# Cities, Heterogeneous Firms, and Trade*

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**Abstract**

We document a novel stylized fact: Using data for several countries, we show that export activity is disproportionately concentrated in larger cities – even more so than overall economic activity. We account for this fact by marrying elements of international trade and economic geography. We extend a standard Quantitative Spatial Economics (QSE) model to include heterogeneous firms that engage in selection along two margins: Entry into cities of heterogeneous productivity and entry into exporting. The model allows us to study the implications of trade policy for within-country economic geography and of geographic policies for international trade. Our model delivers novel predictions for the bi-directional interactions between trade and urban dynamics: On the one hand, trade liberalization shifts employment towards larger cities, and on the other hand, liberalizing land use increases international trade integration. We structurally estimate the model using data for the universe of Chinese and French manufacturing firms.

*JEL: Exporting, Agglomeration, Trade, Economic Geography*

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# 1 Introduction

Over the last decades, two mega-trends have shaped economies across the globe: rapid urbanization and a surge in international trade.[1] The simultaneous unfolding of these trends naturally raises the question whether they are connected. While the underlying drivers of these trends have traditionally been examined by two separate strands of literature – international trade and economic geography – more recently, a literature at the intersection of these fields has emerged.[2] However, important gaps remain in this nascent strand of research. First, work analyzing the impact of international trade on domestic economic geography has typically focused on heterogeneity in *sectoral* specialization across cities and regions, abstracting from the underlying more granular level, in particular, firms.[3] Second, the converse effects of domestic urban policies and shocks on trade flows across countries have received relatively little attention.

In this paper, we study the role played by firm-level heterogeneity in shaping the interactions between economic geography and international trade. We first establish a novel stylized fact: Using data for China, France, Brazil, and the United States, we show that larger cities systematically export a higher fraction of their output than smaller cities, even after controlling for differences in geographic characteristics (Figure 1). More than two-thirds of the association between export intensity and city size can be attributed to variation *within* industries. In turn, we show that the higher within-industry export intensity of larger cities is driven by the extensive margin – a higher proportion of firms participating in export markets. Our results suggest that the location patterns of heterogeneous firms have important implications for the spatial configuration of exporting activity within countries. Crucially, all our stylized facts survive when we instrument contemporaneous city size with historical city population and control for spatial differences in foreign market access. Thus, our facts cannot simply be explained by larger cities benefiting from better foreign market access.[4]

To explain the stylized facts described above we propose a simple mechanism featuring heterogeneous firms that face selection into entry at multiple locations and also selection into exporting in the spirit of Melitz (2003). We first highlight this mechanism in a simplified model which ex-

[1] The average urbanization rate in the world grew from 43 to 55 percent between 1990 and 2010. During the same period, exports as a share of GDP have grown from 30 to 46 percent (https://data.worldbank.org/indicator).

[2] Recent empirical and quantitative contributions to this literature include Autor, Dorn, and Hanson (2013), Dauth, Findeisen, and Suedekum (2014), Redding (2016), Dhingra, Machin, and Overman (2017), Cheng and Potlogea (2020), Lyon and Waugh (2019), and Ducruet, Juhasz, Nagy, and Steinwender (2020). Earlier contributions typically used stylized models to qualitatively explore the effects of trade liberalization on economic geography. These include, for example, Krugman and Livas Elizondo (1996), Monfort and Nicolini (2000),Behrens, Gaigne, Ottaviano, and Thisse (2006b), Behrens, Gaigne, Ottaviano, and Thisse (2006a), Behrens, Gaigne, Ottaviano, and Thisse (2007), and Behrens, Gaigne, Ottaviano, and Thisse (2009).

[3] Notable exceptions include Cosar and Fajgenbaum (2016) and Redding (2016).

[4] It is important to note that for competing models without firm heterogeneity to match our main stylized facts, it is not sufficient for larger cities to have systematically better foreign market access. What is required instead is that larger cities have systematically better foreign *relative to domestic* market access than smaller cities.

tends a standard Rosen-Roback framework by allowing for heterogeneous firms and selection into exporting. We study a setup featuring two symmetric countries. Within countries, cities form in an exogeneously given number of heterogeneous sites that are characterized by differences in productivity. Crucially, we model these productivity differences across locations as differences in the location-specific firm productivity distributions. In particular, entrants to all cities draw their productivities from standard Pareto distributions, with entrants to more productive cities drawing from distributions with thicker upper tails (i.e. lower shape parameters). This modeling choice is motivated by the empirical regularities documented in the literature on city size and productivity (see Combes, Duranton, Gobillon, Puga, and Roux, 2012). Moreover, in keeping with the conventions of the international trade and economic geography literatures, we allow workers to be imperfectly mobile within countries, while assuming that workers are immobile across countries.

The model explains the disproportionate concentration of exporting in larger cities over and above what can be explained by differences in foreign market access.[5] In our model, productive locations i) grow into larger cities and ii) tend to export more. Regarding i), more productive locations feature very productive firms with higher probability, which tends to increase local labor demand. In the presence of imperfectly elastic local labor supply, this in turn leads to these cities becoming larger, featuring higher wages as well as more expensive housing and land. Moreover, in the presence of within country trade costs, the concentration of productive firms in the most productive locations tends to lower the price indices in these locations, which generates an additional agglomeration force that draws populations to these locations. Regarding ii), the fat upper tail of firm productivity in more productive cities implies that these locations feature a larger mass of firms that jump over the "Melitz barrier" and become exporters. This, in turn, causes high productivity locations to also be more export intensive, thus reproducing the positive correlation between export intensity and city size found in the data.

In addition, the model also gives rise to novel feedback loops: For example, the increased local wages in the more productive locations render the selection-into-exporting process more stringent, which tend to amplify productivity differences across locations. That is, higher wages raise firms' marginal costs, requiring even higher productivity differentials to be competitive in international markets.[6] As we discuss below, this "wage backlash" implies that the aggregate gain from trade liberalization are somewhat weaker in our model as compared to Melitz (2003). Nevertheless, the fatter Pareto upper tail of the productivity distribution implies that more productive cities still

[5] In fact, an important strand of the trade literature predicts the opposite pattern: A direct implication of the gravity model – and the underlying Armington assumption – is that larger cities (or countries) are *less* open (Anderson and van Wincoop, 2004).

[6] A similar feedback effect is also present for selection into market entry: Intuitively, high local wages reduce firm profitability for any given firm productivity level and thus have a "cleansing effect" at both the firm entry margin and at the export entry margin. Taken together, these feedback mechanisms from higher wages further augment productivity differences across cities.

have a higher fraction of firms becoming exporters. Finally, similar to Melitz (2003), the model also predicts that – conditional on exporting – export *intensity* at the firm level is unrelated to productivity. This is also consistent with our findings.

The model further allows us to study the interactions between international trade and economic geography. We show that trade liberalization tends to shift population towards larger and more productive cities. On the other hand, deregulating housebuilding tends to increase the size of the larger cities, while at the same time raising exporting and productivity.

Finally, we explore the quantitative implications of our theory. We extend our simple model to a standard QSE framework that allows for a rich specification of trade frictions, asymmetric countries heterogeneity across locations in amenities as well as a richer pattern of productivity differences across space. This "quantitative model"can be seen as an extension of a canonical QSE model in the spirit of Redding (2016) with a mechanism of selection into exporting similar to that in Melitz (2003). We structurally estimate this model using Chinese data.The quantitative model can account for the bulk of the correlation between export intensity and city size observed in the data. Furthermore, to illustrate the quantitative implications of the model, we perform two policy experiments. First, we study the welfare implications of moving to autarky. We benchmark our findings against a similar experiment undertaken in an alternative model that omits domestic geography.[7] We find that the welfare gains associated with international trade are about 24% *larger* in our model relative to a model with no productivity heterogeneity. Intuitively, in our model with geography, exporters locate in bigger cities where face higher wage costs than the less productive, domestic firms. This diminishes the effective productivity advantage of exporters and their weight in the economy, leading to relatively smaller welfare gains from trade. Second, we study the welfare gains associated with increasing housing supply. We find that the effects on welfare and productivity are, to a first-order approximation, similar relative to competing models. Moreover, we find that welfare gains from spatial policies deliver a similar effect when shutting down international trade. Productivity, in contrast, increases about 12 percent more when allowing for international trade. Intuitively, increased housing supply benefits the most productive firms, i.e., those that tend to export and are also located in larger cities. Consequently, exporters grow disproportionately larger. Thus, the trade channel in our model amplifies the productivity gains of increased housing supply by increasing the weight of the most productive firms in the economy, but it does not affect welfare.

Our paper is related to several strands of the literature. Perhaps the most proximate is the recent body of work developing and estimating tractable quantitative spatial equilibrium (QSE) models that permit the study of realistic geographies (c.f. Redding, 2016; Allen and Arkolakis,

[7] We recalibrate this last model to fit the data, such that both models – our baseline and the model without geography – imply similar initial trade participation and productivity distributions.

2014; Caliendo, Parro, Rossi-Hansberg, and Sarte, 2018). We augment these models by allowing for firm heterogeneity and a mechanism of selection into exporting à la Melitz, which allows us to match the stylized facts that motivate our study.

We also contribute to the empirical and theoretical literature studying the role played by firm heterogeneity in international trade. On the empirical side, we document a series of novel stylized facts regarding the economic geography of exporting ("exporter facts," as in Bernard, Jensen, Redding, and Schott, 2007). To the traditional stylized facts about exporters (being larger and more productive) we add a new one: Exporters tend to locate disproportionately in large cities. This, in turn, leads to an economic geography of exporting within countries that is even more uneven than that of overall economic activity. On the theoretical side, our contribution is related to the body of work that analyzes firms' decisions to enter into exporting (Melitz, 2003; Bernard et al., 2007). We show that the same type of selection mechanisms that can be used to account for the exporter facts can also account for the observed positive association between city size and exporting.

Our study is also related to the recent literature at the intersection of economic geography and international trade (c.f. Autor et al., 2013; Dauth et al., 2014; Redding, 2016; Dhingra et al., 2017; Cheng and Potlogea, 2020; Lyon and Waugh, 2019; Ducruet et al., 2020)). These papers have typically focused on the role played by trade liberalization and the patterns of economic specialization across cities and regions in driving the observed heterogeneity in economic performance across space within countries. By contrast, we focus on the more granular firm level, while also considering the reverse role played by internal geography and geographic policies in determining international trade flows.[8]

Finally, our work is related to recent developments in the the systems of cities literature (c.f. Gaubert, 2018; Behrens, Duranton, and Robert-Nicoud, 2014; Hsieh and Moretti, 2019; Gaubert, 2018; Parkhomenko, 2018; Desmet and Rossi-Hansberg, 2013).[9] These papers typically take a different approach from ours to microfounding the positive association between firm productivity and city size: They emphasize the role played by sorting and agglomeration of heterogeneous agents (firms or workers) across space.[10] These papers also proceed to structurally estimate their

[8]Our paper is also related to an older theoretical literature that analyzes the joint determination of international trade flows and within-country economic geography (Krugman and Livas Elizondo, 1996; Monfort and Nicolini, 2000; Paluzie, 2001; Behrens et al., 2006a,b, 2007). As in some of these models, in our framework trade affects the configuration of economic geography, while spatial policy, in turn, can affect trade flows. Moreover, as in these previous models, our framework also captures the fact that domestic policy decisions can have spillovers on other countries via trade channels. We expand this earlier line of research in two dimensions: i) we examine the role of heterogeneous firms, introducing more finely grained dynamics, and ii) unlike these earlier stylized models, our quantitative model can be taken to the data.

[9]Another closely related strand of the literature uses similar conceptual tools, borrowed from the assignment literature, to study how workers – rather than firms – sort across space (c.f. Eeckhout, Pinheiro, and Schmidheiny, 2014; Davis and Dingel, 2014, 2019).

[10]By contrast we microfound the association between average firm productivity and city size by positing exogenous

models and undertake planning and place-based policy counterfactuals that are similar to the ones we analyze in the present study. Our main innovation relative to this strand of literature is that we study these policy counterfactuals in the context of open economies. This allows for the possibility that geographic policies may have additional effects on productivity and welfare via international trade channels.

The rest of the paper is organized as follows: Section 2 presents the data and Section 3, our stylized facts. Section 4 presents a simple model that illustrates the novel forces that we bring to bear to explain our key stylised facts and explores its equilibrium properties. Section 5 presents the quantitative model, our estimation procedure for the model, discusses model fit, and provides a counterfactual analysis. Section 6 concludes.

# 2 Data

Our main empirical analysis uses firm-level data from the 2004 Chinese Economic Census of Manufacturing and from the 2000 French Unified Corporate Statistics System (FICUS). One important advantage of the Chinese and French data is that they provide detailed information on the location of firms. This allows us to study the distribution of firms and exporters across cities. In addition, we use more aggregate information at the city level from the United States (at the MSA level) and Brazil (at the microregion level) for 2012 to confirm the main patterns we derive for China and France. We begin by discussing the Chinese and French data in detail, followed by a description of the U.S. and Brazilian data. For each country, we discuss what constitutes a "city" in our data.

## 2.1 China

Data for the Chinese Economic Census of Manufacturing are collected by the *National Bureau of Statistics*, covering the universe of firms in China, irrespective of their size. The Chinese data contain detailed information on plant characteristics such as sales, spending on inputs and raw materials, employment, investment, and export value. In the data, the reported location of firms reflects the county where their headquarters are based. This feature is unlikely to confound our results because – as Brandt, Van Biesebroeck, and Zhang (2014) show – over 90 percent of firms in China are single-plant firms. Nevertheless, in section ++ we discuss and provide evidence suggesting that this charatcteristic of the data does not drive our results.

In our main analysis, we define Chinese cities as metropolitan areas with contiguous lights in nighttime satellite images. We use the correspondence constructed by Dingel, Miscio, and Davis (2019) to map counties into metropolitan areas with a threshold for light intensity equal to 30.[11]

differences in the productivity distributions that firms draw from at different locations. This significantly simplifies our analysis while preserving our ability to study the key interactions of interest between trade and economic geography.

[11] Counties are the third administrative division in China, below provinces and prefectures – the other administrative division researchers typically use to define cities (e.g., Brandt et al., 2014). For reference, large metropolitan areas (urban population over 1 million) have, on average, about nine counties. In contrast, most small metropolitan areas

This value is in the middle of the set of thresholds provided by these authors. Importantly, our results do not depend on the particular threshold of light intensity. For each metropolitan area, we use information on the urban population of the underlying counties, which is provided by the Chinese Population Census of 2010 (i.e., the Chinese Census distinguishes between rural and urban population within each county). We then define 'city size' as the aggregate urban population of the Metropolitan Area.[12]

The Census of Manufacturing contains information for approximately 1,240,000 firms located in cities where we can match their population information in 2004. We drop firms with zero or missing sales (67,286 observations, corresponding to 5.4% of the sample), with non-manufacturing or missing industry codes (124,310, 10.0% of the sample), or with export intensity above 100% (5,397 observation, 0.4% of the sample). We also drop processing trade (9,672 observations, defined as firms where processing exports account over 90% of their sales). In addition, to ensure meaningful variation in export intensity at the city-level, we only consider cities with at least 250 firms. Our final sample then consists of 916,870 firms located in 629 cities (metropolitan areas).

## 2.2 France

Our analysis for France uses firms from the 2000 Unified Corporate Statistics System (FICUS). FICUS is an administrative data set collected by the French National Statistical Institute (*Institut National de la Statistique et des Études Économiques*, INSEE), and covers the universe of private sector firms. It reports information on domestic and export revenue, industry classification, headquarter location (commuting zones), employment, capital, value-added, and production.

We define cities in France in terms of commuting zones (*zone d'emploi*). We use the definition of commuting zones published by INSEE in 2011 that assigns municipalities (code communes) to commuting zones based on where "*most of the labour force lives and works, and in which establishments can find the part of the labour force*".[13] City size reflects the overall commuting zone population, which we obtain by aggregating municipality-level information from the French Population Census of 1999. As in the case of China, we restrict the analysis to firms with strictly positive information on exports and sales, and for cities with at least 250 firms. The final sample consists of 194,688 firms located in 304 cities.

(population below 100,000) consist of a single county.

[12] A large body of research using information for China defines cities in terms of prefecture-level cities. A prefecture-level city is an integrated political and economic unit, but it often includes rural areas. We avoid defining cities in terms of prefectures because administrative boundaries may fragment economically integrated areas into distinct cities or circumscribe places, including rural areas.

[13] https://www.insee.fr/en/metadonnees/definition/c1361.

## 2.3 United States

In the case of the United States, we define cities in terms of Metropolitan Statistical Areas (MSA). MSAs are defined by the United States Office of Management and Budget as one or more adjacent counties with at least one urban area with a population of at least 50,000 inhabitants, and characterized by a high degree of social and economic integration, as measured by commuting flows to work and school. As Dingel et al. (2019) show, MSAs are well-approximated by cities defined in terms of contiguous areas of lights in nighttime satellite images, as we do in the case of China. Our analysis considers 324 U.S. metropolitan areas with a population over 100,000 inhabitants in 2012.

To develop our main analysis, we combine data from several sources.[14] Data for exports at the MSA level are provided by the International Trade Administration of the U.S. Department of Commerce and include overall exports.[15] We combine this with establishment-level information of sales and employment aggregated at the MSA level from the 2012 Economic Census.[16] Consequently, city-level export intensity is constructed as overall exports over sales across all sectors. Finally, we use MSA population from the population projections of the U.S. Census Bureau.[17]

## 2.4 Brazil

Finally, for the case of Brazil, we consider microregions as the main unit of analysis. Microregions are defined by the Brazilian Institute of Geography and Statistics (IBGE) as urban agglomerations of economically integrated contiguous municipalities with similar geographic and productive characteristics.[18] Although microregions do not directly capture commuting flows (in contrast to U.S. Metropolitan Areas, or French employment zones), they are constructed according to information on integration of local economies, which is closely related to the notion of local labor markets. Our sample includes 420 microregions with more than 100,000 inhabitants in 2012.

To construct export intensity, we use overall exports – available at the level of municipalities – from the COMEX Stat database (which is compiled by the Brazilian *Ministry of Industry, Foreign Trade and Services*).[19] We complement this data source with municipal-level GDP from IBGE.[20]

[14] Most U.S agencies provide tabulations on key economic accounts at the MSA-level. This contrasts with China, where we aggregate county-level information to derive statistics for metropolitan areas.

[15] https://www.export.gov/Metropolitan-Trade-Data.

[16] https://www.census.gov/programs-surveys/economic-census/data/datasets.2012.html

[17] https://www.census.gov/data/tables/2012/demo/popproj/2012-summary-tables.html

[18] A number of researchers have used microregions as their main unit of analysis (see Kovak, 2013; Dix-Carneiro and Kovak, 2015, 2017b, 2019; Costa, Garred, and Pessoa, 2016; Chauvin, Glaeser, Ma, and Tobio, 2017).

[19] The COMEX Stat database can be publicly accessed through an interactive interface in the website http://comexstat.mdic.gov.br. In our analysis, we downloaded the version compiled by the Ministry of Economics from the information in the COMEX Stat database at the munucipal level (https://www.gov.br/produtividade-e-comercio-exterior/pt-br/assuntos/comercio-exterior/estatisticas/base-de-dados-bruta)

[20] https://www.ibge.gov.br/en/statistics/economic/national-accounts/19567-gross-domestic-product-of-municipalities.html

We aggregate both exports and GDP at the level of microregions using the correspondence provided by the IBGE, and compute city-level export intensity as the ratio of overall exports over GDP. Finally, we use population projections from the 2010 population Census to measure city size.[21]

### 2.5 Summary Statistics and Export Intensity

Before turning to our empirical results, we show descriptive statistics for the sample of cities considered in the analysis for China, France, the United States, and Brazil. Table 1 shows statistics for the distribution of population and export intensity for the four samples. Average city size varies importantly across the datasets. U.S. cities are larger on average (about 800,000 inhabitants), followed by China (710,000), Brazil (464,000), and France (193,000). These reflect the fact that population in the U.S. is more concentrated in larger cities.[22] While for the U.S., two-thirds of the cities in our sample have populations above 500,000, in China and Brazil 16 percent of the cities surpass this threshold, and in France, only 9 percent.

