1992222	.086	11.265
CHL	6.91862	6.4896	4.190605	.2632116	.121	3.6068
CHN	761.125	4.4832	1.962923	.4402384	.178	.94263
COL	16.71268	5.5845	3.2264	.3196665	.28	.060186
CZE	4.992159	2.4619	1.142288	.4900428	.1	.91286
DEU	39.15673	4.6424	3.454318	.1992222	.059	13.641
DNK	2.820845	4.1569	3.113902	.1992222	.002	1.4958
ECU	5.235617	5.9557	3.393898	.3229074	.516	.046127
ESP	19.91743	3.8413	2.994701	.1777841	.168	3.458
ETH	35.04184	10.399	2.588883	.5349945	4.839	.0000555
FIN	2.449276	3.5976	2.72174	.1992222	.011	7.1289
FRA	26.58251	4.6302	3.445764	.1992222	.013	4.9101
GBR	28.8867	4.2789	3.199444	.1992222	.01	1.7488
GHA	9.572909	7.7954	3.274362	.4227995	.805	.0023117
GRC	4.974128	4.1852	3.133745	.1992222	.327	.43708
HRV	1.542493	3.9639	2.162359	.3642532	.163	.60923
HUN	4.199713	4.6091	3.430969	.1992222	.404	4.1347
IDN	95.85796	3.6596	.9301664	.6079729	1.367	.13422
IND	449.9748	4.0936	1.841719	.438075	.534	.051341
ISL	.1705188	7.063	5.151563	.1992222	.03	4.4134
ISR	2.786293	9.6432	6.206225	.2552563	.055	2.8556
ITA	24.78156	4.2483	3.177989	.1992222	.221	11.086
JOR	1.375569	4.476	2.242308	.3909156	1.041	.24971
JPN	63.5633	4.8412	3.59371	.1992222	.107	29.805
KAZ	7.118496	12.905	2.255122	.5801377	.111	.13108
KEN	13.74189	5.8858	2.562143	.4245477	.546	.0021388
KGZ	2.091112	11.413	3.402539	.4969423	.125	.0055557
KOR	22.73909	3.3626	2.556965	.1992222	.184	22.567
LBN	1.349003	3.4138	2.13076	.3113646	1.297	.022196
LKA	6.814769	4.7328	1.998691	.4482734	.593	.24005
MDG	8.765504	8.4418	2.215494	.5338649	2.473	.0016206
MEX	42.34926	4.6339	2.972521	.2791834	.295	.39954
MKD	.4833345	8.3418	3.877673	.3877568	.121	.57077
MLI	4.128529	8.8743	5.488623	.2750023	2.043	.0018999
MNG	1.0099	9.888	5.067188	.348526	.161	.016645
MUS	.5560644	7.6275	2.706517	.4713021	.095	.24552
MYS	10.55665	4.6585	1.390972	.5457022	.331	2.6075
NAM	.8121411	11.009	.848148	.6549684	.222	.12246
NGA	44.33492	9.0601	3.712754	.4247245	.836	.0026228
NLD	8.429365	4.9208	3.649523	.1992222	.133	7.4618
NOR	2.462583	4.9634	3.679393	.1992222	.035	5.3157
NZL	2.19356	3.6794	2.779095	.1992222	.002	.68656
PAK	46.0427	3.2829	1.272804	.5122113	.4	.017768
PER	9.724187	8.3642	4.516284	.3332597	.394	.56824
PRT	5.112451	4.9308	3.656535	.1992222	.12	.67188
PRY	2.5537	7.4025	3.224766	.4134835	2.099	.034105
RUS	67.53835	3.334	1.908529	.3562787	.109	.44736
SEN	4.402943	9.0069	4.855768	.3318158	1.224	.0038575
SLV	2.337091	9.5624	4.070957	.4115413	1.293	.083872
SVN	.9435807	3.0156	1.953425	.301463	.148	2.1134
SWE	4.458648	4.4504	3.017819	.2524104	.007	5.2091
THA	37.11946	3.4315	1.233804	.5299165	.08	.27809
TUN	3.485478	4.751	2.375727	.3877046	.119	.35663
TUR	19.59979	3.404	1.294643	.5137255	.368	.63004
UGA	11.82118	9.639	1.161928	.6298676	1.232	.0003305
UKR	21.89569	2.4929	1.071276	.5189639	.256	.066442
URY	1.426255	5.8117	3.331902	.3213193	.513	.53347
USA	146.2552	4.1924	3.716426	.09	.007	2.1705
VNM	43.24669	4.3682	1.589713	.500421	.319	.063265
YEM	5.550821	9.2288	1.986509	.5639008	2.57	.0045258
ZAF	17.7428	5.3984	3.343565	.2895113	.094	1.2068
ZMB	4.852482	12.042	2.946907	.5330302	.332	.073485
ZWE	7.058781	10.385	4.84088	.3803204	3.713	.0099007

