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. We find that the effects of effects of trade liberalization and of urban policies are quantitatively different from those predicted by trade models that ignore economic geography, and by economic geography models that omit international trade (both of which are nested in our framework).

JEL: Exporting, Agglomeration, Sorting, 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 extend a canonical quantitative spatial equilibrium (QSE) model in the spirit of Redding (2016). We include heterogeneous firms and a mechanism of selection into exporting similar to that in Melitz (2003). We study a setup with an arbitrary

[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.

number of potentially asymmetric countries. Within countries, cities form in an exogenously given number of heterogeneous sites that are characterized by differences in productivity, amenities, and trade frictions. Crucially, we model productivity differences across these locations as differences in the location-specific 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. 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, the concentration of productive firms in the most productive locations tends (in the presence of within-country trade costs) 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 have a higher fraction of firms becoming exporters. Finally, similar to Melitz (2003), the model

[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.

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 interaction 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, productivity, and welfare. Moreover, we also show that trade and geographic policies may be complements or substitutes, depending on model parameters.

Finally, we structurally estimate the model using Chinese and French firm-level data. The model can account for the bulk of the correlation between export intensity and city size observed in the data. Furthermore, to explore 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 the context of an alternative model that omits domestic geography.[7] We find that the welfare losses associated with shutting down international trade are about 20% *smaller* in our model relative to the simplified Melitz benchmark. Intuitively, in our model with geography, exporters locate in bigger cities where they 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 aggregate productivity are about 50% larger than in an alternative model that shuts down 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 welfare and productivity gains of increased housing supply by increasing the weight of the most productive firms in the economy.

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, 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,

[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.

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 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

[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 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.

trade channels.

The rest of the paper is organized as follows: Section 2 presents the data and Section 3, our stylized facts. Section 4 introduces the model and its equilibrium properties. Section 5 presents the structural estimation of our 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 sorting 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 also 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. We use the information from the Census to compute measures of city-, industry-, and firm-level export activity. The reported location of firms reflects the county where their headquarters are based.[11] This feature is unlikely to confound our results because – as Brandt et al. (2014) show – over 90 percent of firms in China are single-plant firms. In Online Appendix B.1, we show that firm-level exports from customs data are highly correlated with our main dataset from the Census, and the corresponding export intensities confirm our stylized facts.[12]

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

[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, Van Biesebroeck, and Zhang, 2014).

[12] Although we also have access to official exports information from the Chinese Customs Agency, we avoid using it for three reasons. First, customs exports only consider direct exports, while Census exports consider both direct and indirect exports through intermediaries. Second, data from customs provides no information on the location of the exporters, and the data cannot be matched in a straightforward way to the Census of manufacturing, leading to poor matching rates. Finally, when computing export intensity with Customs information, many firms have unreliable export intensities – about 10% of the firms identified as exporters using customs data have export intensities above 100%.

(2019) to map counties into metropolitan areas with a threshold for light intensity equal to 30.[13] 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.[14]

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 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, employment, capital, value-added, and production.[15]

As is standard in the literature, we define cities in France in terms of commuting zones. City size reflects the overall commuting zone population, which we obtain by aggregating municipality-level information from the French Population Census of 1999.[16] While FICUS is available for the firms operating in all sectors of the French economy, we restrict our main analysis to the *manufacturing* sector for comparability with the Chinese data. Nevertheless, as we discuss in

[13]For reference, large metropolitan areas (urban population over 1 million) have, on average, about nine counties. In contrast, most small metropolitan areas (population below 100,000) consist of a single county.

[14]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.

[15]In a robustness check (reported in Appendix B.2), we combine FICUS with establishment-level information from the Annual Declaration of Social Data (DADS). DADS is an employer-employee dataset that contains information on the location of each establishment owned by the firm. In the appendix, we show that our results are qualitatively unchanged when restricting the data to the set of firms for which all establishments are located in a single commuting zone.

[16]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" (https://www.insee.fr/en/metadonnees/definition/c1361).

Appendix B.2, our main results also hold when generalizing the analysis to all sectors.

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 210 cities.

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.[17] Unlike China, most U.S agencies provide tabulation on key economic accounts at the MSA level. 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 312 U.S. metropolitan areas with a population over 100,000 inhabitants in 2012.