We define export intensity as the share of an industry's sales that are exported. Correspondingly, we define the export intensity in city $i$ ($\rho_i$) as follows:

$$\rho_i = \frac{x_i}{r_i} \tag{1}$$

where $x_i$ and $r_i$ denotes city-level exports and revenues, respectively (i.e., aggregated across all firms operating in city $c$).[23] Table 2 reports summary statistics for export intensity. The distribution of export intensity is positively skewed for all countries in our sample, with a substantially fatter tail in Brazil and China than in France and the United States. In the U.S. and France, all cities have exporting firms; in contrast, about 2 and 6 percent of the cities record no export activity in China and Brazil, respectively. While noteworthy, the presence of cities with zero exports does not affect our results' quantitative implications because these cities represent a small fraction of output (0.3% and 0.9% of the production in China and Brazil, respectively).

## 3 Export Activity and City Size

This section presents our main empirical result. Using data from Brazil, China, France, and the United States, we show that export activity is concentrated in larger cities. Next, we verify that our results hold when using different definitions of export activity and city size and show that our findings reflect, to a large extent, within-industry variation and are not driven by manufacturing alone. Finally, we provide evidence for heterogeneity in firm productivity as the main underlying

[21] https://www.ibge.gov.br/en/statistics/social/education/18391-2010-population-census.html?=&t=microdados.

[22] This is consistent with evidence in Au and Henderson (2006), who show that about half of prefecture-level cities in China are smaller than their optimal size. They argue that this is most likely due to the existence of strong migration restrictions.

[23] For Brazil, aggregate municipal GDP (across all sectors) at the microregion level as a proxy for city-level sales.

mechanism.

### 3.1 Baseline Results

Figure 1 illustrates our main result – the relationship between export intensity and city size. For all countries, we plot log export intensity against city size (log city population) – thus reflecting elasticities – and include several proxies for domestic and international trade costs: Average distance to other domestic cities, distance to the border, distance to the coast, border dummies, and coastal dummies.[24] For all countries, the figure shows a remarkably strong positive relationship.

Table 3 presents the corresponding point estimates for the elasticity between export intensity and city size: We obtain statistically highly significant estimates for all countries, ranging from 0.16 for the U.S. to 0.34 for China. Thus, doubling city size in China is associated with raising export intensity by about one-third. With an average export intensity of 8.8%, this corresponds to an increase in the fraction of exported (relative to total) local output by almost 3 percentage points ($= 0.34 \times 0.088$). Importantly, the coefficient remains positive and highly significant when we include geographical controls (even columns).

### 3.2 Robustness Checks

We implement several tests to check the robustness of our main finding for China and France, where we have the most detailed data.

*Alternative Measures of Export Activity*

Our baseline analysis for China only considers production and export information for the manufacturing industry. This may produce a non-representative picture of the location of overall exporting activity. While this is not a concern for Brazil, France, and the United States, we address this issue by repeating the main analysis using *per capita* exports to proxy for export activity. This measure has the advantage that it scales exports by a size variable – population – that it is invariant to the relative size of the manufacturing and service sectors.[25] Figure D.1 in the appendix plots log per capita exports against city size using the same set of controls as our baseline analysis, and panel A of Table D.1 shows the corresponding elasticities. All coefficients are statistical significant at the 1 percent level, with magnitudes ranging from 0.25 for China to 0.38 in Brazil.

The French data allows us to evaluate how representative manufacturing-based results are from the rest of the economy more directly by comparing the estimated elasticity in this relative to other sectors. Table D.2 in the appendix replicates the analysis in Table 3 for all private companies as

[24] We compute distance to other domestic cities as the shortest straight distance between the cities' centers. We include separate dummies for each main border and coast for France and the US, as trade across these margins is quantitatively important. That is, there are separate dummies for Canada and Mexico in the case of the US. For a city, a border dummy takes on value 1 if the city boundaries overlap with a border segment.

[25] A second issue remains, as the numerator of per capita exports for China still considers manufacturing exports only. However, this issue is less problematic, as overall exports tend to be dominated by manufacturing exports.

well as for five main sectors in France. The Table shows that the baseline elasticity estimated considering all private companies (column 1) is very similar to the elasticity estimated for the manufacturing sector (column 2).

*Population Density*

Next, we explore the robustness of our main stylized fact, which uses city population as a proxy for local scale and agglomeration forces. An alternative measure of agglomeration widely used in the literature is population density (see for instance Combes et al. (2012)). This measure can deviate substantially from city size, especially when cities vary widely in the size of their geographic areas.[26] In figure D.2 in the appendix we illustrate the relationship between log export intensity and log population *density*, while Panel B of Table D.1 shows the corresponding elasticities. In all cases, elasticities remain positive, with magnitudes ranging from 0.09 in Brazil to 0.25 in France. Point estimates are actually larger for France and the U.S. (as compared to our baseline results in Table 3), but somewhat weaker for Brazil and China. Finally, Figure D.3 and Panel C of Table D.1 replicate the analysis using log per capita export as dependent variable in combination with population density as the main explanatory variable. The estimated elasticity in this case is somewhat stronger than when using export intensity as dependent variable, with coefficients varying from 0.19 in Brazil to 0.48 in France.

*Addressing Potential Issues with Multi-Location Firms*

Firm location is only defined at the headquarter-level in all the datasets we employ. This may introduce an upward bias if export-intensive companies with production based in small cities locate their headquarters in large cities. We can directly address this concern for France, where we can identify single and multi-location firms by linking the baseline firm-level data with administrative information from the Annual Declaration of Social Data (DADS). DADS contains information about the labor force employed in every establishment. While this data provides no information on the production location, we use this auxiliary dataset to identify single and multi-location firms. Panel B of Table D.2 shows that elasticities are very similar when restricting the analysis to the sample of firms active in a single commuting zone.[27]

For China, we have no information on the location of the establishments owned by the firms. Nevertheless, as Brandt et al. (2014) show, fewer than 10 percent of firms are multi-plant firms in the Chinese manufacturing industry, and these tend to be relatively large. We thus indirectly control for the possibility that multi-plant firms drive our results, checking the stability of the

[26] See Henderson, Nigmatulina, and Kriticos (2021) for a recent study discussing the power of different measures to estimate urban agglomeration effects in the context of six Sub-Saharan African countries.

[27] In a complementary (unreported) analysis, we exploit the information in DADS to construct alternative city-level export intensity measures allocating firms' production and exports in proportion to the wage bill across establishments of the firm. Results are largely consistent with those in Table 3.

city size coefficient when dropping relatively large firms. Table D.3 in the appendix shows that the estimated elasticity is very similar when dropping these firms – defined in terms of the top 1-10 percentiles of the overall and within-sector employment distribution. The remarkably stable coefficient suggests that – also in the case of China – our baseline city size elasticity results are unlikely to be driven by export-intensive companies locating their headquarters in large cities.

*China-Specific Robustness Checks*

A distinctive element of the Chinese economy is the existence of Special Economic Zones (SEZ) and Coastal Development Areas (CDA), which are intended to promote exports and overall economic activity in selected areas. We show in Table D.4 in the appendix that our main results are not affected by the inclusion of categorical variables for SEC and CDA cities (in row 1 of the table). Second, we show that defining export intensity using information from the Chinese Customs Service – which only includes direct exports and is limited due to poor matching with the Census of manufacturing – barely affects the baseline correlation (row 2 in the table). Third, an important body of literature uses prefecture-level Chinese cities as the main unit of analysis (e.g., Au and Henderson, 2006). Row 3 in Table D.4 shows that our main findings are qualitatively unchanged when using prefecture-level cities. Finally, rows 4 and 5 replicate the analysis in rows 1 and 2 using prefecture-level cities to compute city size.

### 3.3 2SLS Results

An important concern with our empirical results is that third factors may drive the relationship between export intensity and city size. While our regressions include geographic controls, other factors may also confound the relationship – or there may even be a reverse channel, with high exporting activity raising firm efficiency (c.f. Garcia-Marin and Voigtländer, 2019) and leading to larger city size. To further address this issue, we implement a two-stage least squares strategy for our two main countries of analysis – China and France. We use historical city population from the 16th and 19th century as an instrument for modern population. The underlying assumption is that historical population was not determined by the same factors that affect city size and export intensity today. This assumption is reasonable, given the significant changes in transport technology, industry composition and policy over the last centuries. Trade patterns have changed significantly over this period, weakening the link between current and historical exporting. To further support this point, we control for a variety of variables associated with trade costs, such as location on the coast and distance to the border, and show that the coefficients change little when allowing for the possibility that the effect of city size varies with differences in market access.

For China, we instrument current population using prefecture-level population in the 1580s from Bai and Jia (2021).[28] For France, we use population records for 1876 as an instrument for the

[28]Firms in our data are located in 344 prefectures. However, Bai and Jia (2021) only provides historical population

current population. INSEE recently published this information at the level of current municipalities, thus avoiding issues related to changing municipality borders.[29] We aggregate the municipal population records to the commuting zone level, using the official correspondences provided by INSEE.

Table 4 presents our 2SLS results on export intensity and city size. We begin by describing the results for China (columns 1-4). First, column 1 confirms that our elasticity from the baseline OLS regression remains similar in magnitude and highly significant when using prefectures instead of metropolitan areas to define cities. Column 2 presents results from a reduced-form specification, where we directly regress contemporaneous log export intensity on 1580s prefecture-level population. The regressions show a strong positive relationship between the two variables. Next, in column 3, we report the first-stage results, where we regress contemporaneous urban population on historical prefecture-level population. We obtain a strong first stage, with an F-statistic substantially above the Stock-Yogo critical value of 16.4 for 10% maximal IV bias. We also note that the coastal prefecture dummy is the only statistically significant control; no other geographical variable is significant in the first-stage regression. In other words, geographic features that are known to promote trade today do not predict the historical urban population. The estimated first stage coefficient implies that a 10 percent higher historical population in 1580 is related 3% larger population today. Finally, column 4 shows the second stage result. The estimated coefficient on city size is statistically significant and remarkably similar to the OLS coefficient in column 1. This suggests that omitted factors or reverse causality are likely second-order for the baseline OLS relationship between export intensity and city size.

Columns 5-8 in Table 4 present our 2SLS results for France. The reduced-form coefficient is similar to the one for China, while the first-stage coefficient is stronger likely due to the shorter time gap between the instrument (municipality level population in 1876) and endogenous variable (contemporaneous city size). Finally, the 2SLS coefficient (col 6) is similar to its OLS counterpart and statistically significant.

### 3.4 Mechanisms

*Within- and Between-Industries Variation*

To what extent does the positive correlation between export intensity and city size reflect *within*-industry variation, as opposed to more export-intensive industries locating in larger cities? To

information for the 260 prefectures belonging to China proper – i.e., excluding the remaining 74 prefectures from Inner China provinces, such as the Tibet or Inner Mongolia provinces. Our 2SLS regressions for China use the 260 prefectures with available data. See Bai and Jia (2021) for detail on the mapping of historical population records to current prefecture geographical areas. We recompute our control variables using the location and borders of prefecture-level cities, and link them to the prefecture-level dataset.

[29] *Historique des populations communales: Recensements de la population 1876-2019*, available at https://www.insee.fr/fr/statistiques/3698339.

answer this question, we decompose city-level export intensity into its variation occurring within and between (i.e., across) industries. We compute the between-industry component as the counterfactual export intensity measure, $\rho_i^B$, that would result if city-level export intensity only varied due to differences in industry composition across cities. For each sector $s$, we first define its national-level export intensity, $\rho_s$, as the ratio between its national-level exports ($x_s = \sum_i x_{s,i}$) and sales revenues ($r_s = \sum_i r_{s,i}$), so that $\rho_s \equiv x_s/r_s$. We then construct the counterfactual city-level export intensity by multiplying $\rho_s$ with the revenue share of sector $s$ in city $i$, and summing over all sectors $s$:[30]

$$\rho_i^B \equiv \left( \sum_s \frac{r_{s,i}}{r_i} \times \rho_s \right) \tag{2}$$

The within-industry component of export intensity is then defined (in logs) as the residual variation that is not accounted for by differences in the sectoral composition of cities:

$$\ln \rho_i \; = \; \ln \rho_i^B + \ln \rho_i^W \tag{3}$$

Table 5 shows the results of the decomposition for our main datasets, China and France.[31] Note that by construction, the within- and between-industry coefficients add up to the overall elasticity between export elasticity and city size from Table 3. Columns 3 and 6 in Table 5 report the share of the overall variation that is accounted for by the within-industry component. We find that the relationship between export intensity and city size is largely due to variation within industries, accounting for practically all the variation in China, and for almost 43% of the overall variation in France. In other words, our results largely reflect systematic differences in exporting behavior across firms *within* the same industry.

We perform several robustness checks, including a decomposition at the 4-digit industry level, and varying the set of control variables. In all of these cases, the within-industry component remains as important in quantitative terms as in the baseline decomposition in Table 5.

[30]For our baseline specification we define industries at the two-digit level to account for differences in comparative advantage, transport costs, etc. across industries, while keeping industries relatively broad so as to have a sufficient number of exporters within each industry.

[31]The decomposition cannot be performed for Brazil and the United States as for these countries we only have access to aggregate city-level exports (i.e., not by sector).

#### *3.4.1 Mechanisms Driving the Stylized Fact*

To shed light on the drivers behind our results, we study different margins, decomposing city-level export intensity as follows:

$$\rho_i = \underbrace{\left[\frac{x_i}{r_i^x}\right]}_{\frac{\text{Export sales}_i}{\text{Total sales of exporters}_i}} \times \underbrace{\left[\frac{n_i^x}{n_i}\right]}_{\frac{\text{\# Exporters}_i}{\text{\# Firms}_i}} \times \underbrace{\left[\frac{(r_i^x/n_i^x)}{(r_i/n_i)}\right]}_{\frac{\text{Avg. sales of exporters}_i}{\text{Avg. sales of firms}_i}} \tag{4}$$

where the variable $n$ denotes the number of firms, and the superscript $x$ denotes that the corresponding variable is only computed for exporters. The first term on the right-hand-side of equation (4), $(x_i/r_i^x)$, captures the intensive margin of exporting, measuring the export intensity *of exporters* – i.e., dropping non-exporters from the computation of the denominator. The second term, $(n_i^x/n_i)$, corresponds to the fraction of firms in each city that are exporters - i.e., the extensive margin of exporting at the city level. Finally, the last term reflects the average size of exporters $(r_i^x/n_i^x)$, relative to the average firm size $(r_i^x/n_i^x)$. We call this last term the exporter size premium.

To determine the contribution of each of these margins, we apply logarithms to both sides of equation (4) and then regress each of the three components on city size and geographical controls. Table 6 shows the results for China and France, where we have access to microdata to compute each of the terms of the decomposition. We begin discussing the results for the intensive margin. The results in columns 1 and 4 of Table 6 show a *negative* intensive margin for China and a small and insignificant result for France. Thus, the intensive margin does not contribute to our finding for the overall export intensity. This helps us to narrow down potential mechanism because in a wide variety of trade models (including Armington, Eaton and Kortum, 2002; Melitz, 2003; Chaney, 2008, with CES demand side), the intensive margin of export activity is driven by differences in domestic relative to foreign market access. In the absence of variation in international trade costs, exporters in larger cities are predicted to export a *lower* fraction of their output because they have a larger (domestic) market nearby. This negative relationship may be offset by international variable trade costs to the extent that they are lower in larger cities. Thus, our results on the intensive margin suggest that differences in foreign market access across cities (as captured by differences in variable trade costs relative to the rest of the world) cannot account for the city-level association between export intensity and city size.

Next, we discuss the relationship between the extensive margin of exporting and city size – the second term in (4). This margin is related to selection into export markets: In the presence of fixed exporting costs, only the relatively more productive firms find it profitable to engage in exporting (c.f. Melitz, 2003). In standard heterogeneous firm models, differences operating on the extensive margin can be driven by two forces: heterogeneity in fixed export costs across cities, or differences in firm productivity distributions across cities (in particular, differences in the "thickness" of the upper tails of city-level productivity distributions). Intuitively, for fixed productivity distributions across cities, lower fixed export costs lead to a higher fraction of firms being able to pay the fixed cost of exporting. To the extent that these fixed costs of exporting are systematically smaller in larger cities (e.g., because spatially clustered firms can share the costs of acquiring information about foreign markets) this could explain the higher export intensities of larger cities.[32] Alternatively, for constant fixed export costs, a fatter upper tail of the firm productivity distribution means that the productivity of a larger fraction of firms falls above the minimum productivity thresholds that allow profitable participation in export markets. The results in columns 2 and 5 of Table 6 shows that in both China and France, the extensive margin of exporting relates positively to city size, which leaves both lower fixed export costs and a thicker upper tails of firms' productivity distribution as plausible driving forces of the positive correlation between (overall) export intensity and city size.

Finally, we discuss the results for the exporter size premium – the fact that, within cities, average exporters are larger than the average firm (with the latter including both exporters and domestic producers). Variation in this term across cities broadly reflects two forces: differences in productivity distributions across cities and differences in the strength of selection into exporting across cities. To the extent that selection into exporting is systematically stricter in larger cities (either because the variable or the fixed costs of exporting are systematically larger), or that larger cities have systematically fatter upper tails of their firm productivity distribution we would expect to see a positive correlation between city size and the exporter size premium. The converse (i.e., a negative correlation between the exporter size premium and city size) would emerge if selection into exporting was weaker (e.g., due to lower fixed or variable trade costs associated with exporting in larger cities) or the the upper tail of firm productivity distributions are thinner in larger cities. Thus, the correlation of the export size premium with city size provides additional guidance on the forces driving our main results. In particular, if lower variable trade or fixed export costs were driving the city level correlation between export intensity and city size, we would expect a weaker selection into exporting in these locations and, thus, a negative correlation between exporter size premiums and city size. The results in columns 3 and 6 of Table 6 show, in stark contrast with this prediction, a strong positive correlation between the exporter size premium and city size in both China and France. Moreover, in quantitative terms, the exporter size premium margin is substantial: The estimated contribution of this margin to the overall correlation between city size and export intensity is roughly as large as the contribution of the extensive margin of exporting in both China and France. This suggests that explanations based on lower trade costs cannot account for the variation in export intensity across city sizes. Thus, heterogeneity in the upper tails of

[32] In principle, the extensive export margin could also be affected by variation in the international variable trade costs to the extent that these are high enough to deter profitable exports. This mechanism operates similarly to fixed export costs affecting the minimum productivity threshold that determine profitable exporting.

the firm productivity distributions across cities remains the only channel that has the potential of explaining our key stylized fact.[33]

To summarize: Results of the micro decomposition provide suggestive evidence on the mechanisms driving the positive city-level correlation between export intensity and city size. Lower international variable trade costs in larger cities cannot account for the non-positive intensive margin, while lower fixed export costs across cities cannot account for the positive export size premium observed in large cities. Heterogeneity in the dispersion of firms' productivity distribution across cities, in contrast, provides the most promising explanation for the positive association between export intensity and city size that motivates this paper. Next, we develop a model emphasizing this mechanism.