Note Sample Size = 77 countries

Table 16: List of Distortion Schedules

Country	Distortion Schedule (Gamma)	Number of Firms	Country	Distortion Schedule (Gamma)	Number of Firms
AGO	.6722254	256	LKA	.4482734	209
ARG	.2991337	819	MDG	.5338649	238
AZE	.3693044	97	MEX	.2791834	1543
BDI	.5326625	110	MKD	.3877568	153
BGD	.4113453	2196	MLI	.2750023	236
BGR	.4983417	445	MMR	.3868122	116
BIH	.3283681	114	MNG	.348526	149
BLR	.4401456	92	MOZ	.5429615	239
BOL	.5012681	216	MUS	.4713021	96
BRA	.3088995	855	MYS	.5457022	300
BWA	.5814746	135	NAM	.6549684	103
CHL	.2632116	857	NGA	.4247245	829
CHN	.4402384	1210	NIC	.5317814	254
COD	.2657888	310	NPL	.5789122	229
COL	.3196665	954	PAK	.5122113	216
CRI	.3753149	173	PAN	.5701004	94
CZE	.4900428	93	PER	.3332597	628
ECU	.3229074	285	PHL	.3485467	955
EGY	.4844434	1244	PRY	.4134835	165
ESP	.1777841	386	ROU	.4382129	168
EST	.5332062	119	RUS	.3562787	651
ETH	.5349945	279	SEN	.3318158	266
GAB	.8600481	104	SLE	.5029429	122
GEO	.3925214	105	SLV	.4115413	272
GHA	.4227995	335	SRB	.3748484	161
GTM	.3642746	411	SVN	.301463	120
HND	.4692012	235	SWE	.2524104	225
HRV	.3642532	283	THA	.5299165	524
IDN	.6079729	1267	TJK	.5423123	97
IND	.438075	4092	TUN	.3877046	249
IRL	.1865237	387	TUR	.5137255	691
IRQ	.419706	409	UGA	.6298676	297
ISR	.2552563	103	UKR	.5189639	395
JOR	.3909156	224	URY	.3213193	293
KAZ	.5801377	145	USA	.09	
KEN	.4245477	528	UZB	.5236863	187
KGZ	.4969423	102	VNM	.500421	968
KHM	.4391999	109	YEM	.5639008	142
LAO	.5862464	402	ZAF	.2895113	554
LBN	.3113646	116	ZMB	.5330302	365
LBR	.8004216	116	ZWE	.3803204	304

Note Sample Size = 103 countries. US γ_i comes from Hsieh and Klenow [2014].