To develop our main analysis, we combine data from several sources. 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.[18] We combine this with establishment-level information of sales and employment aggregated at the MSA level from the 2012 Economic Census.[19] In our baseline analysis we use information for the manufacturing sector (NAICS 31-33), which is closest to our theoretical framework. Consequently, city-level export intensity is constructed as overall exports over manufacturing sales. Finally, we use MSA population from the population projections of the U.S. Census Bureau.[20]

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.[21] Although microregions do not directly capture commuting flows (in contrast to U.S. Metropolitan Areas), 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.

[17] 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.

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

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

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

[21] 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).

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*).[22] We complement this data source with municipal-level GDP from IBGE.[23] We aggregate both exports and GDP at the level of microregions using the correspondence provided by the IBGE, and we compute city-level export intensity as the ratio of overall exports over GDP. Finally, we use population projections from the 2010 population Census.[24]

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. Recall that for each country, our samples include all cities with more than 250 firms. 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 (780,000), Brazil (463,000), and France (258,000). These reflect the fact that population in the U.S. is more concentrated in larger cities. Indeed, as Figure B.2 in the appendix shows, both China and Brazil have a relatively higher density of small cities than the United States.[25] 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 c as follows:

$$EI_c = \left(\frac{\sum_j \sum_i E_{ijc}}{\sum_j \sum_i R_{ijc}} \right) , \tag{1}$$

where E_{ijc} and R_{ijc} denotes the exports and revenues, respectively, of firm i in sector j in city c.[26] The right part of Table 1 reports summary statistics for export intensity. A noteworthy difference between the four countries is the prevalence of zeros. In the U.S. and France, all cities have exporting firms; in contrast, in China and Brazil about 2 and 6 percent of the cities, respectively, record no export activity. We argue that the existence of cities with zero exports does not affect

[22] http://comexstat.mdic.gov.br/en/home

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

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

[25] 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.

[26] Equation (1) can only be directly applied in the case of primary datasets where we have access to firm-level data (i.e., in China and France). For Brazil and the United States, we proxy for the numerator and denominator in (1) using available city-level information. In particular, for Brazil, we compute export intensity as the ratio of city-level exports to GDP (across all sectors). For the United States, we compute export intensity as the ratio of overall city-level exports (across all sectors) to city-level manufacturing sales.

the quantitative implications of our results, because these cities represent a small fraction of output (0.3% and 0.9% of the production in China and Brazil, respectively). The distribution of export intensity is positively skewed for all countries in our sample, with an a substantially fatter tail in Brazil and China than in France and the United States.

3 Stylized Facts

In this section we present our empirical results. We first examine the distribution of export activity across cities. Next, we show to what extent the city-level results reflect differences in sectoral composition. We then show that differences in export intensity within sectors are primarily driven by differences in the extensive margin of exporting. Finally, we provide suggestive evidence for firm productivity as an underlying mechanism, which is positively correlated with both city size and export intensity.

3.1 Export Activity and City Size

Baseline OLS Results

Figure 1 presents 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 control for several geographical controls proxying for domestic and international trade costs: Average distance to other domestic cities, and distance to the border, distance to the coast, border dummies, and coastal dummies, respectively.[27] The figure shows a strong positive relationship for all countries.[28] Table 2 shows the corresponding point estimates for the elasticity between export intensity and city size: We obtain statistically highly significant estimates for all countries, ranging from 0.20 for France to 0.34 for China. Importantly, the coefficient remains positive and highly significant when we include geographical controls (columns 2, 4, 6 and 8). In all these cases, the estimated elasticities vary between 0.18 and 0.30.

2SLS Results

The main threat for identification is the possibility that third factors drive the relationship between export intensity and city size. To address this concern, we implement a two-stage least squares strategy, using historical city population as an instrument for modern population. The underlying assumption is that historical population was not determined by the same factors leading to differences in city-level export intensity today. Note that this IV approach does not allow to completely rule out the possibility of reverse causality. In particular, higher exports for reasons unrelated to

[27] The former is computed as the shortest straight distance from the center of the city to the nearest port. For France and the US we additionally include distance to the border, as trade across these land borders is quantitatively important (separately for Eastern and Western border in the case of France, and Southern and Northern border in the case of the US).