# 4 Simple Model

In this section we present a simple model that outlines the key mechanism that we put forward as a potential explanation for our novel stylised fact. For the sake of clarity and tractability it omits several features of standard QSE models. These features will be reintroduced in the more general, quantitative model that is taken to the data in section $5$.

## 4.1 Setup

We consider a world economy featuring $2$ symmetric countries. Each country is endowed with an exogenous population $L$ of identical workers and contains an exogenous number of city sites $I$. Within countries each city site has an exogenous and symmetric stock of land $N$. Cities with different population levels $L_c$ emerge endogenously on these sites. Crucially, workers are assumed to be perfectly mobile across locations within countries but immobile internationally.

The key driver of within country economic geography in the model are productivity differences across locations. In our setting production is undertaken by firms that need to pay a sunk cost $F_e$ in units of local labor to enter any city $i$ - these costs are assumed to be symmetric across cities and countries. Firm then draw their productivity (denoted $\psi$) from location-specific productivity distributions $G_i(.)$. In turn these distributions capture the heterogeneity in productivity across locations. For simplicity, we assume that these productivity distributions are standard Pareto distributions with location specific shape parameters denoted $\alpha_i$[34].

Once they've drawn their productivity, firms decide which, if any, markets to serve. In line with Eaton, Kortum, and Kramarz (2011), serving each market involves paying fixed costs. In par-

[33] See Combes et al. (2012) for evidence supporting the systematic fatter upper tails of firm productivity distributions in larger cities in the context of France.

[34] Our notation captures the fact that while cities/locations are heterogeneous within countries, the countries themselves are symmetric. This implies that any location in country $c$ has a "twin"location in country $c'$ characterised by th same productivity distribution of potential entrants. As a result of this country symmetry we drop the country subscripts $c$ throughout our analysis.

ticular, each firms needs to pay a fixed cost $F$ in units of local labor to serve the domestic national market, and a fixed cost $F_x$ to serve the foreign market. Moreover, shipping goods internationally also entails incurring variable transportation costs, that take the iceberg form with $\tau > 1$ units of each good needing to be shipped from any domestic location for one unit of the good to arrive at any foreign location. By contrast, we assume that variable trade costs associated with shipping goods domestically are negligible. We also impose the parametric restriction that $\tau^{\sigma-1}F_x > F$ which ensures that the firms that serve the foreign market represent a strict subset of the firms serving the domestic market.

The assumptions above, that ensure that all locations are symmetric in terms of both their domestic and their foreign market access, are made for tractability and to focus attention on the key mechanism we put forward as an explanation for our stylised facts. We will allow for a rich specification of variable trade costs in the quantitative model that we take to the data in section 5.

**Preferences** Workers are homogenous live in a city of their choice within their home country. They consume a bundle of goods and housing while being paid the applicable local wage $w_i$. Their preferences are given by:

$$U_i = c_i^{\beta} h_i^{1-\beta} \tag{5}$$

where $h$ denotes housing and $c$ is a CES composite of the tradable varieties available at each location $i$:

$$c_i = \left[ \int c_i(x)^{\frac{\sigma-1}{\sigma}} dx \right]^{\frac{\sigma}{\sigma-1}} \tag{6}$$

In each city, housing is built by atomistic local landowners by combining land with capital labor according to the technology:

$$h = k^{1-\gamma} n^{\gamma} \tag{7}$$

where $h$ denotes housing, $k$ denotes capital used in the production of housing, $n$ denotes land and $\gamma$ denotes the cost share of land in producing housing. Both land and housing markets are assumed to be perfectly competitive at the local level. Capital is in turn provided in perfectly elastic supply at the exogenous rental rate $r_K = \kappa = 1$. As is standard in this literature we assume that capital income is fully taxed by local governments and redistributed lump sum to local residents.

**Production** In each country and city, there is a potentially infinite supply of potential entrants. Firms produce differentiated tradable varieties using local labor. Once they've chosen a city to enter and paid the entry cost $F_e$ in units of local labor, firms draw their productivity $\psi$ from a location specific productivity distribution $G_i(.)$. These distributions are assumed to be standard Pareto with shape parameters $\alpha_i$. More productive locations are thus characterised by smaller shape parameters. For a firm of efficiency $\psi$, the production technology is then given by:

$$l(q, \psi) = \frac{q}{\psi} \tag{8}$$

where $l(q, \psi)$ denotes the local labor input required to produce a quantity of output $q$ for a firm of productivity $\psi$.

Firms engage in monopolistic competition and aim to maximize profits via their pricing. In doing so, they take the local price indices as given. Given the CES demand system assumed, profit maximization implies that equilibrium prices are a mark-up over marginal costs. Moreover, the structure of trade costs we assumed ensures that price indices are the same at all locations within countries, and that firms charge a single price for each country they serve. These prices are given by:

$$\begin{aligned} p_i^d(\psi) &= \frac{\sigma}{\sigma-1}\frac{w_i}{\psi} \\ p_i^x(\psi) &= \tau p_i^d(\psi) \end{aligned}$$

where $p_i^d(\psi)$ denotes the profit maximizing price set by a firm of productivity $\psi$ located in $i$ for units delivered to the domestic market while $p_i^x(\psi)$ denotes the profit maximizing price for units sold in the foreign market In turn, operational profits derived from serving each market are given by:

$$\pi_i^d(\psi) = \frac{R}{\sigma}\left(\frac{\psi\rho}{w_i}\right)^{\sigma-1} - w_i F \tag{9}$$

$$\pi_i^x(\psi) = \tau^{1-\sigma}\frac{R}{\sigma}\left(\frac{\psi\rho}{w_i}\right)^{\sigma-1} - w_i F_x \tag{10}$$

where $\pi_i^d$ denotes profits from serving the domestic market, $\pi_i^x$ denotes profits from serving the foreign market while $R$ denotes the aggregate revenues of the tradable sector in each country. Given our assumptions about the fixed and variable costs of serving domestic and foreign markets, which ensure that the firms serving foreign markets are a strict subset of those serving domestic markets, the total profits for a firm of productivity $\psi$ at location $i$ that has achieved successful entry (i.e. serves at least one market) are given by

$$\pi_i(\psi) = \begin{cases} \pi_i^d(\psi) & \text{if} \quad \pi_i^x(\psi) < 0 \\ \pi_i^d(\psi) + \pi_i^x(\psi) & \text{if} \quad \pi_i^x(\psi) > 0 \end{cases} \tag{11}$$

Similarly, firm revenues from serving each market are given by

$$r_i^d(\psi) = R\left(\frac{\psi\rho}{w_i}\right)^{\sigma-1}$$
$$r_i^x(\psi) = \tau^{1-\sigma} r_i^d(\psi)$$

With total revenues for a firm of productivity $\psi$ located at $i$ being given by:

$$r_i(\psi) = \begin{cases} r_d^i(\psi) & \text{if} \quad \pi_x^i(\psi) < 0 \\ r_d^i(\psi) + r_x^i(\psi) & \text{if} \quad \pi_x^i(\psi) > 0 \end{cases}$$

As in Melitz (2003), in equilibrium each location will be characterised by two productivity thresholds: the minimum productivity threshold for successful entry into the domestic market (which we denote $\psi_i^{d*}$) and the minimum productivity threshold for successful entry into the foreign market (which we denote $\psi_i^{x*}$). These thresholds are determined by the zero-profit conditions:

$$\pi_i^d(\psi_i^{d*}) = 0 \tag{12}$$
$$\pi_i^x(\psi_i^{x*}) = 0 \tag{13}$$

Also as in Melitz (2003) it will be useful to define for each location two average productivity measures: the average productivity of all firms serving the domestic market in each location (denoted $\tilde{\psi}_i^d$) and the average productivity of exporters at each location (denoted $\tilde{\psi}_i^x$). These are given by:

$$\tilde{\psi}_i^d = \left[\int_{\psi_i^{d*}} \psi^{\sigma-1} g_i(\psi) d\psi\right]^{\frac{1}{\sigma-1}}$$
$$\tilde{\psi}_i^x = \left[\frac{1}{1-G_i(\psi_i^{x*})}\int_{\psi_i^{x*}} \psi^{\sigma-1} g_i(\psi) d\psi\right]^{\frac{1}{\sigma-1}}$$

With the above notation, the expected profits and revenues of a firm choosing to enter at a given location $i$ (before drawing its productivity) are given by

$$\bar{\pi}_i = \pi_i^d(\tilde{\psi}_i^d) + p_i^x \pi_i^x(\tilde{\psi}_i^x) = \frac{w_i F_e}{1-G_i(\psi_i^{d*})} \tag{14}$$
$$\bar{r}_i = r_i^d(\tilde{\psi}_i^d) + p_i^x r_i^x(\tilde{\psi}_i^x) \tag{15}$$

where $p_i^x = \frac{1-G_i(\psi_i^{x*})}{1-G_i(\psi_i^{d*})}$ represents the probability of a firm based in location $i$ exporting to a foreign country, and the second equality in equation (14) captures the free entry condition for firms contemplating entry at location $i$.

Finally, using the free entry condition at each location allows us to solve for the measure of firms in each city:

$$M_i = \frac{R_i}{\bar{r}_i} = \frac{L_i}{\sigma[(\psi_i^{d*})^{\alpha_i} F_e + F + p_i^x F_x]} \tag{16}$$

where $M_i$ denotes the measure of active firms at location $i$, while $R_i = w_i L_i$ denotes total expenditure at location $i$.

**Residential choice in spatial equilibrium** Spatial equilibrium requires that utility is equalised at all inhabited locations within countries, as mobility frictions are assumed negligible. This yields

$$U_i = \beta^\beta (1-\beta)^{1-\beta} \frac{v_i}{(p_i^h)^{1-\beta}} = \bar{U} \qquad \forall i \tag{17}$$

Where $p_i^h$ denotes the price of housing at location $i$ (note that the tradable good composite has the same price at all locations within countries and was chosen as a numeraire, hence its price is 1). In turn the price of housing can be written as:

$$p_i^h = \left(\frac{r_K}{1-\gamma}\right)^{1-\gamma} \left(\frac{r_i}{\gamma}\right)^\gamma = \left(\frac{1}{1-\gamma}\right)^{1-\gamma} \left(\frac{r_i}{\gamma}\right)^\gamma \tag{18}$$

where $r_i$ denotes the land rental rate at location $i$, $r_K$ denotes the rental rate of capital, and the second equality results from our assumption that capital is available in perfectly elastic supply at $r_k = \kappa = 1$.

In line with the literature, we assume that land and capital income in each location is fully taxed by local governments and redistributed lump sum to workers that reside in each location. Thus, total income in location $i$ is given by labor income plus expenditure on residential land:

$$v_i L_i = w_i L_i + (1-\beta) v_i L_i = \frac{w_i L_i}{\beta} \tag{19}$$

while the total income of each worker is given by

$$v_i = \frac{w_i}{\beta} \tag{20}$$

Finally, land market clearing yields the equilibrium land rent from equating land income with expenditure on land:

$$r_i = \frac{1-\beta}{\beta} \gamma \frac{w_i L_i}{N_i} \tag{21}$$

**General equilibrium** The general equilibrium of the model is represented by a measure of workers for each location $L_i$, a set of entry thresholds for firms at each location $\psi_i^{d*}$, a set of entry into exporting thresholds for each location $\psi_i^{x*}$, a set of firm measures for each location $M_i$, a set of wages for each location $w_i$ and a set of land rents for each location $r_i$ such that the following set of equilibrium conditions hold: .

1. Zero profit condition for marginal entrant at each location $i$

$$\pi_i^d(\tilde{\psi_i^d}) = w_i F k_i(\psi_i^{d*}) \tag{22}$$

where $k_i(\psi) = [(\frac{\tilde{\psi}_i(\psi)}{\psi})^{\sigma-1} - 1]$

2. Zero profit condition for marginal entrant into exporting at each location $i$

$$\pi_i^x(\tilde{\psi_i^x}) = w_i F_x k_i(\psi_i^{x*}) \tag{23}$$

3. Free entry condition

$$\bar{\pi}_i = \pi_i^d(\tilde{\psi_i^d}) + p_i^x \pi_i^x(\tilde{\psi_i^x}) = \frac{w_i F_e}{1 - G_i(\psi_i^{d*})} \tag{24}$$

4. Spatial equilibrium for workers among all domestic locations

$$U_i = \bar{U} \qquad \forall i \tag{25}$$

5. Market clearing for land in each city

$$r_i = \frac{1-\beta}{\beta}\gamma\frac{w_i L_i}{N_i} \tag{26}$$

6. National labour markets clear

$$\sum_i L_i = L \tag{27}$$

## 4.2 Matching the stylized facts

With the preliminaries above, we now proceed to describe the properties of the equilibrium concerning the distribution of exporting activity across space. These properties in turn speak directly to the stylized facts we have documented. We begin with an auxiliary result that will facilitate our exposition.

**Lemma 1.** *Cities with better exogenous productivity distributions (i.e. smaller shape parameters $\alpha_i$ of the posited standard Pareto productivity distributions) will have higher average firm productivity in equilibrium*

**Proof:** See appendix.

Intuitively, cities whose exogenous productivity distributions have a smaller shape parameter exhibit a fatter upper tail. Thus these cities are more likely to feature firms with very high productivity draws which will tend to push up local labour demand. With elastic local labour supply, this higher local demand will be reflected in higher equilibrium wages in these cities. In turn, higher local wages tend to increase the stringency of the selection of entry process in the more productive cities, as low productive firms become more likely to exit (i.e. choose to serve no markets) without producing in these locations. This endogenous selection mechanism will tend to augment the productivity differences between the firms in the two cities. We will thus proceed by calling cities with more attractive exogenous productivity distributions simply "more productive"cities. We now proceed to stating the main theoretical result of the paper, that connects city size with export intensity

**Proposition 1.** *In equilibrium, the more productive city:*

1. *Is larger, has higher wages, more expensive housing and higher export intensity.*
2. *Moreover, this higher aggregate export intensity is driven by the extensive margin of firms' export participation.*

**Proof:** See appendix.

As mentioned before, the presence of highly productive firms in the more productive cities will be result in higher local labour demand in these locations. With elastic local labour supply, this higher local demand will be reflected in both prices and quantities, such that these locations will feature both higher equilibrium wages and and higher populations. Furthermore, higher local wages and larger populations will push up the demand for housing, leading to higher land prices in the more productive cities. All in all, the more productive cities are thus larger and display higher wages, housing rents and land rents.

Most importantly for our purposes, more productive cities also display higher aggregate export intensities. As in Melitz (2003), the productivity thresholds for exporting and for entry are proportional to each other and the proportions are common to all locations and given by:

$$\frac{\psi_i^{x*}}{\psi_i^{d*}} == \tau \left(\frac{F_x}{F}\right)^{\frac{1}{\sigma-1}} \qquad \forall i \tag{28}$$

However, in the more productive cities, the presence of a fatter upper tail implies that a higher mass of firms jumps over the local "Melitz barrier" and become exporters. This in turn leads to more productive locations having a higher export intensity. Importantly, given the CES demand structure we impose, the higher export intensity of more productive locations is driven exclusively by the extensive margin (i.e. the fraction of firms that export), with the intensive margin of exporting (i.e. the export intensity of exporters) being constant across space[35]. Taken together, our simple model predicts that more productive cities will be both larger and feature higher export intensities, and can thus account for the positive correlation between export intensity and city size that we observe in the data. Moreover, it is important to note that the main mechanism we propose to account for the association between city size and exporting, local productivity differences driven by the upper tail of the firm productivity distribution is consistent with empirical evidence (see Combes et al. (2012)).

### 4.3 Theoretical Results: Comparative Statics

One of the key features of our model is that allows us to study the joint determination of international trade and economic geography. In this section we briefly outline some of the comparative static properties of the simple model discussed in the previous section. In particular we highlight how the model allows us to study the impact of trade policy on internal geography as well as the impact geographic policies on international trade.

Let us first consider the implications of international trade liberalization on internal geography. In our simplified setting, the spatial reallocation of employment associated with trade liberalization is straightforward to characterise and is outlined in the proposition below

**Proposition 2.** *A reduction in the variable international trade costs $\tau$ leads to a shift in population towards larger cities, as well as an increase in aggregate productivity and welfare.*

**Proof:** See appendix

Intuitively, trade liberalization leads to an increase in the size of exporters relative to non-exporters (as export revenues rise relative to domestic sales). This tends to push up the demand for labor in each country's more productive cities, as these locations feature a higher fraction of firms who are exporters. In turn this leads to an increase in the size of each countries'most productive cities at the expense of less productive locations. Moreover, trade liberalization increases aggregate productivity via two channels: First, trade liberalization makes the firm selection process becomes more stringent in all locations (the productivity threshold for successful entry goes up in all locations). Second, as outlined above, trade liberalisation shifts more factors towards the more productive citis of each country. In turn, this increase in aggregate productivity is reflected in an increase in real wage levels in both countries, which leads to an increase in aggregate welfare.

Moving on to the analysis of geographic policy, the proposition below characterises the impli-

[35]This feature of the model is a direct result of the fact that, like in Melitz (2003), conditional on exporting, firm level export intensity is constant with respect to firm productivity.

cations of a generalised increase in housing supply elasticities in all locations:

**Proposition 3.** *Planning policies that increase the housing supply elasticity lead to an increase in country-level export intensity and aggregate productivity.*

**Proof:** See appendix

Intuitively, relaxing housing supply restrictions reduces the cost of housing in all locations, thus making all cities more attractive. However, this effect is stronger for larger and more productive cities, as these locations were more constrained by the scarcity of land and housing. As a result of this mechanism, workers shift towards the most productive cities. This shift in factors in turn causes an increase in aggregate productivity and an increase in aggregate export intensity. This is because the relative mass of firms shifts to the more productive locations, and firms in these location are more likely to display high productivity and become exporters.

# 5 Quantitative Analysis

In this section we explore the quantitative implications of incorporating firm heterogeneity and the selection mechanisms embedded in our simple model into a standard Quantitative Spatial Economics (QSE) framework. To do this we first extend the simple model presented in the previous section to a more general QSE setting. We then calibrate the model to Chinese data and discuss model fit, with a focus on our main motivating stylized fact. Finally, we employ the model to undertake counterfactual policy analysis. We provide quantitative results for the effect of (i) trade liberalization and (ii) spatial policies on welfare and productivity.

## 5.1 Quantitative Model

To make our framework amenable to quantitative analysis, we adapt and extend the simple model presented in the previous section in four ways:

1. First we allow for countries to be asymmetric. Moreover, given that we will take the model to the data using data from a single country, China, we will explicitly model the internal geography of only one country. China will be assumed to contain $N$ cities, while modeling the rest of the world as another, larger country, with no internal geography (i.e. we model it as a single city/ region). Locations within China will be indexed with subscripts $i$ and $n$ while the rest of the world will carry subscripts $c$.

2. We allow for a richer specification of productivity differences across locations. In particular while we maintain the assumption that firm productivity is drawn from location specific Pareto distributions, we allow these distributions to differ across locations both in their shape parameters $\alpha_i$ and in their location parameters $A_i$ (i.e. the distributions are no longer standard Pareto).

3. We allow for a richer specification of transportation frictions. In particular we allow for a full matrix of bilateral transportation costs across locations. These variable transportation costs are denoted $d_{ni}$ and retain the iceberg transport cost formulation: $d_{ni}$ units of a commodity need to be shipped from $i$ for one unit of the commodity to arrive at the destination $n$.