Table 17: List of Trade Elasticities

Country	Trade Elasticity (Beta)	Country	Trade Elasticity (Beta)
AGO	10.236	KWT	6.4475
ALB	9.5268	LAO	11.034
ARE	3.0489	LBN	3.4138
ARG	3.9909	LBY	8.2837
ARM	10.43	LCA	9.48
ATG	10.553	LKA	4.7328
AUS	3.5309	LSO	7.9502
AUT	3.5547	LTU	3.2353
AZE	10.292	LUX	5.7834
BDI	9.6659	LVA	5.0598
BEL	4.4156	MAC	9.5619
BEN	9.7114	MAR	4.999
BFA	9.5	MDG	8.4418
BGD	5.8238	MDV	9.7823
BGR	3.9724	MEX	4.6339
BHR	7.334	MKD	8.3418
BHS	8.1801	MLI	8.8743
BIH	7.0157	MLT	4.9926
BLR	7.783	MNG	9.888
BLZ	10.722	MOZ	13.827
BOL	10.648	MUS	7.6275
BRA	3.5624	MWI	12.945
BRB	10.508	MYS	4.6585
BTN	9.6059	NAM	11.009
BWA	13.3	NCL	11.305
CAF	10.674	NER	9.8341
CAN	4.7685	NGA	9.0601
CHE	4.5036	NIC	8.6894
CHL	6.4896	NLD	4.9208
CHN	4.4832	NOR	4.9634
CIV	9.7705	NPL	9.1774
CMR	9.2635	NZL	3.6794
COG	11.603	OMN	5.2177
COL	5.5845	PAK	3.2829
CPV	10.414	PER	8.3642
CRI	7.0882	PHL	4.7934
CYP	5.1586	PNG	11.948
CZE	2.4619	POL	3.5122
DEU	4.6424	PRT	4.9308
DMA	8.392	PRY	7.4025
DNK	4.1569	PYF	12.118
DOM	9.3966	QAT	5.6732
DZA	6.1716	ROM	3.4935
ECU	5.9557	RUS	3.334
EGY	4.5457	RWA	9.2707
ERI	9.3941	SAU	4.9353
ESP	3.8413	SDN	8.6262
EST	4.3631	SEN	9.0069
ETH	10.399	SGP	3.6275
FIN	3.5976	SLB	10.172
FJI	11.324	SLV	9.5624
FRA	4.6302	SUR	11.138
GBR	4.2789	SVK	3.7734
GHA	7.7954	SVN	3.0156
GIN	9.9702	SWE	4.4504
GMB	9.5613	SWZ	10.414
GNQ	11.526	SYC	9.9284
GRC	4.1852	SYR	5.0572
GRD	8.5436	TCD	10.754
GUY	12.141	TGO	8.5476
HKG	5.3973	THA	3.4315
HRV	3.9639	TJK	14.146
HTI	10.663	TKM	12.71
HUN	4.6091	TON	8.5295
IDN	3.6596	TTO	10.042
IND	4.0936	TUN	4.751
IRL	3.9436	TUR	3.404
IRN	4.2633	TZA	7.5297
ISL	7.063	UGA	9.639
ISR	9.6432	UKR	2.0268
ITA	4.2483	URY	5.8117
JAM	9.5609	USA	4.1924
JOR	4.476	UZB	13.712
JPN	4.8412	VEN	7.9536
KAZ	12.905	VNM	4.3682
KEN	5.8858	YEM	9.2288
KGZ	11.413	ZAF	5.3984
KHM	7.2397	ZAR	10.492
KNA	9.5903	ZMB	12.042
KOR	3.3626	ZWE	10.385

Note Sample Size = 160 countries.