[28] While the relationship is somewhat less precisely estimated for Brazil, it is statistically significant.

our mechanism, such as differences in market access, could lead to firm-level efficiency gains (c.f. Garcia-Marin and Voigtländer, 2019), wich in turn drive the growth of cities. Nevertheless, given the significant changes in transport technology, industry composition and policy over the last century, trade patterns are likely to have changed significantly over this period weakening the link between current and historical exporting, supporting our assumption. 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.

Table 3 presents 2SLS results on export intensity and city size for China, using 1580's prefecture-level population from Bai and Jia (2021) to instrument for the current urban population.[29] Results for France, using commuting zone population from 1876 are similar and thus relegated to the appendix. Column 1 shows that the OLS elasticity stays positive and highly significant when using prefectures instead of metropolitan areas to define cities. If any, the coefficient is slightly larger than the baseline elasticity estimated based on metropolitan areas, with a point estimate of 0.32. Columns 2-4 show the baseline instrumental variable results. Column 2 presents results from a reduced form specification, where we directly regress contemporaneous log export intensity on 1580's 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 instrument the contemporaneous urban population with historical Chinese 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. Most importantly, historical city population is the most significant determinant of the current urban population. Indeed, except for the coastal prefecture dummy –which is the only significant control– no other geographical variable is statistically significant in the first stage regression. The estimated first stage coefficients implies that a 10 percent higher historical population in 1580 is related 3.02% larger population today.

Column 4 shows the second stage result. Again, the estimated coefficient on city size is positive and highly significant at the 5% level and remarkably similar to the OLS coefficient in column 1. This suggests that omitted factors not included in our baseline specification are most likely second-order for the relationship between export intensity and city size.

One concern with the 2SLS results in Table 3 is that the exclusion restriction may be violated if city size in 1580 is determined by differences in (international) market access, which in turn might be correlated with cities' export intensity today. To address this concern, column 5 reports second stage coefficients for the subset of prefectures that are not located on the coast. As the first stage in column 3 shows, being located in the coast is the only market access factor significantly

[29] Firms in our data locate in 344 prefectures. However, Bai and Jia (2021) only provide historical population information for the 260 prefectures belonging to China proper – i.e., excluding provinces from Inner China, such as the Tibet or Inner Mongolia provinces. See Bai and Jia (2021) for details.

related to contemporaneous city size. Thus, by restricting the analysis to the subset of land-locked prefectures we greatly reduce the possibility that differences in market access drive the relationship between export intensity and city size. As column 5 shows, the city size coefficient barely changes when restricting the sample to the set of cities not in the coast. Finally, column 6 performs a different test, including the interaction between city size and the coastal dummy. If differences in market access drove the second-stage city size coefficient in column 4, we would expect a highly significant positive interaction and a smaller (or even non-significant) level city size effect. Reassuringly, we obtain a negative and small non-significant interaction term while the baseline coefficients stay unchanged, suggesting that differences in market access does not drive the estimated relationship between export intensity and city size.

Additional 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. First, firm location is only defined at the headquarter level in all datasets. 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 link the baseline firm-level data with establishment-level employer-employee data that details the location of each productive establishment. Table B.5 shows that the estimated city size elasticity is quantitatively similar to our baseline estimates and statistically significant when restricting the analysis to the sample of firms that are active in a single commuting zone (column 2), or when we assume both domestic and export revenue are distributed proportionally to the wage bill across establishments of the firm (column 3). In both cases the estimated elasticity is quantitatively similar to our baselines estimates and statistically significant. Furthermore, we show that the positive correlation between export intensity and city size does not just hold within manufacturing but also when including all private sector firms (column 4).

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 city size coefficient when dropping relatively large firms. Table B.3 in the appendix shows that the estimated elasticity is very similar when dropping these firms – defined in terms of the upper percentiles of the overall and within-sector employment distribution. This suggests that the baseline city size elasticity is most likely not significantly driven by export-intensive companies with production based in small cities locating their headquarters in large cities.

Second, an important body of literature uses prefecture-level Chinese cities as the main unit of analysis (e.g., Au and Henderson, 2006). We show in Table B.4 in the appendix that our main findings are qualitatively unchanged when using prefecture-level cities (in rows 5-8 of the table).