4. Finally, while we maintain the assumption of prohibitive costs to international migration, we introduce non-negligible within country migration costs. As is standard in the literature we model these mobility frictions as location-specific shocks to worker preferences. Worker preferences are therefore assumed to be given by:

$$U_i(\omega) = b_i(\omega) c_i(\omega)^{\beta} h_i(\omega)^{1-\beta} \tag{29}$$

Where $b_i(\omega)$ denote location specific amenity shocks that are drawn independently across locations and workers within China from a Fréchet distribution:

$$F_i(b) = e^{-B_i b^{-\epsilon}} \tag{30}$$

The scale parameters $B_i$ determine average amenity levels for each location $i$ and the shape parameter $\epsilon$ controls the dispersion of amenities across workers for each location.
With the above specification of preferences, the indirect utility function at each location is given by:

$$U_i(\omega) = \frac{b_i(\omega) v_i}{P_i^{\beta} (p_i^h)^{1-\beta}} \tag{31}$$

Where $P_i$ denotes the price index at each location $i$ (as we now have within country transportation frictions and allow for differences in foreign market access across locations, these price indices will now differ by location). Moreover, since utility is a monotonic function of the amenity draw, it thus also have a Frechet distribution

$$F_i(U) = e^{-\phi_i U^{-\epsilon}} \tag{32}$$

where $\phi_n$ is given by

$$\phi_i = B_i (v_i / P_i^{\beta} (p_i^h)^{1-\beta})^{\epsilon} \tag{33}$$

Within China, the population share of each location is given by

$$\frac{L_i}{L} = \frac{B_i (v_i / P_i^{\beta} (p_i^h)^{1-\beta})^{\epsilon}}{\sum_{k \in N} B_k (v_k / P_k^{\beta} (p_k^h)^{1-\beta})^{\epsilon}} \tag{34}$$

While the expected utility at each location within China, (which is the most reasonable measure of welfare) is given by

$$\bar{U} = \delta \left[ \sum_{k \in N} B_k (v_k / P_k^{\beta} (p_k^h)^{1-\beta})^{\epsilon} \right]^{\frac{1}{\epsilon}} \tag{35}$$

where $\delta = \Gamma\left((\epsilon - 1)/\epsilon\right)$ with $\Gamma(.)$ denoting the Gamma function.

With the adaptations and extensions above, we can proceed to define the equilibrium of the quantitative model as follows.

**General Equilibrium of the Quantitative Model** The general equilibrium of the "quantitative model" outlined above is represented by a measure of workers for each location within China $L_i$, a set of entry thresholds for firms at each location within China $\psi_i^{d*}$, a set of entry into exporting thresholds for each location $\psi_i^{x*}$, a set of firm measures for each location $M_i$, a set of wages for each location $w_i$ and a set of land rents for each location $r_i$, as well as their corresponding variables for the rest of the world $w_c, \psi_c^{d*}, \psi_c^{x*}, M_c, r_c$ such that the following set of equilibrium conditions hold:

1. Expenditure and revenues are equalized for all locations

$$w_i L_i = \sum_{n \in N \cup \{c\}} \pi_{ni} w_n L_n \quad \forall i \in N \cup \{c\} \tag{36}$$

Where $\pi_{ni}$ denotes the expenditure share of goods sourced from $i$ in the overall expenditure of location $n$. These expenditure shares are in turn given by

$$\pi_{ni} = \frac{M_i (w_i d_{ni})^{1-\sigma} (\tilde{\psi}_i^d)^{\sigma-1}}{\sum_{k \in N} M_k (w_k d_{nk})^{1-\sigma} (\tilde{\psi}_k^d)^{\sigma-1} + p_c^x M_c (w_c d_{nc})^{1-\sigma} (\tilde{\psi}_c^x)^{\sigma-1}} \tag{37}$$

$$\pi_{ci} = \frac{p_i^x M_i (w_i d_{ci})^{1-\sigma} (\tilde{\psi}_i^x)^{\sigma-1}}{\sum_{k \in N} p_k^x M_k (w_k d_{ck})^{1-\sigma} (\tilde{\psi}_k^x)^{\sigma-1} + M_c (w_c)^{1-\sigma} \tilde{\psi}_c^{d\,\sigma-1}} \tag{38}$$

$$\pi_{cc} = \frac{M_c (w_c)^{1-\sigma} (\tilde{\psi}_c^d)^{\sigma-1}}{\sum_{k \in N} p_k^x M_k (w_k d_{ck})^{1-\sigma} (\tilde{\psi}_k^x)^{\sigma-1} + M_c (w_c)^{1-\sigma} (\tilde{\psi}_c^d)^{\sigma-1}} \tag{39}$$

$$\pi_{nc} = \frac{p_c^x M_c (w_c d_{nc})^{1-\sigma} (\tilde{\psi}_c^x)^{\sigma-1}}{\sum_{k \in N} M_k (w_k d_{nk})^{1-\sigma} (\tilde{\psi}_k^d)^{\sigma-1} + p_c^x M_c (w_c d_{nc})^{1-\sigma} (\tilde{\psi}_c^x)^{\sigma-1}} \tag{40}$$

where as before $M_i$ denotes the measure of firms at each location $i$ while $(\tilde{\psi}_i^d)$ and $(\tilde{\psi}_i^x)$ represent the measures of average productivity defined in section 4.

2. Zero profit condition for marginal entrants at each location $i$

$$\pi_i^d(\tilde{\psi_i^d}) = w_i F k_i(\psi_i^{d*}) \tag{41}$$

where $k_i(\psi) = [(\frac{\tilde{\psi}_i(\psi)}{\psi})^{\sigma-1} - 1]$

3. Zero profit condition for marginal entrant into exporting at each location $i$

$$\pi_i^x(\tilde{\psi_i^x}) = w_i F_x k_i(\psi_i^{x*}) \tag{42}$$

4. Free entry condition at all locations

$$\bar{\pi}_i = \pi_i^d(\tilde{\psi_i^d}) + p_i^x \pi_i^x(\tilde{\psi_i^x}) = \frac{w_i F_e}{1 - G_i(\psi_i^{d*})} \tag{43}$$

5. Price indices at each location are given by

$$P_i = \left(\frac{M_i}{\pi_{ii}}\right)^{\frac{1}{1-\sigma}} \left(\frac{\sigma}{\sigma-1}\frac{w_i}{\tilde{\psi_i^d}}\right) \tag{44}$$

6. The measure of firms at each location is given by

$$M_i = \frac{R_i}{\bar{r}_i} = \frac{\alpha_i - \sigma + 1}{\alpha_i \sigma} \frac{(\tilde{\psi_i^x})^{\alpha_i}}{(\tilde{\psi_i^x})^{\alpha_i} F + (\tilde{\psi_i^d})^{\alpha_i} F_x} L_i \tag{45}$$

7. The share of the population at each location is given by:

$$\frac{L_i}{L} = \frac{B_i (v_i / P_i^\beta (p_i^h)^{1-\beta})^\epsilon}{\sum_{k \in N} B_k (v_k / P_k^\beta (p_k^h)^{1-\beta})^\epsilon} \tag{46}$$

where $v_i = w_i/\beta$ and the price of housing $p_i^h$ is given by

$$p_i^h = \left(\frac{1}{1-\gamma}\right)^{1-\gamma} \left(\frac{r_i}{\gamma}\right)^\gamma$$

8. Land markets clear in each city

$$r_i = \frac{1-\beta}{\beta} \gamma \frac{w_i L_i}{N_i} \tag{47}$$

### 5.2 Calibration

In this section we aim to calibrate the key parameters and exogenous variables of the quantitative model outlined above using Chinese data. These parameters and exogenous variables include: $\beta$, the share of tradable goods in consumption, $\gamma$ the revenue share of land in construction, $\sigma$ the elasticity of substitution between tradable varieties,$\epsilon$ the shape parameters of the amenity shock distribution, the set of fixed costs $F, F_x, F_e$; the variable cost matrix $d_{ni}$ as well as the key set of locational fundamentals $\alpha_i, A_i, B_i$.

The calibration procedure extends Redding (2016) for the case of heterogeneous firms in a model with fixed production and export costs. We proceed in two steps. In the first stage, we calibrate the parameters and exogenous variables that can be directly linked to the data or to the existing empirical literature ($\sigma, \beta, \gamma, \epsilon, \alpha_n, d_{ni}$, and $d_{nc}$). Table 7 summarizes these parameters with their corresponding target moments. We set the value of the elasticity of substitution ($\sigma = 2.5732$) such that the theoretical markup $\sigma/(\sigma-1)$ matches the average empirical markup across all firms – computed at the firm-level using the procedure outlined by De Loecker and Warzynski (2012). We set the housing expenditure share $(1-\beta)$ to 23.4 percent, matching official statistics produced by the National Bureau of Statistics of China.[36] Next, we calibrate the land cost share in housing production ($\gamma$) to match the median housing supply elasticity across Chinese cities estimated in Wang, Chan, and Xu (2012). We choose a value of 3.18 for $\epsilon$, which is in line with the estimates using Indonesian data in Bryan and Morten (2019).[37] Regarding the Pareto shape parameter, we derive estimates of the firm's productivity distribution by running city-by-city log-rank regressions on domestic revenues and then multiply the resulting coefficient by $(\sigma-1)$ as suggested by di Giovanni, Levchenko, and Rancière (2011). Finally, we calibrate the variable trade cost between any domestic location and the RoW, $d_c$, to match the aggregate export intensity across all cities in China.

In the second stage, we use the parameters derived in the first stage together with data on population ($L_n$), wages ($w_n$), average domestic and export revenues ($\tilde{r}_i^d$ and $\tilde{r}_i^x$), and the share of exporters in each city ($N_n^x/N_n$) to recover the amenity parameter ($B_n$), the Pareto scale parameter ($A_n$), the export entry productivity threshold ($\psi_{xi}^*$), and fixed production and export costs ($F$,$F_x$). In a nutshell, this second part of the calibration procedure can be sub-divided into five steps (we relegate a more detailed exposition to Appendix C). We first recover the fixed production and export costs ($F$,$F_x$), plugging in information on wages and average domestic and export revenues across all locations into the expressions describing overall domestic and export profits for the

[36] See http://www.stats.gov.cn/english/PressRelease/202201/t20220118_1826649.html. The value we adopt for the housing expenditure share is in line with Davis and Ortalo-Magne (2011), who report a stable housing expenditure share over time and across MSA in the United States of around 0.25.

[37] We are not aware of any similar estimates produced for China.

marginal firms entering each respective market. Second, we compute the mass of firms in each city, which are proportional to the actual city-level population according to (16). Third, we use the free entry condition and the assumed Pareto distribution assumption to substitute out threshold average productivity as a function of the scale parameter $A_n$ in each location. Fourth, we substitute for the variables derived in the previous steps plus information on wages and population in each city in (**??**), resulting in a system of $N + 1$ equations with $N + 1$ unknowns that are solved to derive the values of the productivity scale parameter $A_n$ in each location. Finally, we derive the values of the amenity parameters $B_n$ in each city, solving the system of equations described by (**??**) after computing the equilibrium value for the land rents and the equilibrium price index in each location.

### 5.3 Export Intensity and City Size

After parameterizing the model, we evaluate its ability to account for the higher export intensity of larger cities. The goal of this exercise is to determine to what extent the model can replicate the slope of the relationship between export intensity and city size observed in the data. Note that our calibration strategy does not target this moment. Thus, this exercise can be seen as a test of the mechanisms highlighted by the model – heterogeneous productivity distributions across cities and selection into exporting.

Figure 3 illustrates the fit of the model to the data, plotting binned scatter diagrams for city-level (log) export intensity and (log) city size.[38] Both model and data include regression lines to compare their estimated elasticity (i.e., the slope of these lines). As the figure shows, the model produces a strong positive relationship between city size and export intensity that closely resembles the observed relationship in the data. Furthermore, the regression coefficient is estimated at a value of 0.178 (with a standard error 0.023), accounting for almost two-thirds of the data variation.

The fit of our model to the aggregate data is remarkable, as the model only considers a single mechanism to generate the positive relationship between export intensity and city size: Heterogeneous productivity distributions across city sizes. This mechanism introduces a force that endogenously causes the positive correlation, as smaller Pareto shape parameters lead to larger and more export-intensive cities. This differs from alternative mechanisms that can only replicate the positive correlation between export intensity in a hard-wired way (e.g., city-specific fixed or variable trade costs). As we explain next, these alternative mechanisms can only account for the stylized fact between export intensity and city size if relative foreign trade costs are systematically lower in larger cities. In general, it is not clear whether this condition should be expected to hold, leading to context-specific predictions: In some cases, these mechanisms can produce a positive relationship, while in others, a negative relationship between export intensity and city size.

[38] To make model and data comparable, the figure controls for the same set of geographic characteristics included in Table 3 when plotting the data.

*Alternative Mechanisms*

We benchmark the performance of our baseline model against three competing alternatives. We first allow for heterogeneous firms and selection into exporting as in the full model but restrict the productivity distribution to be the same everywhere. This exercise, which we denote as "fixed shape parameter model," aims to illustrate the contribution of allowing for heterogeneous Pareto shape parameters across cities to fit the main stylized fact. Second, we consider a model where aggregate export intensity varies solely due to differences in *variable* trade costs across cities. In this model, cities have different average productivity, but firms are homogeneous – along the lines of Redding (2016). Therefore, any difference in export intensity across cities reflects variation in foreign relative to domestic market access. Finally, we discuss the ability of a model with city-specific *fixed* export costs to explain the positive relationship between export intensity and city size. Importantly, as in the full model, all competing models allow for differences in cities' average productivity and local amenities. Thus, these exercises shed light on the quantitative importance of allowing different productivity distributions across cities to fit the data while keeping all other model features constant.

We begin by discussing the fit of the fixed shape parameter model to the main stylized fact. We calibrate this model following the same strategy as the full model but restrict the Pareto shape parameter to take a constant value across cities. In terms of fitting the main stylized fact, we expect this model to produce a null correlation between export intensity and city size, as both overall sales and export sales at the city-level move proportionately with mean city productivity in this model. Figure 4 shows this prediction in the fitted model. Export intensity does not vary across city sizes, validating the importance of allowing heterogeneous productivity distributions across cities to fit the main stylized fact.

Next, we explore whether allowing for variable trade costs (with homogenous firms) could account for the positive correlation between export intensity and city size. With no firm heterogeneity or selection into exporting, cities' export intensity varies only due to differences in *foreign relative to domestic* market access, affecting the intensive margin of exports. Note that this variation does not necessarily correlate with city size. For instance, one could argue that larger cities have better foreign market access in China as they tend to locate along the coastal line. However, they also have better domestic market access than small, inland cities because larger cities cluster on the coast. Thus, it is a-priori unclear whether the data supports this mechanism as a driver of the correlation between export intensity and city size. Indeed, the negative intensive margin estimated in Table 6 suggests that a precise calibration of variable trade costs should lead to larger cities being *less* export intensive. Nevertheless, to explore the potential of this mechanism, we choose a benign calibration for the variable trade costs, allowing that, on average, larger cities have a better ratio of foreign to domestic market access than small cities. In particular, we follow Redding

(2016) in assuming that the logarithm of variable trade costs ($d_{ni}$) between domestic locations $n$ and $i$ are a log-linear function of the logarithmic straight-line distance between $n$ and $i$, divided by 100: $\ln d_{ni} = \phi \ln(\text{dist}_{ni}/100)$, with $\phi = 0.33$.[39] To calibrate the variable trade cost between any domestic location and the RoW, $d_{nc}$, we assume that the cost of taking goods to the RoW is equal to the value of taking them to the nearest port multiplied by a constant $\zeta$ (so that $d_{nc} = d_{np} \times \zeta$). We calibrate $d_{np}$ using the linear distance between city $n$ and its nearest port and apply the parameterization that we used before for $d_{ni}$, and set $\zeta$ to match the aggregate export intensity across all cities in China.

Figure 5 plots the predicted export intensity of the variable trade cost model against city size. This model produces a weak correlation between export intensity and city size. The slope is precisely estimated at a value of 0.042 (robust standard error 0.012), accounting for about 15 percent of the relationship estimated in the data. Thus, only a minor fraction of the variation in the Chinese data can be explained by differences in variable trade costs across location pairs.

Finally, we explore whether a model with heterogeneous firms and city-specific fixed export costs could explain the observed correlation between export intensity and city size. For this mechanism to work, it would require larger cities to have lower fixed export costs. We verify if this condition holds in the data by inverting the fixed export cost city-by-city from the equilibrium condition for the fraction of exporters in each city as a function of fixed production cost, average export intensity within exporters, and parameters. Panel A of Figure 6 plots each city's calibrated fixed export cost against city size. The figure shows a strong negative correlation, i.e., fixed costs of exporting tend to be lower in larger cities. This suggests that this mechanism may indeed produce higher export intensity in larger cities. Then, in Panel B of Figure 6, we plot the predicted export intensity implied by this model. The figure shows a weak, positive correlation between export intensity and city size. The regression coefficient is estimated at a value of 0.049 (robust standard error 0.008), accounting for only 18 percent of the baseline OLS elasticity – about one-fourth of the contribution of the full model. The low contribution of the fixed export cost model is intuitive: Lower fixed export costs leads to a larger fraction of exporters in larger cities. However, the *incremental* exporters in large cities are not productive enough to lead to sizable differences in city-level exports.

To summarize: None of the competing models can account for the strong positive correlation between city-level export intensity and city size. While feasible, the data does not support an explanation based solely on variable trade cost. We show that, even when allowing a favorable calibration for this mechanism, a model with variable trade costs produces only a weak positive correlation between export intensity and city size. We find some support for the fixed cost mechanism:

[39] We set $d_{ni}$ to one for location pairs separated by less than 100 kilometers, as for these cases the effect of distance on trade is most likely negligible.

Fixed export costs are lower in larger cities. However, with fixed productivity shape parameters, the implied differences in export probability do not generate significant differences in aggregate city-level export intensity across city sizes, as the additional exporters are not productive enough to boost export intensity in larger cities. Overall, the results in this section suggest that allowing for dispersion in firm productivity across cities has a first-order relevance to accounting for larger cities being more export intensive.

### 5.4 Counterfactual Analysis

This section analyzes the general equilibrium effect of trade and spatial policies. Our goal is to illustrate how economic geography and international trade interact in the model. We first explore the quantitative relevance of economic geography for the computation of gains from trade in terms of productivity and welfare. We then discuss how international trade affects the effectiveness of spatial policies.

#### *5.4.1 Gains from Trade Liberalization*

We begin by computing the welfare and productivity gains associated with trade openness in our model. We implement this counterfactual exercise as a symmetrical decline in the international variable trade cost $d_{ci}$ from prohibitive levels to levels consistent with observed trade flows. As $d_{ci}$ decreases, firms with productivity above the export productivity threshold increase their exports and their share of production sold in foreign markets. Importantly, the decrease in variable trade cost allows exporters to offer their products at a lower cost in all destination markets, lowering aggregate prices in all countries (given the symmetry assumption). This, in turn, induces entry into export markets, as the lower aggregate prices decreases the value of the entry into exporting. All in all, trade liberalization leads to a reallocation of economic activity towards more productive firms, which grow as a result, leading to an increase in aggregate productivity. Welfare also increases because real incomes grow as the aggregate price index decreases.

Relative to a model without geography, we expect welfare gains from trade in our model to be different for two reasons. First, population migrates towards sites with better market access in the open economy, increasing land prices and therefore leading to different welfare gains from trade relative to an economy where labor is immobile.[40] Our model adds a second reason leading to different gains from trade: Aggregate trade elasticities are variable, as our model features heterogeneous productivity shape parameters across cities. This implies that domestic and export productivity cutoffs show a stronger response in larger cities, leading to higher aggregate productivity gains from trade and raising welfare gains from trade relative to models with homogeneous productivity distributions.