Table 18: Effects of Correlated Distortions - Country by Country Analysis

	Open Economy			Closed Economy		
Country	Total Gain (%)	Reallocation Gain (%)	Entry Gain (%)	Total Gain (%)	Reallocation Gain (%)	Entry Gain (%)
ARG	21.974	18.6341	3.3399	15.045	11.6036	3.4414
AZE	6.4103	4.5357	1.8746	3.0394	1.0902	1.9492
BDI	23.9	19.5178	4.3822	1.8124	-2.8211	4.6335
BGD	20.063	15.9257	4.1373	9.2606	4.9746	4.286
BIH	7.9073	5.8311	2.0762	2.3497	.0439999	2.3057
BLR	24.01	20.6559	3.3541	11.456	7.7899	3.6661
BOL	10.053	6.5716	3.4814	-2.055	-5.6363	3.5813
BRA	30.076	26.0257	4.0503	22.337	18.239	4.098
BWA	75.355	71.21111	4.1439	40.436	36.0281	4.4079
CHL	5.5936	3.9728	1.6208	3.7989	2.1342	1.6647
CHN	61.659	55.2895	6.3695	53.173	46.7214	6.4516
COL	10.732	8.044701	2.6873	6.0506	3.2846	2.766
ECU	9.0382	6.5203	2.5179	3.5281	.8882999	2.6398
ESP	5.9071	4.6578	1.2493	3.8656	2.5683	1.2973
ETH	15.731	11.6355	4.0955	-5.0035	-9.3563	4.3528
GHA	12.325	9.13	3.195	2.6533	-.7140999	3.3674
HRV	49.638	44.9575	4.6805	29.247	24.2461	5.0009
IND	114.69	107.7836	6.9064	90.516	83.5003	7.0157
ISR	4.3491	3.37038	.97872	2.4466	1.3907	1.0559
JOR	33.506	28.7158	4.7902	15.266	10.1995	5.0665
KAZ	73.121	68.9235	4.1975	41.357	36.8491	4.5079
KEN	26.359	22.0149	4.3441	11.665	7.1427	4.5223
KGZ	23.418	20.323	3.095	11.609	8.3419	3.2671
LBN	33.714	29.7144	3.9996	16.512	12.1721	4.3399
LKA	61.825	55.619	6.206	36.729	30.3817	6.3473
MDG	36.908	32.2701	4.6379	9.7503	4.395101	5.3552
MEX	10.836	8.4685	2.3675	6.5283	3.9227	2.6056
MKD	13.585	11.0811	2.5039	7.0939	4.4476	2.6463
MLI	-.439	-1.7135	1.2745	-1.814	-3.1303	1.3163
MNG	5.9134	4.2237	1.6897	2.8443	1.0235	1.8208
MUS	38.217	34.2337	3.9833	21.959	17.6104	4.3486
NGA	6.5477	3.7075	2.8402	.67757	-2.24013	2.9177
PER	3.8019	1.8517	1.9502	1.5194	-.465	1.9844
PRY	8.2924	5.129601	3.1628	-1.0826	-4.4745	3.3919
RUS	82.676	77.0962	5.5798	59.921	54.1948	5.7262
SEN	2.1171	.3890001	1.7281	-1.3071	-3.1341	1.827
SLV	3.115	.6222	2.4928	-1.544	-4.1354	2.5914
SVN	66.527	62.2776	4.2494	41.58	36.9435	4.6365
SWE	19.303	17.2081	2.0949	14.215	11.962	2.253
TUN	39.213	34.804	4.409	24.141	19.4511	4.6899
URY	9.2743	6.738299	2.536	3.8107	1.1294	2.6813
YEM	57.691	52.1682	5.5228	21.608	15.8411	5.7669
ZAF	10.826	8.4973	2.3287	7.7187	5.3326	2.3861
ZMB	24.98	21.365	3.615	9.8762	6.1665	3.7097
ZWE	.46939	-1.45621	1.9256	-4.6028	-6.6457	2.0429

Note Sample Size = 45 countries.

Table 19: Decomposition of Trade Channel

Country	Initial Home Share (%)	Trade Channel (%)	Better Allocation (%)	Trade Creation (%)
ARG	70.718	46.05517	30.87411	69.12589
AZE	49.197	110.9067	71.33706	28.66294
BDI	33.293	1218.693	83.55954	16.44046
BGD	61.341	116.649	51.59498	48.40502
BIH	20.179	236.5238	85.27909	14.72091
BLR	26.654	109.5845	81.69333	18.30667
BOL	56.152	-589.1971	67.90639	32.09361
BRA	86.957	34.64655	15.40536	84.59464
BWA	23.678	86.35622	93.46619	6.533813
CHL	67.329	47.24262	49.71376	50.28624
CHN	85.397	15.95923	41.12095	58.87905
COL	66.63	77.37084	42.4095	57.5905
ECU	49.477	156.1776	55.31249	44.68751
ESP	64.17001	52.81199	29.87135	70.12865
ETH	31.902	-414.3999	84.04252	15.95748
GHA	42.377	364.5159	68.62092	31.37908
HRV	44.312	69.71997	50.35425	49.64575
IND	83.063	26.70688	30.18971	69.81029
ISR	26.6	77.76098	86.09075	13.90925
JOR	48.711	119.4812	51.83671	48.16329
KAZ	24.973	76.80442	93.74895	6.251045
KEN	55.92	125.9666	54.22988	45.77012
KGZ	33.353	101.7228	84.93574	15.06426
LBN	35.629	104.1788	47.42102	52.57898
LKA	75.304	68.32748	36.71642	63.28358
MDG	3.4351	278.5319	104.4358	-4.435776
MEX	27.147	65.98503	85.80857	14.19143
MKD	40.413	91.50256	71.37622	28.62378
MLI	53.558	-75.79934	73.08598	26.91402
MNG	26.964	107.9035	97.79809	2.201912
MUS	23.37	74.03798	87.99184	12.00816
NGA	61.609	866.3503	59.82635	40.17365
PER	73.362	150.2238	47.48398	52.51602
PRY	33.464	-865.9708	74.75057	25.24943
RUS	75.33	37.975	24.49725	75.50275
SEN	38.444	-261.9692	73.63801	26.36199
SLV	49.461	-301.7487	73.59429	26.40571
SVN	34.549	59.99759	43.1936	56.8064
SWE	39.143	35.79317	55.88321	44.11679
TUN	44.548	62.4332	59.51457	40.48543
URY	46.799	143.3752	58.4532	41.5468
YEM	46.06	166.9891	81.14674	18.85326
ZAF	71.353	40.25678	40.57581	59.42419
ZMB	54.878	152.9313	74.75105	25.24895
ZWE	27.874	-110.1979	80.36774	19.63226