The estimated elasticity is somewhat larger in this case (0.31 once geographical controls are included). Third, a distinctive element of China 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 B.4 that our main results are not affected by the inclusion of categorical variables for SEC and CDA cities (in row 1 of the table). Finally, we show that defining export intensity using information from the Chinese Customs Service – which only includes direct exports and leads and is limited due to poor matching with the Census of manufacturing – barely affects the baseline correlation (rows 4 and 8 in the table).

In sum, the strong correlation between cities export intensity and city size establishes our first stylized fact:

Stylized Fact 1. *Export intensity increases with city size*

3.2 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 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, $EI_c^{Between}$, that would result if city-level export intensity only varied due to differences in city-level industry composition. For each sector j, we first define its national-level export intensity, $\overline{EI}_j$, and then construct the counterfactual city-level export intensity by interacting (national-level) industry export intensities with each city's industrial composition:[30]

$$EI_c^{Between} \equiv \left(\sum_j \frac{R_{jc}}{R_c} \times \overline{EI}_j \right) \tag{2}$$

where $R_{jc} = \sum_i R_{icj}$ are total sales revenues of all firms i in sector j in city c, and R_c are total local sales revenues. The within-industry component is then defined simply as the part of the overall variation of export intensity not accounted for by differences in the sectoral composition of cities: $EI_c^{Within} \equiv EI_c / EI_c^{Between}$. In logarithms, we obtain the following decomposition of EI_c:

$$\ln EI_c \; = \; \ln EI_c^{Between} + \ln \underbrace{\left(EI_c / EI_c^{Between} \right)}_{\text{within-sector } (EI_c^{Within})} \tag{3}$$

[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.

Table 4 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 2. We report the share of the overall variation 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 65% of the overall variation in China, and for almost 70% in France. The evidence from the decomposition exercise leads us to our second stylized fact:

Stylized Fact 2. *About two-thirds of the overall variation in export intensity across city sizes is due to differences within industries, while one-third is due to differences in industry composition across cities.*

This stylized fact can be interpreted as a refinement to Stylized Fact 1. It suggests that the positive elasticity between export intensity and city size we document in section 3.1 for Brazil, China, France and the United States, reflects differences in the exporting behavior across firms *within* the same industry.

3.3 Firm-Level Analysis and Mechanisms

To improve our understanding of the drivers behind our main result (Stylized Fact 1), we study exporting behavior at the firm level for China and France. In particular, we focus on the relationship between city size and the extensive and intensive margin of exporting. Table 5 reports the results, weighting regressions by firms' sales shares within each city. This weighting avoids that the many small firms with zero or very small exports dominate our results.[32] In column 1 of Table 5 we examine the extent to which the extensive margin of exporting can account for the higher export intensity of large cities in China. We regress an export dummy for firms with strictly positive exports on the logarithm of city size. The city size coefficient is positive and highly significant. Its magnitude indicates that a doubling in city size is associated with an increase in the proportion of exporting firms by 7.1 percentage points (p.p.), relative to a (weighted) average proportion of

[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).

[32] Small firms (fewer than 25 employees) dominate the Chinese Census of Manufacturing: They account for more than 50 percent of firms in all city sizes, and about one-half of small firms have fewer than 10 employees. At the same time, small firms account for only 6 percent of the aggregate production value, and fewer than 2% of them are exporters. This is in stark contrast to the export activity among medium-sized and large firms, among which more than 20 percent are exporters. While this is consistent with a large literature showing that larger, more productive firms sort into exporting (c.f. Melitz, 2003; Bernard et al., 2007), it gives rise to a downward bias in unweighted regressions: The dominance of small firms in China dilutes the coefficient of interest, because they are distributed relatively homogeneously across all city sizes and have a low unconditional export probability. Weighting by firm-level sales shares has the additional benefit that it is consistent with our city-level analysis (because smaller firms naturally contribute less to overall city-level sales and exports. We could also weight observations by firms' sales. This alternative, however, would implicitly give a higher weight to larger cities.

exporting firms of 26.2 percent.[33] For France, we also obtain a highly significant relationship between city size and the extensive margin of exporting (column 3 in Table 5). However, the magnitude is smaller – doubling city size is associated with a 1.8 p.p. higher frequency of exporting (compared to a weighted sample mean of 75.1 percent).[34] We stress that these results can only be interpreted as a correlation because, as our model in the next section suggests, firm location is endogenous.