[40] See Redding (2016) for a formal exposition of this mechanism in the context of models with constant and increasing returns to scale and geography but homogeneous firms.

Table 8 computes the aggregate productivity and welfare gains from trade liberalization in our model. As in section 5.3, we compare our model to the same increasing returns to scale model in Redding (2016) with geography and homogeneous firms and to a model with heterogeneous firms, but constant productivity shape parameters across cities. Importantly, to make these estimates comparable to the literature, we introduce endogenous agglomeration forces in all analyzed models by allowing heterogeneity in domestic and international variable trade costs across location pairs. Our model produces higher gains from trade for both welfare and aggregate productivity than the two competing alternatives.[41] Aggregate productivity increases about twice compared to the fixed share parameter model – 7.6% vs. 3.9%. The homogeneous firm model also features aggregate productivity gains from the reallocation of production from less to more productive cities. These gains, however, are negligible and estimated to be less than 0.1 percentage points of the aggregate productivity level in autarky. Our model also delivers substantially larger gains in terms of welfare: Welfare gains from trade are about one-quarter larger than the homogeneous firms' benchmark and 15 percent larger than the gains estimated in the fixed shape parameter model. This suggests that our mechanism is quantitatively important for the computation of aggregate productivity and welfare effects.

#### *5.4.2 International Trade and the Effect of Spatial Policies*

The second counterfactual exercise studies the productivity and welfare effect of the reduction in land-use restrictions studied by Gaubert (2018). We compare the response in the open and closed economy cases. We implement this policy as a (multilateral) reduction in the parameter $\gamma$, which measures the intensity of land use in the housing production function.[42] Changing this parameter affects both housing supply and the cost of labor across cities. In particular, a reduction in the value of $\gamma$ increases the housing supply elasticity, and flattens the wage schedule across city sizes.

In the model, a less restrictive spatial policy leads to a higher aggregate productivity level. As $\gamma$ decreases, land and thus housing gets cheaper, leading to improvements in aggregate total factor productivity due to reallocation of resources. Relative to the closed economy case, the effect of a reduction in land use restrictions on aggregate productivity and welfare may be higher or lower, as detailed in Proposition 4. On the one hand, weakening housing supply restrictions increases the fraction of firms that are exporters and trade intensity, bringing about additional gains from trade. On the other hand, reallocation effects across space may be higher or lower than in the closed economy model, and this latter effect may dominate the gains from trade effect.

We proceed in three steps to analyze the effect of changes in $\gamma$. First, we calibrate the land

[41] To simplify comparisons, we normalize productivity and welfare in both models relative to the actual open economy.

[42] More generally, policies in the open economy case may lead to cross-country spillovers when they are not applied symmetrically in all countries. While this may lead to interesting quantitative results, for now we focus on the the case of multilateral policies to emphasize the different responses of the economies in the open and closed economy cases.

intensity parameter $\gamma$. As in Gaubert (2018), we set this parameter to match the median housing supply elasticity across Chinese firms (see Wang et al., 2012). Second, we solve the general equilibrium of the baseline economy as in section 5.3. Finally, we simulate the various counterfactual economies, where we change the value of $\gamma$. This involves recomputing general equilibrium objects. In particular, we vary $\gamma$ so that the housing supply elasticity varies between the 25th and the 75th percentile of the housing supply elasticity across Chinese cities (as defined by Wang et al., 2012). Finally, we compute aggregate TFP and welfare for all economies. For the closed economy, we proceed in a similar way, but we set the variable trade cost equal to a large number, while we keep the rest of parameters fixed at their open economy values.

**Cross Model Comparison.** Figure 7 computes welfare (panel A) and productivity (panel B) gains from spatial policies in our model and the two competing models analyzed in the gains from trade counterfactual. To simplify comparisons, we compute for each model welfare or productivity relative to the level in the economy calibrated to fit actual values in the Chinese economy. Accordingly, when the housing supply elasticity takes the baseline value used to calibrate the model ($5.4$), the value for normalized aggregate welfare and TFP are zero.

We find substantial welfare and productivity gains from spatial policies: Releasing land regulations such that the housing supply elasticity increases lead to aggregate welfare and productivity gains in all models of the same order of magnitude to a first-order approximation. In quantitative terms, increasing the housing supply elasticity from the median to the 75th percentiles ($9.71$) leads to welfare gains of approximately 28 percent and productivity of about 2 percent in all models.

**Open vs. Closed Economy Considerations.** Finally, for the baseline model, we investigate in Figure 8 whether open economy considerations affect the computation of aggregate welfare (panel A) and productivity (panel B) gains from spatial policies. We find that welfare gains are unaffected by open economy considerations to a first-order approximation. In closed and open economies, welfare increases by about 28 percent when moving the economy from the median to the 75th percentile. However, we find more significant gains from spatial policies in the open economy for productivity. In quantitative terms, moving the economy from the median to the 75th percentiles of the housing supply elasticity distribution leads to productivity gains 12 percent larger in the open economy. Thus, open economy considerations increase the estimated effectiveness of spatial, but they do not affect welfare.

## 6 Conclusion

Trade policy has received renewed interest in recent years, as globalization has been blamed for widening spatial disparities in many developed countries (Ezcurra and Pose, 2013; Dix-Carneiro and Kovak, 2017a; Potlogea, 2018)). In response to this interest, a nascent literature has begun to analyze the interplay between trade and economic geography within countries.

In this paper, we contribute to this literature in three ways. First, using information from four major trading nations – China, France, the United States and Brazil – we have documented a novel and highly robust stylized fact: Exporting is more unevenly distributed than overall economic activity, and in particular, it is disproportionately concentrated in larger cities. Importantly, this stylized fact cannot be fully accounted for by larger cities benefitting from better foreign market access. Second, we show that a relatively simple framework - an extension of the standard quantitative spatial equilibrium (QSE) framework to include firm heterogeneity and a mechanism of selection into exporting in the spirit of Melitz (2003) - can explain this stylized fact. The intuition of the model is straightforward: the presence of a large number of productive firms in a certain location will tend to make that location more populous (i.e. a larger city) but also more integrated into international trade. Third, we structurally estimate the model using Chinese firm-level data to recover the key model primitives. We then use the model to undertake counterfactual policy analyses.

Our model is designed to assess the effects of both trade policies and (domestic) spatial policies, giving rise to novel interactions between these two levers. We find that the corresponding welfare implications are richer and differ from those in the more parsimonious standard models that are nested in our framework: a standard trade model that ignores within-country geography, and an economic geography model that shuts down international trade.

Our theoretical framework opens the door for fascinating future work that exploits the interplay of international trade and domestic economic geography. For example, our model naturally lends itself to exploring the rich interactions between policies that reduce internal trade costs (e.g. infrastructure investments) and those that affect international trade costs (e,g, trade agreements).

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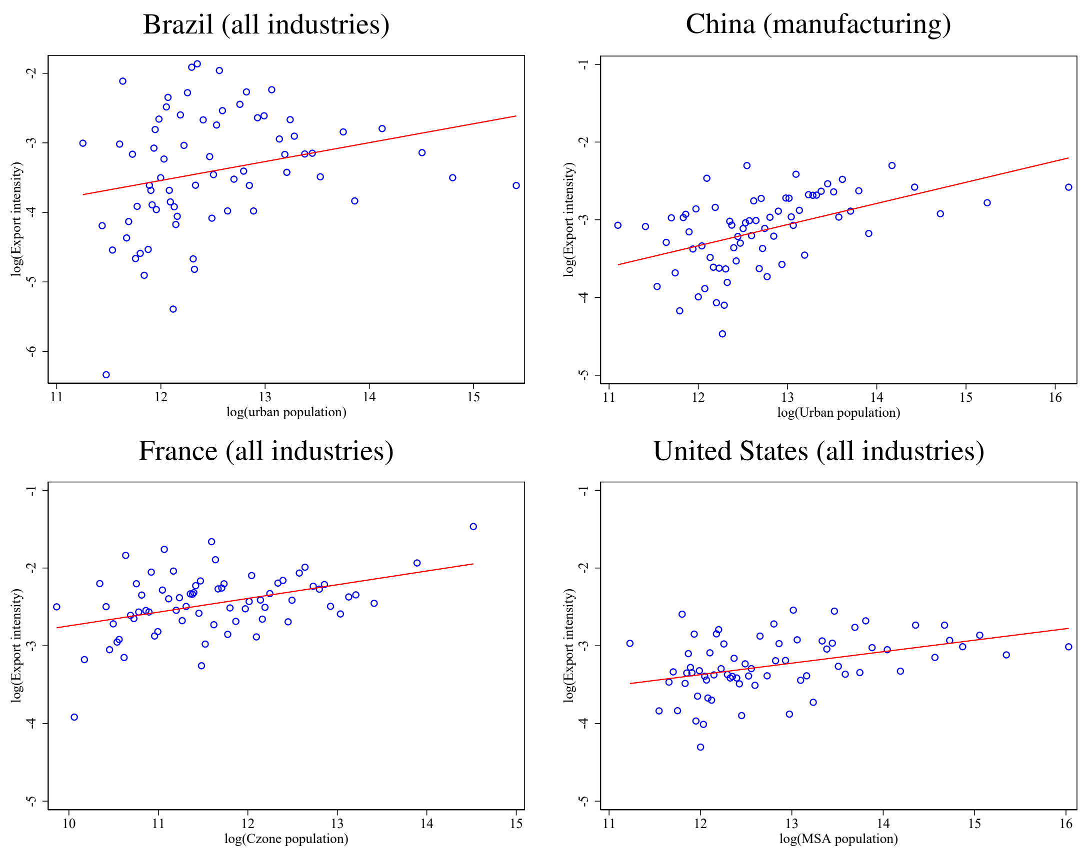
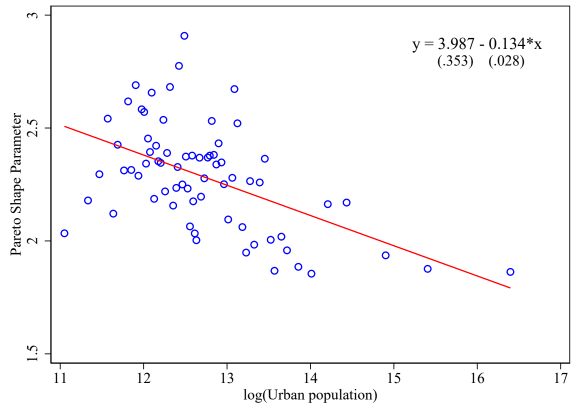
# FIGURES

Figure 1: Log Export intensity and Log City size in China, Brazil, France and the United States



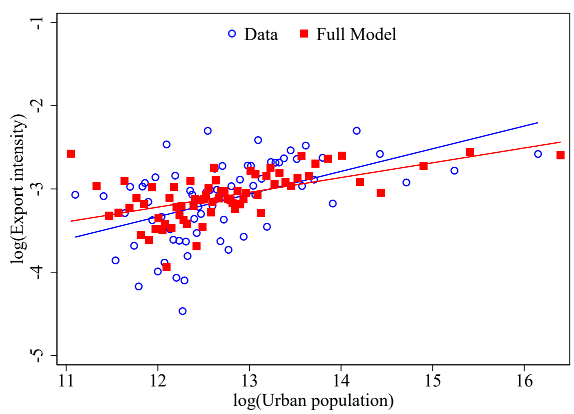

*Notes*: The figure shows the relationship between city size and export intensity. Cities are defined in terms Microregions for Brazil, Metropolitan Areas for China (as defined by Dingel et al., 2019, using lights at night with a threshold equal to 30) and the United States; and Commuting Zones for France. The analysis considers cities with positive exports and at least 250 manufacturing firms for China and France. For Brazil and the United States, the analysis considers cities with a population above 100,000 inhabitants.

Figure 2: Estimated Pareto Shape Parameter for China and City size



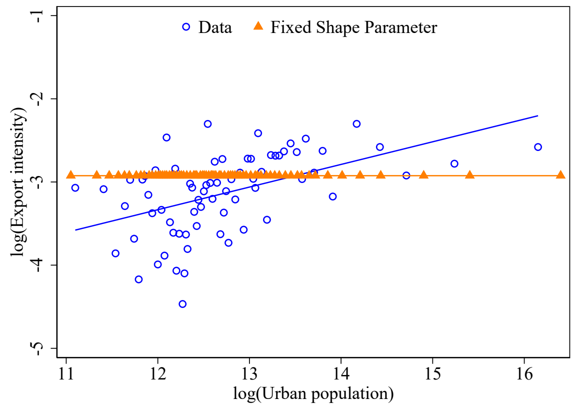

*Notes*: The figure shows a binned scatter plot between the estimated city-level Pareto shape parameter and city size for China. Cities are defined in terms of metropolitan areas. The Pareto shape parameter is estimated from rank-size regression run city-by-city at the firm level following di Giovanni et al. (2011).

Figure 3: Baseline Model: Predicted Export Intensity vs. City Size



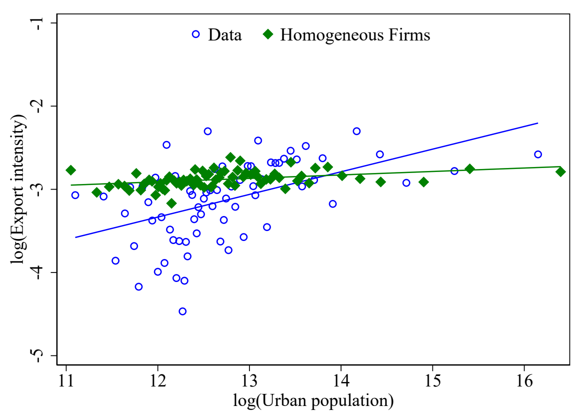

*Notes*: The figure plots a binned scatter plot between export intensity and city size for the Chinese data (blue-hollow circles) and the baseline model (red-solid squares) presented in section 4 calibrated for the Chinese manufacturing sector. The calibration of the model is presented in section 5.2 and discussed in more detailed in appendix C. Both, data and model includes a least squares regression line.

Figure 4: Fixed Shape Parameter Model: Predicted Export Intensity vs. City Size



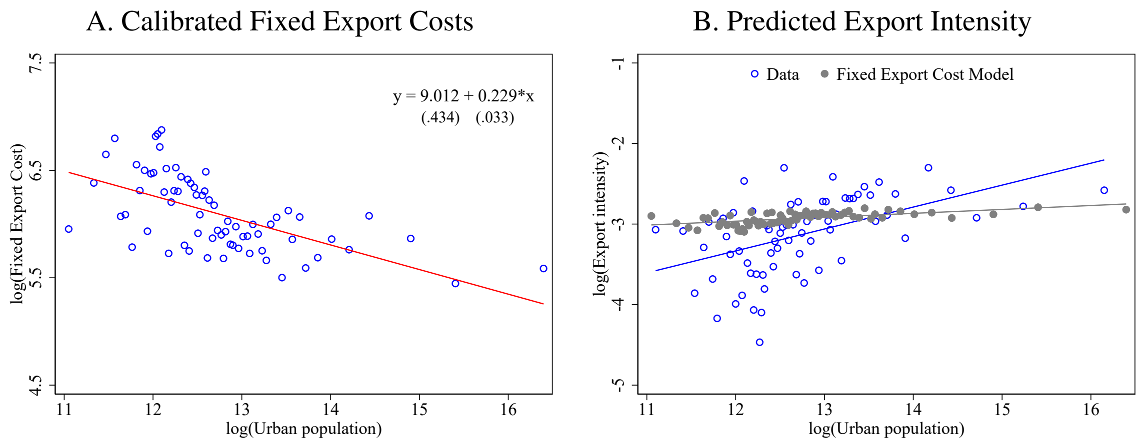

*Notes*: The figure plots a binned scatter plot between export intensity and city size for the Chinese data (blue-hollow circles) and the fixed shape parameter model (orange-solid triangles) presented in section 5.3 calibrated for the Chinese manufacturing sector. The fixed shape parameter model allows for heterogeneous firms and selection into exporting as in the baseline model but restrict the productivity distribution to be the same in all cities. The calibration of the model follows the same strategy as the full model (see notes to Figure 3 but restricts the Pareto shape parameter to take a constant value across cities. Both, data and model includes a least squares regression line.

Figure 5: Variable Trade Costs Model: Predicted Export Intensity vs. City Size



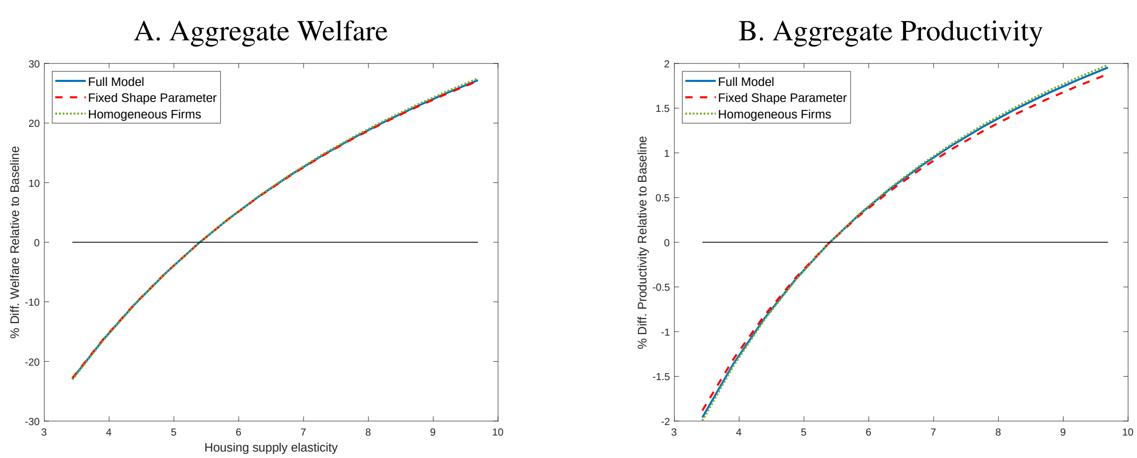

*Notes*: The figure plots a binned scatter plot between export intensity and city size for the Chinese data (blue-hollow circles) and the variable trade costs model (green-solid diamonds) presented in section 5.3 calibrated for the Chinese manufacturing sector. The variable trade costs model allows for variable domestic and export variable trade costs but restricts productivity to be homogeneous within cities. Section 5.3 discuss the calibration of variable trade costs. Both, data and model includes a least squares regression line.

Figure 6: Fixed Export Cost Model: Calibrated values and Predicted Export Intensity




*Notes*: The figure plots a binned scatter plot between export intensity and city size for the Chinese data (blue-hollow circles) and the variable trade costs model (green-solid diamonds) presented in section 5.3 calibrated for the Chinese manufacturing sector. The variable trade costs model allows for variable domestic and export variable trade costs but restricts productivity to be homogeneous within cities. Section 5.3 discuss the calibration of variable trade costs. Both, data and model includes a least squares regression line.