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.

Table 20: Effects of Distortions and Symmetric Costs - Global Analysis

Country	Gain, US distortion (%) - Open	Gain, Symmetric Trade Costs (%)	Gain, US distortion (%) - Closed
ARG	51.283	4.6467	15.045
AUS	37.564	5.3172	9.9096
AUT	39.333	9.3929	8.0636
AZE	162.81	67.057	3.0394
BDI	370.43	133.77	1.8124
BEL	27.541	8.2395	4.3996
BGD	90.165	24.542	9.2606
BGR	71.578	28.898	0
BIH	137.16	57.547	2.3497
BLR	127.3	52.79	11.456
BOL	148.02	71.576	-2.055
BRA	36.733	.89264	22.337
BWA	255.01	73.575	40.436
CAN	29.518	11.515	7.4829
CHE	34.827	12.527	4.5242
CHL	41.888	16.438	3.7989
CHN	63.689	.71287	53.173
COL	78.456	26.874	6.0506
CZE	26.886	10.653	0
DEU	12.244	1.7005	4.7305
DNK	54.105	17.292	10.924
ECU	106.44	46.399	3.5281
ESP	18.982	.92811	3.8656
ETH	215.08	95.662	-5.0035
FIN	47.623	4.6393	10.61
FRA	18.5	1.9228	6.755
GBR	23.426	2.8801	8.0373
GHA	164.32	70.096	2.6533
GRC	67.719	18.755	3.3227
HRV	137.87	24.503	29.247
HUN	44.551	16.414	2.3184
IDN	28.424	5.2999	0
IND	131.28	1.2773	90.516
ISL	123.13	56.386	2.8694
ISR	73.35	37.704	2.4466
ITA	13.921	1.1702	3.7144
JOR	156.4	46.475	15.266
JPN	8.4156	.60601	3.6032
KAZ	180.59	54.169	41.357
KEN	171.09	56.736	11.665
KGZ	261.88	98.231	11.609
KOR	20.155	2.3647	7.0559
LBN	204	39.995	16.512
LKA	144.24	18.364	36.729
MDG	181.11	63.697	9.7503
MEX	32.145	12.431	6.5283
MKD	143.82	58.979	7.0939
MLI	179.2	80.346	-1.814
MNG	245.97	97.611	2.8443
MUS	183.39	60.992	21.959
MYS	39.704	18.198	0
NAM	149.23	71.013	0
NGA	113.16	53.227	.67757
NLD	23.562	6.847	3.3253
NOR	54.446	17.868	4.8405
NZL	71.088	19.516	13.006
PAK	66.595	9.2697	0
PER	60.214	27.336	1.5194
PRT	55.289	24.185	3.4243
PRY	139.74	68.249	-1.0826
RUS	96.992	2.3119	59.921
SEN	168.72	77.384	-1.3071
SLV	118.48	64.21	-1.544
SVN	128.97	17.163	41.58
SWE	46.646	9.8662	14.215
THA	33.263	9.9567	0
TUN	109.98	26.43	24.141
TUR	23.171	2.0277	0
UGA	199.44	80.528	0
UKR	37.804	7.2316	0
URY	102.18	46.642	3.8107
USA	3.2551	1.0581	0
VNM	55.727	18.036	0
YEM	235.92	79.162	21.608
ZAF	38.405	8.9105	7.7187
ZMB	127.42	56.656	9.8762
ZWE	137.4	67.528	-4.6028

Note Sample Size = 77 countries.