Next, we analyze the intensive margin of exporting, regressing the logarithm of export intensity on city size for the sub-sample of firms with strictly positive exports. In this way, we aim to study if the forces of sorting, selection and agglomeration could lead a more pronounced export orientation in larger cities. Results in columns 2 and 4 in Table 5 suggests that the intensive export margin is relatively weaker than the extensive margin in explaining the positive correlation between city-level export activity and city size. For China, the city size coefficient is *negative* and statistically insignificant, while for France, the city size coefficient is only significant at the 10 percent level and quantitatively small: Doubling city size is associated with an increase in export intensity of exporters by about 0.5 p.p., based on an estimated elasticity of 0.067 and a mean export intensity of 0.290 (weighted by firms' sales shares, as in the regressions in Table 5).

Taken together, these results suggest that the higher within-industry export intensity of large cities is most likely driven by a higher export participation of firms in large cities. We summarize this in the following stylized fact:

Stylized Fact 3. *The extensive margin of exporting is important: Within industries, firms located in larger cities are significantly more likely to participate in exporting. On the other hand, there is at best mixed evidence on the intensive margin of exporting.*

These suggestive findings provide partial justification for a central pillar in our theoretical framework: firm-level productivity, which is typically higher in larger cities due to firm sorting and agglomeration. Given the importance of the extensive over the intensive margin, our model emphasizes selection into exporting as the key driver of differences in export intensity across city sizes. We turn to the presentation of our model in the next section.

4 Model

To account for the stylized facts documented above, we present a model of selection and agglomeration of firms across cities, together with selection into exporting. The model extends a standard

[33] The unweighted average export participation among Chinese firms is 10.8%.

[34] The unweighted average export participation among French firms is 29.4%. The smaller coefficient for France can be explained by the fact that French firms face lower export costs (both fixed and variable) because of their proximity to the large EU markets, with low regulatory and other frictions. Thus, the export cut-off for France is lower and reached also by firms in smaller cities than in China. In line with this reasoning, we find that there are exporters even in very small French cities. In contrast, in China, there are many cities with no exporters. Consequently, the gradient of export participation with respect to city size is flatter in France.

quantitative spatial economics framework in the spirit of Redding (2016) to include heterogeneous firms and a mechanism of selection into exporting similar to that in Melitz (2003).

4.1 Setup

We consider a world economy featuring C potentially asymmetric countries. Each country is endowed with an exogenous population L_c of identical workers and contains an exogenous number of city sites I_c. Within countries we index city sites by i and each city site has an exogenous stock of land N_{ci}. Cities with different population levels L_{ci} emerge endogenously on these sites. Crucially, workers are assumed to be mobile across locations within countries, but have idiosyncratic preference draws for each domestic location. As is standard in the economic geography literature workers are assumed to be immobile internationally.

As in Redding (2016), the key drivers of within country economic geography are heterogeneity across locations (i.e. city sites) in productivity, amenities, land supply and geographical location relative to one another and relative to other countries.

The main difference relative to the set-up of Redding (2016) is the specification of 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 ψ) from location-specific productivity distributions. In turn these distributions capture the heterogeneity in productivity across locations. For simplicity, we assume that these productivity distributions are Pareto distributions with identical scale parameters but differing shape parameters (denoted α_{ci}).

Once they've drawn their productivity, firms decide whether to produce and which markets to serve. Production involves paying fixed costs f in units of local labor, while shipping goods outside of the city is subject to trade costs. Within countries, bilateral trade costs are assumed to take the iceberg form, such that $d_{ij} > 1$ units of each good need to be shipped from location i to location j for one unit to arrive at domestic location j, with $d_{ii} = 1$. Internationally, shipments are also subject to the same iceberg transportation costs, but they are also subject to fixed exporting costs. Thus, for each new country a firm seeks to export to it must pay sunk exporting cost f_x in units of local labor of the city where the firm is based.