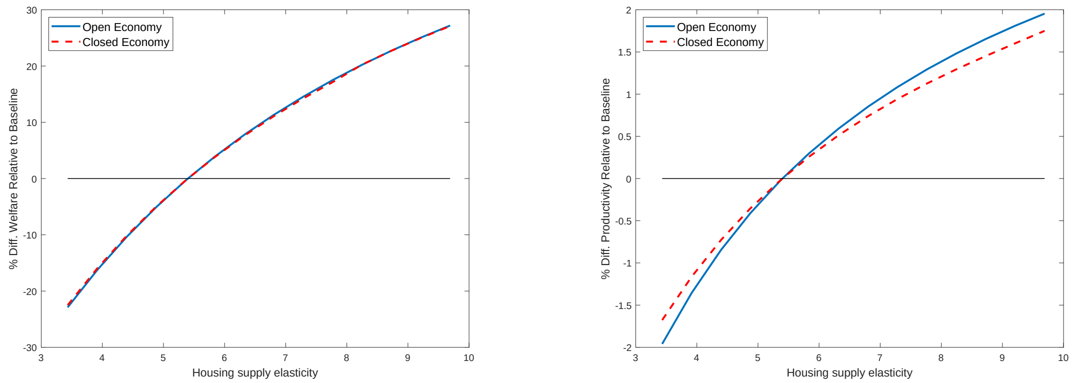
Figure 7: Welfare and Productivity Effect from Housing Supply Elasticity Changes Across Models




*Notes*: The figure plots a binned scatter plot between export intensity and city size for the Chinese data (blue-hollow circles) and the variable trade costs model (green-solid diamonds) presented in section 5.3 calibrated for the Chinese manufacturing sector. The variable trade costs model allows for variable domestic and export variable trade costs but restricts productivity to be homogeneous within cities. Section 5.3 discuss the calibration of variable trade costs. Both, data and model includes a least squares regression line.

Figure 8: Welfare and Productivity Effect from Housing Supply Elasticity Changes: Open vs. Closed Economy Models

A. Aggregate Welfare B. Aggregate Productivity




*Notes*: The figure plots a binned scatter plot between export intensity and city size for the Chinese data (blue-hollow circles) and the variable trade costs model (green-solid diamonds) presented in section 5.3 calibrated for the Chinese manufacturing sector. The variable trade costs model allows for variable domestic and export variable trade costs but restricts productivity to be homogeneous within cities. Section 5.3 discuss the calibration of variable trade costs. Both, data and model includes a least squares regression line.

# TABLES

Table 1: City Size (Population, in ’000s): Descriptive Statistics

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | | | Percentiles | | | | |
| | Obs. | Mean | 25th | 50th | 75th | 90th | 95th |
| Brazil (Microregions) | 316 | 463.6 | 140.7 | 203.1 | 364.0 | 811.9 | 1,469.3 |
| China (Metropolitan areas) | 629 | 709.3 | 182.8 | 290.3 | 494.0 | 918.8 | 1,798.8 |
| France (Commuting zones) | 304 | 192.5 | 54.2 | 99.2 | 209.1 | 408.5 | 543.4 |
| United States (Metropolitan areas) | 324 | 799.3 | 158.4 | 275.2 | 636.6 | 1,929.2 | 3,176.1 |

*Notes*: The Table shows statistics for the city-size distribution in Brazil, China, France, and the United States. Cities are defined in terms Microregions for Brazil, Metropolitan Areas for China (as defined by Dingel et al., 2019, using lights at night with a threshold equal to 30) and the United States; and Commuting Zones for France. The analysis considers cities with positive exports and at least 250 manufacturing firms for China and France. For Brazil and the United States, the analysis considers cities with a population above 100,000 inhabitants.

Table 2: City-Level Export Intensity: Descriptive Statistics

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | | | | Percentiles | | | | |
| | Industries | Obs. | Mean | 25th | 50th | 75th | 90th | 95th |
| Brazil (Microregions) | All industries | 316 | 8.99 | 0.97 | 4.90 | 10.1 | 24.0 | 37.2 |
| China (Metropolitan areas) | Manufacturing | 629 | 8.59 | 2.15 | 5.37 | 11.1 | 21.0 | 30.3 |
| France (Commuting zones) | All industries | 304 | 8.54 | 5.60 | 9.24 | 13.6 | 19.7 | 25.0 |
| United States (Metropolitan areas) | All industries | 324 | 5.61 | 2.51 | 4.00 | 6.61 | 10.2 | 15.2 |

*Notes*: The Table shows statistics for city-level export intensity in Brazil, China, France, and the United States. Cities are defined in terms Microregions for Brazil, Metropolitan Areas for China (as defined by Dingel et al., 2019, using lights at night with a threshold equal to 30) and the United States; and Commuting Zones for France. The analysis considers cities with positive exports and at least 250 manufacturing firms for China and France, and with population over 100,000 for Brazil and the United States. City-level export intensity is defined as manufacturing exports over manufacturing sales for China and France; overall exports over manufacturing sales for the United States, and overall exports over GDP for the case of Brazil.

Table 3: Export Intensity and City size in Brazil, China, France, and the United States

Dependent Variable: City-Level Log Export Intensity

| | —— Brazil —— | | —— China —— | | —— France —— | | — United States — | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| ln City Size | .329*** | .272*** | .339*** | .272*** | .210*** | .176*** | .156*** | .148*** |
| | (.121) | (.125) | (.052) | (.047) | (.043) | (.038) | (.037) | (.038) |
| ln Distance to the coast | | .013 | | -.458*** | | .071 | | .037 |
| | | (.115) | | (.056) | | (.075) | | (.059) |
| ln Distance to the border | | -1.193*** | | .516*** | | -.135** | | -.183*** |
| | | (.180) | | (.104) | | (.066) | | (.055) |
| ln mean distance to other cities | | -3.790*** | | 2.785*** | | -.681* | | .085 |
| | | (.743) | | (.450) | | (.384) | | (.212) |
| Coastal Dummy | | 1.015*** | | -.510*** | | .119 | | .014 |
| | | (.461) | | (.187) | | (.168) | | (.178) |
| Border Dummy | | -1.990** | | 1.932*** | | .203 | | .743** |
| | | (.521) | | (.556) | | (.173) | | (.285) |
| Mean Export Intensity: | .096 | .096 | .088 | .088 | .106 | .106 | .056 | .056 |
| $R^2$ | .020 | .208 | .043 | .264 | .086 | .214 | .037 | .155 |
| Observations | 296 | 296 | 615 | 615 | 304 | 304 | 324 | 324 |

*Notes*: The Table analyzes the relationship between city size and export intensity. Cities are defined in terms of Metropolitan Areas for China and the United States, commuting zones for France, and Microregions for Brazil. For China and France, the analysis considers cities with positive exports and at least 250 firms. For Brazil and the United States, the analysis considers cities with a population above 100,000 inhabitants. City-level export intensity is defined as manufacturing exports over manufacturing sales for China; overall exports over sales for the France and the United States, and overall exports over (city-level) GDP for the case of Brazil. Robust standard errors in parentheses. Key: ** significant at 1%; ** 5%; * 10%.

Table 4: Export Intensity and City Size: 2SLS Results

| | China | | | | France | | | |
|---|---|---|---|---|---|---|---|---|
| Specification: | OLS | RF | FS | IV | OLS | RF | FS | IV |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Dependent Variable | ln Export Intensity | ln Export Intensity | ln City Size | ln Export Intensity | ln Export Intensity | ln Export Intensity | ln City Size | ln Export Intensity |
| ln City Size | 0.321*** | — | — | 0.361** | 0.139*** | — | — | 0.096** |
| | (0.113) | | | (0.180) | (0.038) | | | (0.049) |
| ln Historical Population | — | 0.116** | 0.321*** | — | — | 0.094* | 0.970*** | — |
| | | (0.0551) | (0.0487) | | | (0.050) | (0.052) | |
| ln distance to the coast | 0.296** | 0.308** | 0.0430 | 0.293** | .089 | .069 | -.232*** | .092 |
| | (0.123) | (0.133) | (0.0625) | (0.125) | (.395) | (.074) | (.057) | (.072) |
| ln distance to the border | 0.761*** | 0.799*** | 0.138 | 0.749*** | -.108 | -.137** | -.257*** | -.112* |
| | (0.157) | (0.158) | (0.119) | (0.172) | (.066) | (.067) | (.041) | (.066) |
| ln mean distance to other cities | 3.761*** | 3.715*** | -0.268 | 3.812*** | -.183 | -.280 | -1.155*** | -.169 |
| | (0.633) | (0.605) | (0.471) | (0.595) | (.395) | (.400) | (.311) | (.390) |
| Coastal Dummy | 0.492*** | 0.685*** | 0.622*** | 0.461*** | .111 | .130 | -.011 | .131 |
| | (0.140) | (0.131) | (0.135) | (0.174) | (.165) | (.163) | (.134) | (.162) |
| Border Dummy | -0.205 | -0.243 | -0.0768 | -0.215 | .169 | .149 | -.168 | .165 |
| | (0.507) | (0.522) | (0.259) | (0.509) | (.175) | (.178) | (.130) | (.174) |
| First Stage F-Statistic | — | — | — | 43.4 | — | — | — | 349.7 |
| Mean Dep. Var. | -2.89 | -2.89 | 14.27 | -2.89 | -2.43 | -2.43 | 11.64 | -2.43 |
| $R^2$ | .352 | .324 | .377 | .352 | .152 | .125 | .637 | .148 |
| Observations | 260 | 260 | 260 | 260 | 297 | 297 | 297 | 297 |

*Notes*: This Table examines the effect of city size on export intensity in China (columns 1 to 4) and France (columns 5 to 8), instrumenting contemporaneous city size with historical population. The analysis for China is run at the prefecture level, and uses 1580 prefecture-level population from Bai and Jia (2021) to instrument for city size. The analysis for France is run at the commuting zone level, and uses the population records for 1876 produced by INSEE as an instrument for current population. Column 1 and 5 report Ordinary Least Squares (OLS) estimates. Column 2 and 6 report the reduced form (RF) for log export intensity against historical population. The first stage (FS) results of the Instrumental Variables (IV) regressions are reported in column 3 and 7, together with the (cluster-robust) Kleibergen-Paap rKWald F-statistic. The corresponding Stock-Yogo value for 10% maximal IV bias is 16.4. Second stage results are reported in column 4 and 8. Robust standard errors (in parentheses). Key: *** significant at 1%; ** 5%; * 10%.

## Table 5: Within-Between Sectoral Decomposition

Dep. Var.: Within- and Between Components of City-Level Export Intensity

| | China | | | France | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Specification: | Within | Between | % Within | Within | Between | % Within |
| log(City Size) | .289*** | -.017 | >100% | .076*** | .100*** | 43.4% |
| | (.0455) | (.0113) | | (.023) | (.023) | |
| Geog. Controls | Yes | Yes | — | Yes | Yes | — |
| Mean Dep. Var. | | | — | -0.29 | -2.16 | — |
| $R^2$ | .235 | .159 | — | .202 | .160 | — |
| Observations | 615 | 615 | — | 304 | 304 | — |

*Notes*: To compute the between-industry component, we first calculate city-industry export intensities at the national average for each industry and then interact them with the sales share of the industry in each city. The within-industry component is computed as the difference between the logarithm of the overall export intensity and the across component (which is also expressed in logs). Geographical controls include the average distance to other domestic cities, distance to the border, distance to the coast, border dummies, and coastal dummies. Robust standard errors in parentheses. Key: *** significant at 1%; ** 5%; * 10%.

## Table 6: Export Activity and City Size: Micro-Level Evidence

| | China | | | France | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | $\ln\left[\text{Intensive margin}\right]$ | $\ln\left[\text{Extensive margin}\right]$ | $\ln\left[\text{Size premium}\right]$ | $\ln\left[\text{Intensive margin}\right]$ | $\ln\left[\text{Extensive margin}\right]$ | $\ln\left[\text{Size premium}\right]$ |
| log(City Size) | -.179*** | .212*** | .239*** | .027 | .070*** | .079*** |
| | (.0331) | (.0331) | (.0361) | (.0283) | (.0186) | (.0229) |
| Geog. Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Mean Dep. Var. | -1.28 | -3.40 | 1.55 | -1.55 | -2.75 | 1.84 |
| $R^2$ | .12 | .41 | .11 | .091 | .396 | .11 |
| Observations | 615 | 615 | 615 | 304 | 304 | 304 |

*Notes*: The Table decomposes Chinese cities' overall export intensity (panel A) and within-industry export intensity (panel B) into three components (all in logs): Export intensity of exporters (columns 1 and 4); the ratio of exporting to overall firms – the extensive margin (columns 2 and 5); and the relative sales between exporters and all firms – the size premium (columns 3 and 6). See notes to Table 5 for the definition of within-industry export intensity. Cities are defined in terms of Metropolitan Areas; the analysis considers cities with positive exports and at least 250 manufacturing firms. City-level export intensity is defined as manufacturing exports over manufacturing sales. Geographical controls consider the average distance to other domestic cities, distance to border, distance to the coast, border dummies, and a coastal dummy. Robust standard errors in parentheses. Key: ** significant at 1%; ** 5%; * 10%.

Table 7: Calibrated Parameters and Target Moments

| **Parameters** | **Calibration Strategy** |
|---|---|
| I. Calibrated Parameters | |
| $\beta$ | Housing expenditure share (Davis & Ortalo-Magne 2011) |
| $\sigma$ | Average sectoral markup (De Loecker & Warzinsky, 2012) |
| $\epsilon$ | Bryan and Morten (2014) |
| $F$ | Average domestic sales/ Average wages |
| $F_x$ | Average export sales/ Average wages |
| $d_{ni}$ | Straight-line distance to the power of $0.33$ (Redding/Sturm 2008) |
| $d_{Fi}$ | Straight-line distance to nearest port to the power of $0.33$ multiplied by 5.43 (baseline), 6.78 (heterogeneous firms), and 10.28 (Krugman)† |
| II. Estimated Parameters | |
| $\alpha_n$ | Firm-level rank-size regressions by city |

*Notes*: The Table summarizes the target moments we use to calibrate the model.
†: Multiplier calibrated to match median export intensity across all cities

Table 8: Welfare and Productivity Gains from Trade Liberalization

| Model | (1) Productivity Level | (2) Productivity Dispersion | (3) Aggregate Welfare | (4) Aggregate Productivity |
|---|---|---|---|---|
| Homogeneous Firms Model | City-Specific | None | 3.4% | >0.1% |
| Heterogeneous Firms Model | City-Specific | Economy-wide | 3.7% | 3.9% |
| Full Model | City-Specific | City-Specific | 4.2% | 7.6% |

*Notes*: The Table shows the estimated gains from trade in terms of aggregate welfare and measured total factor productivity (TFP) for different versions of the model presented in section 4. 'Homogeneous firms model' computes gains assuming homogeneous firms. 'Heterogeneous firms model' allows for firm heterogeneity, but restricts the Pareto shape parameter of the productivity distribution to be equal across cities. 'Full model' allows for city-varying productivity dispersion, with the Pareto shape Parameters being estimated with a city-specific rank-size regression following di Giovanni et al. (2011).

# Online Appendix

## Cities, Heterogeneous Firms, and Trade

Jan David Bakker Alvaro Garcia-Marin Andrei Potlogea
Nico Voigtländer Yang Yang

## A Technical Appendix

## B Proofs

### B.1 Lemma 1

Substituting equations 22, 23 into 24 and solving for the entry threshold for serving the domestic market we can obtain a closed form solution for these thresholds for all locations $i$:

$$\psi_i^{d*} = \left\{ \frac{1}{F_e} \frac{\sigma - 1}{\alpha_i - \sigma + 1} \left\{ F + \left[ \frac{1}{\tau} \left( \frac{F}{F_x} \right)^{\frac{1}{\sigma-1}} \right]^{\alpha_i} F_x \right\} \right\}^{\frac{1}{\alpha_i}} \tag{A.1}$$

Similarly using the equation defining average productivity for the firms in the city

$$\tilde{\psi_i^d} = \left[ \int_{\psi_i^{d*}} \psi^{\sigma-1} g_i(\psi) d\psi \right]^{\frac{1}{\sigma-1}}$$

$$\tilde{\psi_i^x} = \left[ \frac{1}{1 - G_i(\psi_i^{x*})} \int_{\psi_i^{x*}} \psi^{\sigma-1} g_i(\psi) d\psi \right]^{\frac{1}{\sigma-1}}$$

And noting that the assumed productivity distributions are standard pareto with shape parameters we can derive closed form expressions for the average productivities of exporters and of firms serving the domestic market as a function of the relevant thresholds

$$\tilde{\psi_i^d} = \left( \frac{\alpha_i}{\alpha_i - \sigma + 1} \right)^{\frac{1}{\sigma-1}} \psi_i^{d*} \quad \forall i \tag{A.2}$$

$$\tilde{\psi_i^x} = \left( \frac{\alpha_i}{\alpha_i - \sigma + 1} \right)^{\frac{1}{\sigma-1}} \psi_i^{x*} \quad \forall i \tag{A.3}$$

Finally given equation 28 and the definition of the probability of exporting yields

$$p_i^x = \frac{1 - G_i(\psi_i^{x*})}{1 - G_i(\psi_i^d *)} = \left( \frac{\psi_i^{d*}}{\psi_i^{x*}} \right)^{\alpha_i} = \left[ \frac{1}{\tau} \left( \frac{F}{F_x} \right)^{\frac{1}{\sigma-1}} \right]^{\alpha_i} \tag{A.4}$$

It is straightforward to check that the RHS expressions of equations $A.1$, $A.2$, $A.3$ and $A.4$ are all strictly decreasing in $\alpha_i$ which yields the result that cities with lower shape parameters have higher domestic and exporting thresholds, higher average productivity of both domestic firms and exporters, and a higher fraction of exporters. Taken together these results guarantee that these cities display higher average firm productivity. We will in what follows simply refer to them as more productive cities.

### B.2 Proposition 1

To prove this proposition let us consider an arbitrary pair of cities $i$ and $i'$ with city $i$ assumed more productive than city $i'$.

Let us first consider the zero-profit conditions of firms serving the domestic market at each location. Combining these zero profit conditions with the expression of domestic profits outlined in equation $9$ yields the following expressions for the revenues of firms found at the entry threshold of the domestic market in each location:

$$r_i^d(\psi_i^{d*}) = \sigma w_i F \tag{A.5}$$

$$r_{i'}^d(\psi_{i'}^{d*}) = \sigma w_{i'} F \tag{A.6}$$

Using the relationship

$$r_i^d(\psi) = R\left(\frac{\psi\rho}{w_i}\right)^{\sigma-1}$$

We can derive the following expressions for locations $i$ and $i'$

$$R(\psi_i^{d*}\rho)^{\sigma-1} = \sigma w_i^{\sigma} F \tag{A.7}$$

$$R(\psi_{i'}^{d*}\rho)^{\sigma-1} = \sigma w_{i'}^{\sigma} F \tag{A.8}$$

where $\rho$ is given by $\rho = (\sigma-1)/\sigma$. Dividing $A.7$ by $A.8$ yields after some rearranging

$$\frac{w_i}{w_{i'}} = \left(\frac{\psi_i^{d*}}{\psi_{i'}^{d*}}\right)^{\frac{\sigma-1}{\sigma}} \tag{A.9}$$

Which given our previous results in Lemma $1$ establishes that the more productive cities have higher entry productivity thresholds leads to the conclusion that more productive cities display higher wages in equilibrium.