Preferences Workers 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_{ci}. Moreover, their utility is affected by idiosyncratic utility shocks that are specific to each location. As a result, the utility of a worker ω is given by:

$$U_{ci}(\omega) = b_{ci}(\omega)c_{ci}(\omega)^{\beta}h_{ci}(\omega)^{1-\beta} \tag{4}$$

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

$$c_{ci} = \left[\int c_{ci}(x)^{\frac{\sigma-1}{\sigma}} dx \right]^{\frac{\sigma}{\sigma-1}} \tag{5}$$

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

$$h = k^{1-\gamma} n^{\gamma} \tag{6}$$

where h denotes housing, k denotes capital used int the production of housing, n denotes land and γ 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 produced from the local composite tradable good via the linear technology

$$k_{ci} = \kappa c_{ci} \tag{7}$$

where c_{ci} is given by equation (5). Note that the efficiency of transforming the composite consumption good into capital is assumed to be homogenous across cities and countries.

As in Redding (2016), The idiosyncratic amenity shocks $b_{ci}(\omega)$ capture the idea that workers have heterogeneous preferences for living in each location. These amenity shocks are drawn independently across locations and workers from a Fréchet distribution:

$$G_{ci}(b) = e^{-B_{ci} b^{-\epsilon}} \tag{8}$$

where the scale parameter B_{ci} determines average amenities for location i in country c and the shape parameter ϵ controls the dispersion of amenities across workers for each location.

Production In each country and city, there is a potentially infinite supply of potential entrants. Firms produce differentiated tradable varieties using 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 ψ from a location specific productivity distribution. These distributions are assumed to be standard Pareto (i.e. scale parameter equal to 1) with shape α_{ci}, with more productive locations being characterised by smaller shape parameters. For a firm of efficiency ψ, the production technology is then given by:

$$l(q) = f + \frac{q}{\psi} \tag{9}$$

where $l(q)$ denotes the local labor input required to produce a quantity of output q, and f denotes the fixed cost of production .

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 and the free entry condition imply that equilibrium prices are a mark-up over marginal costs:

$$p_{ij}(\psi) = \frac{\sigma}{\sigma - 1} \frac{d_{ij} w_i}{\psi} \tag{10}$$

where $p_{ij}(\psi)$ denotes the profit maximizing price set by a firm of productivity ψ located in i delivering a unit of output to location j. The presence of fixed production costs implies that each location i will be characterised by a minimum productivity threshold ψ_i^* below which firms exit without producing. Above this threshold firms will enter and at least serve all domestic locations (i.e. all locations within their countries). Moreover, the presence of fixed exporting costs, will imply that for each location i (in a country c) and foreign country c' there will be a threshold of firm productivity $\psi_{ic'}^{x}{}^*$ such that firms above this productivity threshold will serve all locations j in country c'. Revenues from sales to location j in a country c' for a firm with productivity ψ based in location i in country c are given by:

$$r_{ij,j\in c'}(\psi) = R_j \left(\frac{\psi \rho}{w_i d_{ij}} \right)^{\sigma - 1} P_j^{\sigma - 1} \mathbb{1}_{c'} \tag{11}$$

where R_j are total expenditures at location j, ρ is given by $\rho = (\sigma - 1)/\sigma$ and $\mathbb{1}_{c'}$ is an indicator variable equal to 1 if a firm of productivity ψ in location i serves locations in country c' in equilibrium. Total revenues for a firm of productivity ψ based in location i is given by

$$r_i(\psi) = \sum_j R_j \left(\frac{\psi \rho}{w_i d_{ij}} \right)^{\sigma - 1} P_j^{\sigma - 1} \mathbb{1}_{c'} \tag{12}$$

Equating expenditures and firm revenues at each location and imposing the free entry condition then yields the measure of firms at each location

$$M_i = \frac{R_i}{\bar{r}_i} = \frac{L_i}{\sigma[\psi_i^{*\alpha_i} f_e + f + \sum_{c', c' \neq c} p_{ic'}^x f_x]} \tag{13}$$

where α_i is the shape of the Pareto productivity distribution at location i, ψ_i^* is the productivity threshold for successful entry at location i, and $p_{ic'}^x$ represents the probability of a firm based in location i exporting to a foreign country $c' \neq c$