From the spatial equilibrium conditions we can write:

$$\frac{v_i}{v_{i'}} = \frac{w_i}{w_{i'}} = \left(\frac{r_i}{r_{i'}}\right)^{\gamma(1-\beta)} \tag{A.10}$$

which substituting for $r_i$ via equation 21 yields after some manipulation

$$\frac{L_i}{L_{i'}} = \left(\frac{w_i}{w_{i'}}\right)^{\frac{1-\gamma(1-\beta)}{\gamma(1-\beta)}} = \left(\frac{\psi_i^{d*}}{\psi_{i'}^{d*}}\right)^{\frac{(\sigma-1)[1-\gamma(1-\beta)]}{\gamma\sigma(1-\beta)}} \tag{A.11}$$

which given the result established above that more productive cities will have higher wages also implies that more productive cities will feature larger populations in equilibrium.
Moving on to export intensity, we can write the export intensity of a given location $i$ as

$$Expint_i = \frac{\int_{\psi_i^{x*}}^{\infty} r_i^x(\psi) M_i \mu_i(\psi) d\psi}{\int_{\psi_i^{d*}}^{\infty} r_i^d(\psi) M_i \mu_i(\psi) d\psi + \int_{\psi_i^{x*}}^{\infty} r_i^x(\psi) M_i \mu_i(\psi) d\psi} \tag{A.12}$$

where $\mu_i(.)$ denotes the endogenous productivity distribution given by

$$\mu_i(\psi) = \begin{cases} 0 \quad if \quad \psi \leq \psi_i^{d*} \\ \frac{1}{1-G_i(\psi_i^{d*})} g_i(\psi) \quad if \quad \psi > \psi_i^{d*} \end{cases} \tag{A.13}$$

Substituting for $r_i^x(\psi)$ and $r_i^d(\psi)$ in equation A.13 and simplifying yields:

$$Expint_i = \frac{\tau^{1-\sigma} p_i^x \tilde{\psi}_i^x}{\tilde{\psi}_i^d + \tau^{1-\sigma} p_i^x \tilde{\psi}_i^x} \tag{A.14}$$

By substitution for $\tilde{\psi}_i^d$ and $\tilde{\psi}_i^x$ from $A.2$ and $A.3$ and further noting equation $(28)$ equation $A.14$ further simplifies to

$$Expint_i = \frac{p_i^x F_x}{F + p_i^x F_x} \tag{A.15}$$

The expression on the RHS of $A.15$ can easily be shown to be increasing in the probability of exporting of firms located at each location $i$, $p_i^x$ and hence given that more productive cities have already been shown to have higher exporting probabilities, they will also have higher export intensities. This completes our proof of proposition $1$

### B.3 Proposition $2$

To prove this proposition it will again be useful to consider the case of two arbitrary locations $i$ and $i'$ with location $i$ assumed more productive $\alpha_i < \alpha_{i'}$.

First let us consider Proposition 2's prediction regarding movements in relative population. From equation $A.11$ we can write that:

$$sgn\left(\frac{\partial}{\partial\tau}\frac{L_i}{L_{i'}}\right) = sgn\left(\frac{\partial}{\partial\tau}\frac{\psi_i^{d^*}}{\psi_{i'}^{d^*}}\right) \tag{A.16}$$

Substituting for $\psi_i^{d^*}$ and $\psi_{i'}^{d^*}$ via $A.1$ and differentiation yields:

$$\frac{\partial}{\partial\tau}\frac{\psi_i^{d^*}}{\psi_{i'}^{d^*}} = \frac{\psi_i^{d^*}\psi_{i'}^{d^*}F_xF}{(\psi_{i'}^{d^*})^2\tau(F+p_i^xF_x)(F+p_{i'}^xF_x)}(p_{i'}^x - p_i^x) < 0 \tag{A.17}$$

Which establishes that the relative successful entry productivity threshold will grow in favour of the more productive cities when trade is liberalised (i.e. $\tau$ declines) and hence relative the relative population of the more productive cities will also grow when trade liberalizes. Given that this result was established for an arbitrary pair of cities, this implies that international trade liberalisation will be associated with a general shift in population more productive (and larger) cities.

Moving on to the implications of trade liberalisation to aggregate (country-level GDP), we define aggregate GDP as

$$TFP_{Agg} = \frac{Q}{L} = \frac{R}{L} \tag{A.18}$$

Where $Q$ denotes total output of the tradable composite good, $R = \sum_k w_k L_k$ denotes aggregate revenues/ expenditure, and the second equality results from our choice of the tradable composite good as the numeraire. In other words, proving that trade liberalization results in an increase in aggregate TFP is equivalent to showing that it results in an increase aggregate revenues.
To show this first let us consider the effect of trade liberalization on wages at each location $i$. From equation $A.11$ and labor market clearing condition in equation $(27)$ we can derive the following expression for equilibrium populations at each location $i$

$$L_i = \frac{\left(\psi_i^{d^*}\right)^{\frac{(\sigma-1)[1-\gamma(1-\beta)]}{\gamma\sigma(1-\beta)}}}{\sum_{k=1}^{N}\left(\psi_k^{d^*}\right)^{\frac{(\sigma-1)[1-\gamma(1-\beta)]}{\gamma\sigma(1-\beta)}}}L \tag{A.19}$$

Further, using equation $A.7$, substituting $R = \sum_k w_k L_k$ and then each $L_k$ using equation we can derive the following expression for wages at each location $i$

$$w_i = \left(\frac{L}{\sigma F}\right)^{\frac{1}{\sigma-1}} \rho\left(\psi_i^{d^*}\right)^{\frac{\sigma-1}{\sigma}} \left(\frac{\sum_{k=1}^{N}\left(\psi_k^{d^*}\right)^{\frac{(\sigma-1)}{\gamma\sigma(1-\beta)}}}{\sum_{k=1}^{N}\left(\psi_k^{d^*}\right)^{\frac{(\sigma-1)[1-\gamma(1-\beta)]}{\gamma\sigma(1-\beta)}}}\right)^{\frac{1}{\sigma-1}} \tag{A.20}$$

Differentiation the expression on the RHS of equation $A.20$ with respect to $\tau$ yields:

$$\frac{\partial w_i}{\partial \tau} = \left(\frac{L}{\sigma F}\right)^{\frac{1}{\sigma-1}} \rho \frac{\sigma-1}{\sigma}(\psi_i^{d*})^{\frac{-1}{\sigma}} \frac{\partial \psi_i^{d*}}{\partial \tau} \left(\frac{\sum_{k=1}^{N}(\psi_k^{d*})^{\frac{(\sigma-1)}{\gamma\sigma(1-\beta)}}}{\sum_{k=1}^{N}(\psi_k^{d*})^{\frac{(\sigma-1)[1-\gamma(1-\beta)]}{\gamma\sigma(1-\beta)}}}\right)^{\frac{1}{\sigma-1}}$$

$$+ \left(\frac{L}{\sigma F}\right)^{\frac{1}{\sigma-1}} \rho(\psi_i^{d*})^{\frac{\sigma-1}{\sigma}} \left(\frac{\sum_{k=1}^{N}(\psi_k^{d*})^{\frac{(\sigma-1)}{\gamma\sigma(1-\beta)}}}{\sum_{k=1}^{N}(\psi_k^{d*})^{\frac{(\sigma-1)[1-\gamma(1-\beta)]}{\gamma\sigma(1-\beta)}}}\right)^{\frac{1}{\sigma-1}-1} \frac{1}{\sigma-1}$$

$$\times \frac{\left[\sum_{i=1}^{N}\sum_{j=1}^{N}(\psi_i^{d*})^{\frac{(\sigma-1)}{\gamma\sigma(1-\beta)}}(\psi_j^{d*})^{\frac{(\sigma-1)[1-\gamma(1-\beta)]}{\gamma\sigma(1-\beta)}}\left(\frac{1}{\psi_j^{d*}}\frac{\sigma-1}{\sigma}\frac{\partial \psi_j^{d*}}{\partial \tau}\right)\right]}{\left[\sum_{k=1}^{N}(\psi_k^{d*})^{\frac{(\sigma-1)[1-\gamma(1-\beta)]}{\gamma\sigma(1-\beta)}}\right]^2} < 0$$

Where the signing of the RHS expression can be done that noting that all terms featuring partial derivatives of domestic productivity thresholds are negative. We were thus able to show that trade liberalisation increases wages at all locations, while also redistributing labor towards the most productive cities that also feature the highest wages. We can thus write for any trade liberalisation episode:

$$TFP_{Agg}^{BL} = \frac{\sum_{k=1}^{N} w_k^{BL} L_k^{BL}}{L} \leq \frac{\sum_{k=1}^{N} w_k^{BL} L_k^{AL}}{L} < \frac{\sum_{k=1}^{N} w_k^{AL} L_k^{AL}}{L} = TFP_{Agg}^{AL} \tag{A.21}$$

where the superscripts $BL$ and $AL$ denote variables before and after liberalisation, the first inequality uses our labour redistribution results, keeping wages constant, and the second uses our result about the impact of liberalisation on wages at all locations. We thus conclude that trade liberalisation are associated with an increase in aggregate productivity.

To analyze the effect of trade liberalisation on welfare, note that substituttion equation $(21)$ in equation $(18)$ and then substitution the resulting equation in equation $(17)$ gives us the following expression for welfare at each location $i$

$$U_i = \bar{U} = \left[\frac{(1-\beta)(1-\gamma)}{\beta}\right]^{(1-\gamma)(1-\beta)} N^{\gamma(1-\beta)} \frac{w_i^{1-\gamma(1-\beta)}}{L_i^{\gamma(1-\beta)}} \tag{A.22}$$

Let us consider then the welfare of workers in the lowest productivity city

$$U_{min} = \bar{U} = \left[\frac{(1-\beta)(1-\gamma)}{\beta}\right]^{(1-\gamma)(1-\beta)} N^{\gamma(1-\beta)} \frac{w_{min}^{1-\gamma(1-\beta)}}{L_{min}^{\gamma(1-\beta)}} \tag{A.23}$$

We know that for this city, trade liberalization is associated with an increase in wages, as wages in all locations increase, and a decrease in population (as this city shrinks relative to all other cities).

Hence it must be the case that welfare of workers in this city rises after trade liberalization. Given the requirements of spatial equilibrium, that must also imply that welfare rises everywhere in the aftermath of trade liberalization.

### B.4 Proposition 3

To see the effects of an increase in housing supply elasticity on export intensity and aggregate TFP, it is important to note from equations $A.1$, $A.4$ and $A.15$ that changing the housing supply elasticities will not affect the entry thresholds, probability of exporting or export intensities of any locations. Thus any effect on aggregate export intensity or aggregate productivity will result simply from reallocating population, production and expenditure across domestic locations. We can thus write:

$$Expint = \sum_{i=1}^{N} \frac{w_i L_i}{\sum_{k=1}^{N} w_k L_k} Expint_i \tag{A.24}$$

Note that using $A.19$ and $A.20$ we can write:

$$w_i L_i = \left(\frac{L}{\sigma F}\right)^{\frac{1}{\sigma-1}} \rho L (\psi_i^{d*})^{\frac{\sigma-1}{\gamma\sigma(1-\beta)}} \frac{\left[\sum_{k=1}^{N} (\psi_k^{d*})^{\frac{(\sigma-1)}{\gamma\sigma(1-\beta)}}\right]^{\frac{1}{\sigma-1}}}{\left[\sum_{k=1}^{N} (\psi_k^{d*})^{\frac{(\sigma-1)[1-\gamma(1-\beta)]}{\gamma\sigma(1-\beta)}}\right]^{\frac{\sigma}{\sigma-1}}} \tag{A.25}$$

For any pair of cities $i$ and $i'$, with $i$ more productive, we can therefore obtain:

$$\frac{\partial}{\partial\gamma}\left(\frac{w_i L_i}{w_{i'} L_{i'}}\right) = \frac{\log(\psi_{i'}^{d*}) - \log(\psi_{i'}^{d*})}{[(\psi_{i'}^{d*})^{\frac{\sigma-1}{\gamma\sigma(1-\beta)}}]^2} < 0 \tag{A.26}$$

Which implies that relaxing housing supply constraints (i.e. reducing $\gamma$) increases the revenue share of more productive, high export intensity cities, and thus increases aggregate (i.e. country level) export intensity.

As in Proposition 2, to determine the impact of changing housing supply elasticity on aggregate TFP it suffices to determine the impact of relaxing housebuilding contraints (i.e. lowering $\gamma$) on aggregate revenues. In turn we can write aggregate revenues using equation $A.25$:

$$R = \sum_{k=1}^{N} w_k L_k = \left(\frac{L}{\sigma F}\right)^{\frac{1}{\sigma-1}} \rho L \left[\underbrace{\frac{\sum_{k=1}^{N} (\psi_k^{d*})^{\frac{(\sigma-1)}{\gamma\sigma(1-\beta)}}}{\sum_{k=1}^{N} (\psi_k^{d*})^{\frac{(\sigma-1)[1-\gamma(1-\beta)]}{\gamma\sigma(1-\beta)}}}}_{E}\right]^{\frac{\sigma}{\sigma-1}} \tag{A.27}$$

It is easy to see that

$$sgn(\frac{\partial R}{\partial \gamma}) = sgn(\frac{\partial E}{\partial \gamma}) \tag{A.28}$$

By differentiating we can show that

$$\frac{\partial E}{\partial \gamma} = \sum_{i=1}^{N}\sum_{j=1}^{N}[\log(\psi_i^{d*}) - \log(\psi_j^{d*})][(\psi_i^{d*})(\psi_j^{d*})]^{\frac{(\sigma-1)[1-\gamma(1-\beta)]}{\gamma\sigma(1-\beta)}}[(\psi_j^{d*})^{\frac{\sigma-1}{\sigma}} - (\psi_i^{d*})^{\frac{\sigma-1}{\sigma}}] \times EXP < 0 \tag{A.29}$$

where $EXP$ is a strictly positive expression. This establishes that decreases in $\gamma$ - i.e. increases in housing supply elasticity $(1-\gamma)/\gamma$ - result in an increase in aggregate revenues and hence an increase in aggregate TFP. This completes our proof of Proposition 3.

## C Calibration Procedure

This appendix outlines the steps we follow to recover the fundamental parameter $(A_n, B_n, \psi_i^*, F, F_X)$ using externally calibrated parameters and information of population, wages, revenues and export participation. The algorithm for obtaining the values for these variables follows the following steps:

**Step 1.** Compute average productivity using the Pareto distribution assumption to obtain an expression for threshold productivity in terms of average productivity in each city. Note that due to the Pareto productivity assumption, domestic revenues for the threshold productivity firm can be written as a scaled version of average domestic revenues. Combining this expression with the definition of threshold productivity in the domestic market (**??**) yields the following expression for the average domestic sales of firms located at location $i$ as a function of the fixed production cost $F$ and parameters:

$$r_d^i(\tilde{\psi}_i) = \frac{\alpha_i}{\alpha_i - \sigma + 1}\sigma w_i F \tag{A.30}$$

Using data on average domestic sales for each location and data on average wages for each location allows to calibrate the fixed cost of production $F$, minimizing the distance between left and right hand side of equation (A.30). We assume that ROW's firms face the same fixed cost of production.

**Step 2.** Following a similar procedure than in the previous step yields the following expression for the average export sales of exporters located at location $i$:

$$r_x^i(\tilde{\psi_{xi}}) = \frac{\alpha_i}{\alpha_i - \sigma + 1}\sigma w_i F_x \tag{A.31}$$

Using data on average export sales for each location and data on average wages for each location allows to calibrate the fixed cost of exporting $F_x$. Again, we assume ROW's firms face same fixed cost of exporting.

**Step 3.** Compute the measure of firms $M_i$ in each location using information on the fraction of exporters in each city, $p_i^x$, and the values for the fixed production and export cost derived in the previous step:

$$M_i = \frac{R_i}{\bar{r}_i} = \frac{L_i}{\sigma(F + p_i^x F_x)\frac{\alpha_i}{\alpha_i - \sigma + 1}} \tag{A.32}$$

**Step 4.** Use the free entry condition $\bar{\pi}_i = \pi_i^d(\tilde{\psi}_i) + p_i^x \pi_i^x(\tilde{\psi}_{ix}) = w_i F_e/(1 - G_i(\psi_i^*))$ and the functional form for the Pareto cumulative distribution to get an expression for $\psi_i^*$ as a function of known parameters $\{F, F_x, \sigma, \alpha_i\}$ and the unknown scale parameter $A_i$. Normalize $F_e = 1$.

$$\psi_i^* = A_i \left[ \left( \frac{\sigma - 1}{\alpha_i - \sigma + 1} \right) \left( \frac{F + p_x^i F_x}{F_e} \right) \right]^{\frac{1}{\alpha_i}} \tag{A.33}$$

**Step 5** Substituting for $p_i^x$, $p_c^x$, $M_i$, $M_c$ in equations (**??**), (**??**), (**??**) and (**??**); expressing all $\tilde{\psi}_{ix}$ and $\tilde{\psi}_i$ in terms of $A_i$, and plugging the resulting equations into the system of equations defined by equation (**??**) results in a system of $N+1$ equations with $N+1$ unknowns that can be solved for all the $A_i$.

**Step 6** Use the $A_i$'s derived in the previous step and equations (A.2)-(A.33) to derive the location specific successful entry thresholds $\psi_i^*$ and average productivity $\tilde{\psi}_i$ for all locations.

**Step 7** Use equation (**??**) to obtain land rents. Assume each location has a land endowment equal to one ($H_n = 1$). Rest of the world has land endowment equal to $H_x = 14.8 \sum_{k \in N} H_k$.

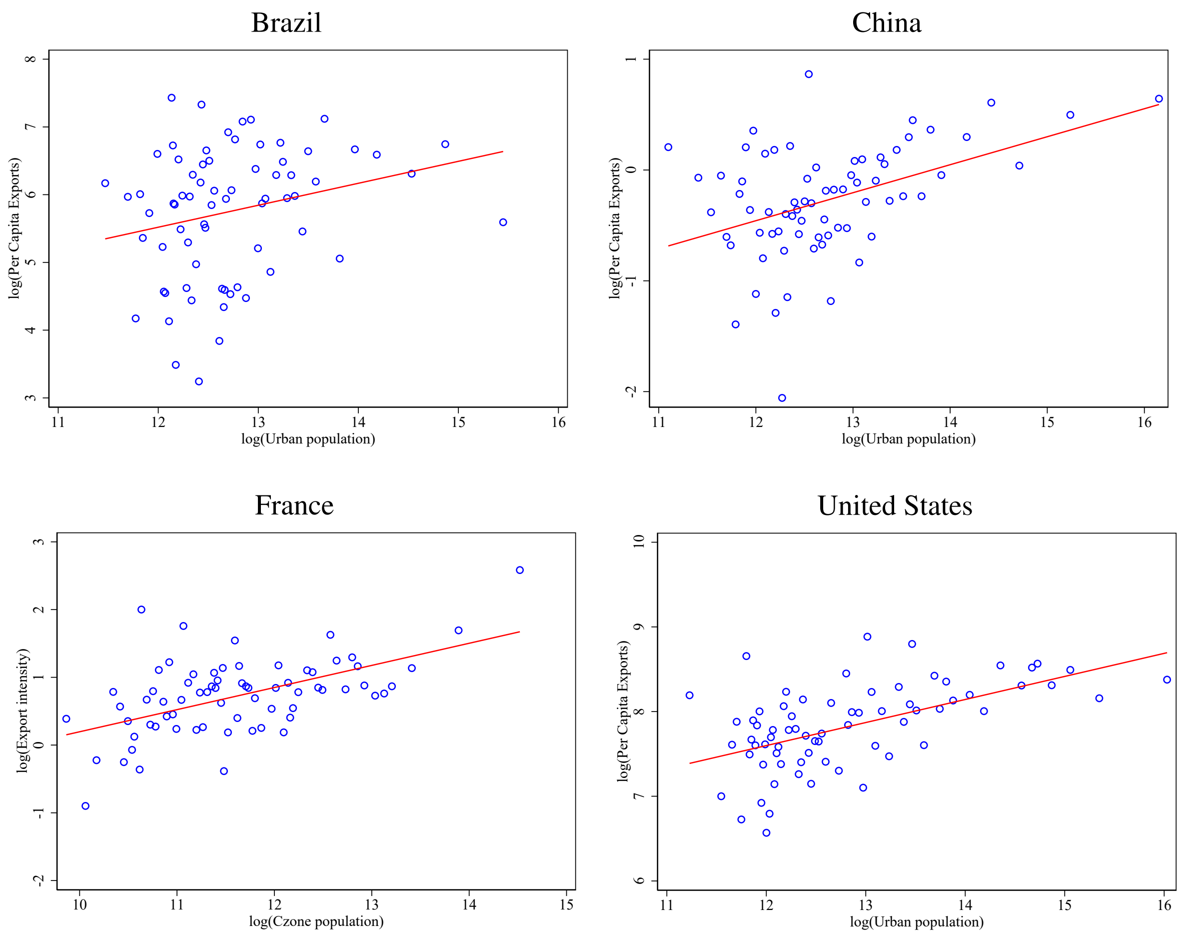
**Step 8** Use the $M_i$'s, $p_i^x$'s and $\tilde{\psi}_i$'s derived in previous steps to compute the price indices $P_n$ at each location domestic location and in the RoW.

**Step 9** Using the rents derived in Step 7, the prices derived in Step 8, solve the system of equations described by (**??**) to obtain the amenity primitives $B_i$, thus completing the calibration.

# D Additional Figures and Tables

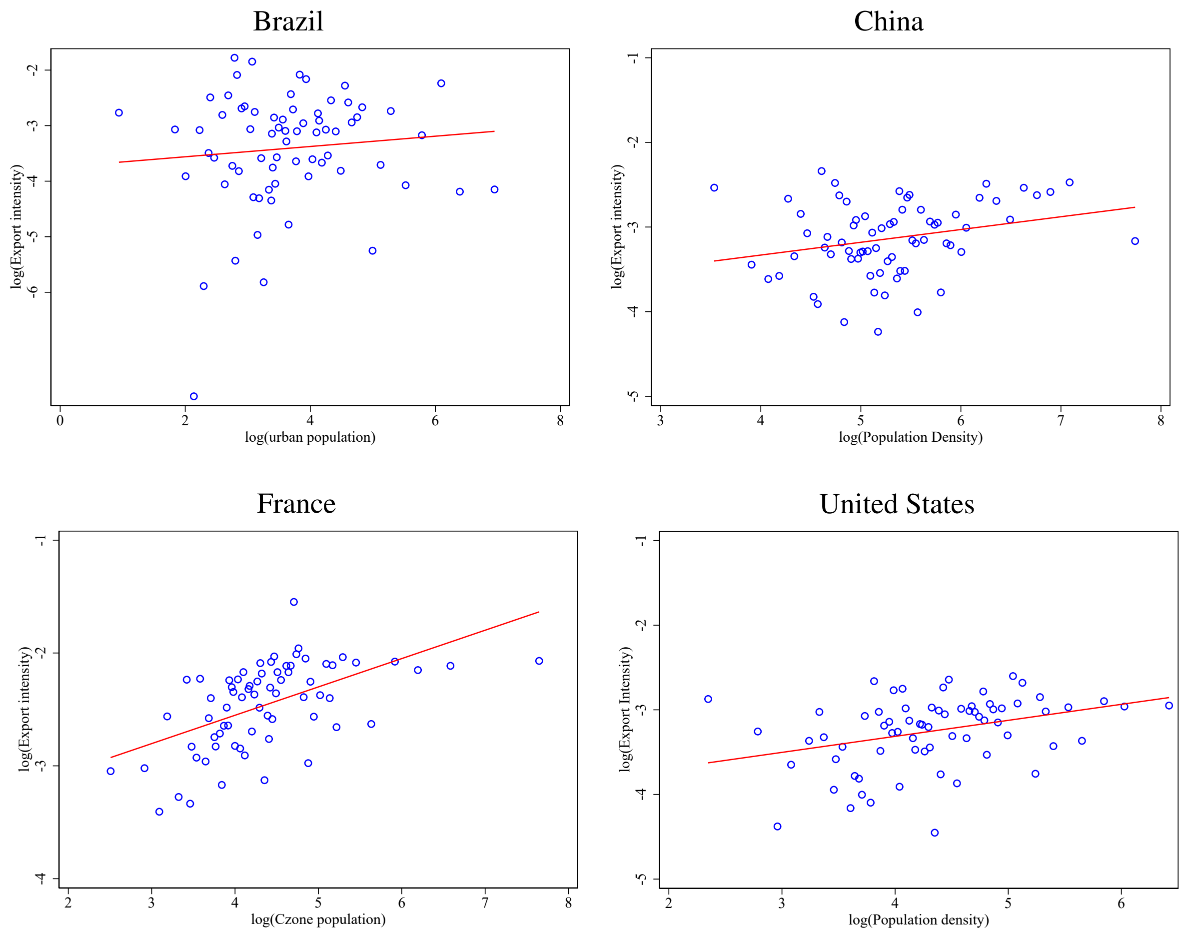
## D.1 Aggregate Results

Figure D.1: Per-capita exports and city size (in logs) in Brazil, China, France and the United States



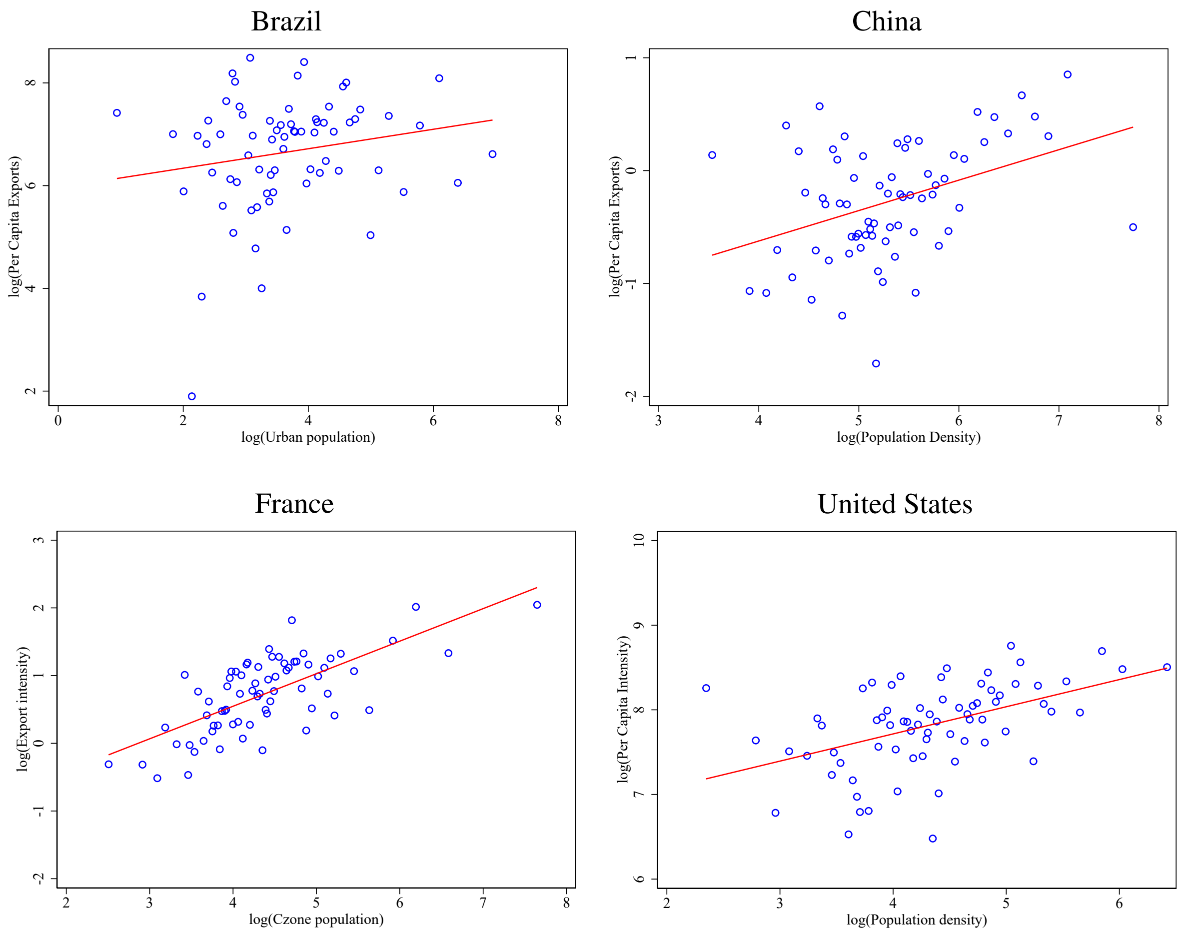

*Notes*: The figure shows the relationship between city size and per capita exports. Cities are defined in terms of metropolitan areas in the cases of China and the United States, and in terms of microregions for the case of Brazil. For all countries, the analysis only considers cities with positive exports and population over 100,000 inhabitants.

Figure D.2: Export intensity and city density (in logs) in Brazil, China, France and the United States




*Notes*: The figure shows the relationship between city size and per capita exports. Cities are defined in terms of metropolitan areas in the cases of China and the United States, and in terms of microregions for the case of Brazil. For all countries, the analysis only considers cities with positive exports and population over 100,000 inhabitants.

Figure D.3: Per-capita exports and city density (in logs) in Brazil, China, France and the United States




*Notes*: The figure shows the relationship between city size and per capita exports. Cities are defined in terms of metropolitan areas in the cases of China and the United States, and in terms of microregions for the case of Brazil. For all countries, the analysis only considers cities with positive exports and population over 100,000 inhabitants.

Table D.1: Per Capita Export and City size in Brazil, China, France, and the United States

| | Brazil | | China | | France | | United States | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| **A. Dependent Variable: City-Level Per Capita Exports** | | | | | | | | |
| log City Population | .462*** | .376*** | .319*** | .253*** | .351*** | .327*** | .264*** | .284*** |
| | (.132) | (.128) | (.062) | (.052) | (.058) | (.053) | (.043) | (.045) |
| Geog. Controls | No | Yes | No | Yes | No | Yes | No | Yes |
| Mean Dep. Var.: | 6.65 | 6.65 | -0.27 | -0.27 | 0.72 | 0.72 | 7.82 | 7.82 |
| $R^2$ | .030 | .280 | .030 | .290 | .133 | .220 | .080 | .200 |
| Observations | 296 | 296 | 615 | 615 | 304 | 304 | 324 | 324 |
| **B. Dependent Variable: City-Level Export Intensity** | | | | | | | | |
| log City Density | .155* | 0.093 | .161** | .151** | .258*** | .251*** | .131** | .197*** |
| | (.080) | (.099) | (.065) | (.061) | (.044) | (.052) | (.056) | (.057) |
| Geog. Controls | No | Yes | No | Yes | No | Yes | No | Yes |
| Mean Dep. Var.: | -3.41 | -3.41 | -3.14 | -3.14 | -2.46 | -2.46 | -3.25 | -3.25 |
| $R^2$ | .014 | 0.199 | .007 | .242 | .117 | .248 | .020 | .190 |
| Observations | 296 | 296 | 615 | 615 | 304 | 304 | 324 | 324 |
| **C. Dependent Variable: City-Level Per Capita Exports** | | | | | | | | |
| log City Density | .252*** | .189* | .324*** | .270*** | .442*** | .481*** | .263*** | .319*** |
| | (.090) | (.103) | (.081) | (.071) | (.052) | (.053) | (.060) | (.068) |
| Geog. Controls | No | Yes | No | Yes | No | Yes | No | Yes |
| Mean Dep. Var.: | 6.65 | 6.65 | -0.27 | -0.27 | 0.72 | 0.72 | 7.82 | 7.82 |
| $R^2$ | .028 | .270 | .021 | .287 | .193 | .298 | .060 | .170 |
| Observations | 296 | 296 | 615 | 615 | 304 | 304 | 324 | 324 |

*Notes*: The Table analyzes the relationship between city size and per capita exports. Cities are defined in terms of Metropolitan Areas for China and the United States, commuting zones for France, and Microregions for Brazil. For China and France, the analysis considers cities with positive exports and at least 250 manufacturing firms. For Brazil and the United States, the analysis considers cities with a population above 100,000 inhabitants. City-level export intensity is defined as manufacturing exports over manufacturing sales for China and France; overall exports over manufacturing sales for the United States, and overall exports over GDP for the case of Brazil. Geographical controls include the average distance to other domestic cities, distance to border, distance to the coast, border dummies, and a coastal dummy. Robust standard errors in parentheses. Key: ** significant at 1%; ** 5%; * 10%.

Table D.2: Export Activity and City Size: Additional Specifications for France

| | All Industries (1) | Manufac-turing (2) | Non Tradables (3) | Primary Sector (4) | Tradable Services (5) | Wholesale & Retail (6) |
|---|---|---|---|---|---|---|
| A. Multiple and Single Location Firms | | | | | | |
| log City Population | .176*** | .215*** | .312*** | -.001 | .366*** | .290*** |
| | (.038) | (.052) | (.066) | (.102) | (.066) | (.056) |
| Geog. Controls | yes | yes | yes | yes | yes | yes |
| Mean Dep. Var.: | -2.46 | -1.77 | -5.16 | -3.30 | -4.12 | -3.43 |
| $R^2$ | .214 | .305 | .163 | .096 | .140 | .129 |
| Observations | 304 | 304 | 303 | 273 | 301 | 304 |
| B. Single Location Firms Only | | | | | | |
| log City Population | .215*** | .216*** | .427*** | -.202 | .587*** | .386*** |
| | (.044) | (.046) | (.081) | (.217) | (.092) | (.062) |
| Geog. Controls | yes | yes | yes | yes | yes | yes |
| Mean Dep. Var.: | -2.57 | -1.90 | -5.18 | -3.91 | -4.20 | -3.58 |
| $R^2$ | .257 | .281 | .200 | .084 | .177 | .163 |
| Observations | 304 | 303 | 301 | 126 | 296 | 304 |

*Notes*: The Table replicates results in Table 3 for France using different subsamples. For all regressions, the dependent variable corresponds to the natural logarithm of export intensity, computed as the ratio of city-level exports and sales. Cities are defined in terms of commuting zones. The analysis only considers cities with at least 250 firms. Geographical controls include a dummy variable for cities located on the Mediterranean coast and the Atlantic coast, the distance to the Western and the Spanish border and the average distance to other domestic commuting zones. Robust standard errors in parentheses. Key: *** significant at 1%; ** 5%; * 10%.

Table D.3: Export intensity and City Size: Dropping Large Companies for China

| | Coeff./ St. Dev. | Obs./ $R^2$ | Geographic Controls | Employment Threshold |
|---|---|---|---|---|
| Dropping largest 1% | 0.272*** | 607 | yes | Overall |
| | (0.047) | 0.260 | | |
| Dropping largest 5% | 0.263*** | 585 | yes | Overall |
| | (0.047) | 0.260 | | |
| Dropping largest 10% | 0.273*** | 549 | yes | Overall |
| | (0.051) | 0.258 | | |
| Dropping largest 1% | 0.272*** | 606 | yes | Within sectors |
| | (0.047) | 0.262 | | |
| Dropping largest 5% | 0.267*** | 574 | yes | Within sectors |
| | (0.048) | 0.260 | | |
| Dropping largest 10% | 0.283*** | 528 | yes | Within sectors |
| | (0.053) | 0.260 | | |

*Notes*: The Table replicates results in Table 3 dropping large companies to control for firms reporting sales and exports in the location of the companies' headquarters offices. Brandt et al. (2014) shows that multi-establishment firms are infrequent in the Chinese Census of manufacturing, and these tend to be relatively large. Thus, by dropping large firms, we indirectly control for the possibility that our results are driven by firms reporting their sales and exports to the location of the companies' headquarters. Rows 1–3 compute the employment threshold for dropping large firms across all manufacturing sectors, while rows 4–6 compute the employment threshold within 2-digit ISIC sectors.

Table D.4: Export intensity and City Size: Further Robustness Check for China

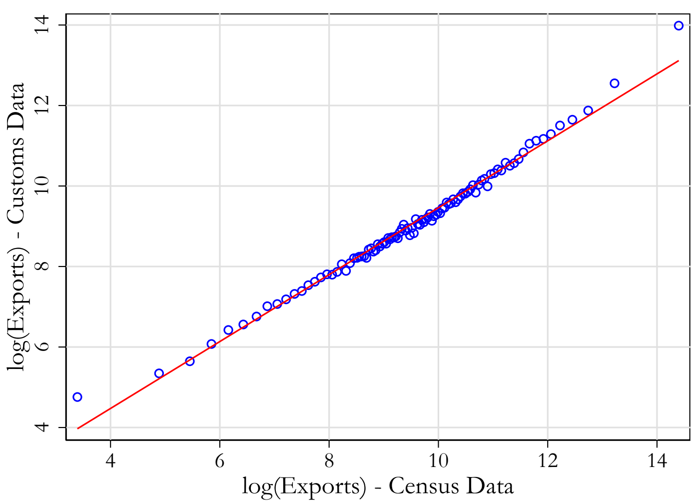
| | Coeff./ St. Dev. | Obs./ $R^2$ | Geographic Controls | SEZ and CDA Dummies | City definition |
|---|---|---|---|---|---|
| Urban population, additional controls | 0.272*** | 615 | yes | yes | MA |
| | (0.0467) | 0.262 | | | |
| Urban Population, Customs exports | 0.234*** | 576 | yes | yes | MA |
| | (0.0525) | 0.206 | | | |
| Urban population, geographic controls | 0.310*** | 329 | yes | no | Prefecture |
| | (0.0999) | 0.265 | | | |
| Urban population, additional controls | 0.314*** | 329 | yes | yes | Prefecture |
| | (0.0955) | 0.266 | | | |
| Urban Prefectures, Customs exports | 0.290*** | 322 | yes | yes | Prefecture |
| | (0.1103) | 0.244 | | | |

*Notes*: The Table replicates results in Table 3 under different controls, agglomeration measures, and city definitions. All regressions include the same set of geographical controls as Table 3, and two dummies for cities located in Special Economic Zones (SEZ) and Coastal Development Areas (CDA). For all regressions, the dependent variable is the natural logarithm of export intensity. “Additional Controls” include ++. “Geographic Controls” comprise ++.

## D.2 Additional Empirical Results

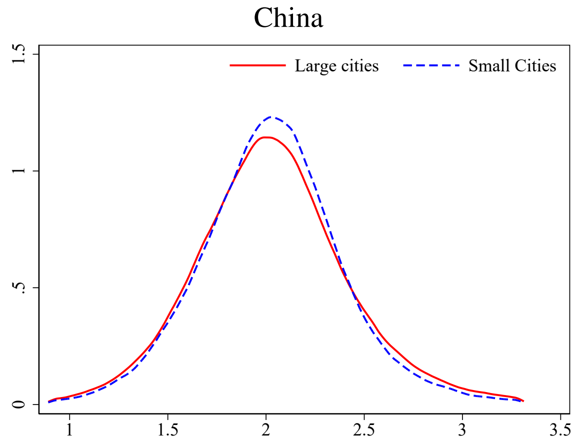
### *D.2.1 Additional Robustness Checks*

Figure D.4: Firm Export: Chinese Census of Manufacturing vs. Customs Administration




*Notes*: The figure plots a binscatter diagram between firm-level export information from the Chinese Census of Manufacturing and official export information from the Chinese Customs Administration. Both variables are in logarithms. The procedure we follow to match customs information to the Census of Manufacturing allows us to match one-third of the exporters in the Customs dataset. The correlation between exports from the two sources of information is 0.75.

Figure D.5: Firm Productivity Distribution by City Size




*Notes*: The figure shows the the (revenue) productivity distribution China and France. For each panel, the figure plots the corresponding distribution for large (population above 1 million) and small (population below 1 million) cities. Productivity is computed as the residual term of the revenue-based Cobb-Douglas production function. The production funciton coefficients are computed using the Gandhi, Navarro, and Rivers (2020) methodology.