Expenditure shares and price indices Given the set-up outlined above, the share of location j's expenditures on goods produced in location i is given by

$$s_{ji,j\in c'} = \frac{\int_{\psi^{x}_{ic'}{}^{*}} r_{ij}(\psi) M_i g_i(\psi) d\psi}{\sum_{k\in c'} \int_{\psi_k{}^{*}} r_{kj}(\psi) M_k g_k(\psi) d\psi + \sum_{k\in c\, c\neq c'} \int_{\psi^{x}_{kc'}{}^{*}} r_{kj}(\psi) M_k g_k(\psi) d\psi} \tag{14}$$

if the cities are located in different countries and by

$$s_{ji,j\in c'} = \frac{\int_{\psi_i{}^{*}} r_{ij}(\psi) M_i g_i(\psi) d\psi}{\sum_{k\in c'} \int_{\psi_k{}^{*}} r_{kj}(\psi) M_k g_k(\psi) d\psi + \sum_{k\in c\, c\neq c'} \int_{\psi^{x}_{kc'}{}^{*}} r_{kj}(\psi) M_k g_k(\psi) d\psi} \tag{15}$$

if they are located in the same country. Price indices at each location are given by:

$$P_i = \left[\sum_{k\in c} \int_{\psi^*_k} p_{ki}(\psi)^{1-\sigma} M_k g_k(\psi) d\psi + \sum_{k\in c', c'\neq c} \int_{\psi^{x}_{kc}{}^{*}} p_{ki}(\psi)^{1-\sigma} M_k g_k(\psi) d\psi \right]^{\frac{1}{1-\sigma}} \tag{16}$$

Residential choice in spatial equilibrium Given the Frechet distribution of idiosyncratic shocks to amenities we assumed, the probability that a worker in country c chooses to live and work in location i is given by:

$$\frac{L_{ci}}{L_c} = \frac{B_i (v_i / P_i^{\beta} p_{hi}^{1-\beta})^{\epsilon}}{\sum_{k\in c} B_k (v_k / P_k^{\beta} p_{hk}^{1-\beta})^{\epsilon}} \tag{17}$$

where the Frechet shape paremeter ϵ pins down the elasticity of population with respect to real income, v_i denotes the total income of a worker at location i (more on this below), and p_{hi} denotes the price of housing at location i[35]. Thus, each location faces local labour supply curve that is upward sloping in real income, as higher incomes must be paid to attract workers with lower idiosyncratic preference for the location. Expected utility for a worker in country c is:

$$\bar{U}_c = \delta \left[\sum_{k\in c} B_k (v_k / P_k^{\beta} p_{hk}^{1-\beta})^{\epsilon} \right]^{\frac{1}{\epsilon}} \tag{18}$$

where $\delta = \Gamma((\epsilon - 1)/\epsilon)$ and $\Gamma(.)$ is the Gamma function. As in Redding (2016), an implication of the idiosyncratic Frechet amenity shocks for utility is that expected utility conditional on living in location i is the same across all locations within a country and equals expected utility for the country as a whole[36]. Therefore, although real income differs across locations within countries, expected utility is equalised across cities within countries. This common value of expected utility provides the relevant measure of welfare that we will use to evaluate the consequences of trade and

[35] In turn p_{hi} can be written $p_{hi} = (\kappa P_i)^{1-\gamma} r_i^{\gamma}$ where r_i denotes the land rental rate at location i

[36] The intuition for this result is as follows: on the one hand, more attractive location characteristics directly raise the utility of a worker with a given idiosyncratic utility draw, which increases expected utility. On the other hand, more attractive location characteristics attract workers with lower idiosyncratic utility draws, which reduces expected utility. With a Fréchet distribution of utility, these two effects exactly offset one another.

spatial policies.

We assume that expenditure on land in each location is redistributed lump sum to workers that reside in that location. Thus, total income in location i is given by labor income plus expenditure on residential land:

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

In turn, labor income in each location equates total expenditure on goods produced in that location:

$$w_i L_i = \sum_j s_{ji} w_j L_j \tag{20}$$

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

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

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 ψ_i^*, a set of entry into exporting thresholds for each location and country pair ${\psi_{ic'}^{x}}^*$, 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.

4.2 Theoretical Results: Matching the Stylized Facts with a Simplified Model

To illustrate the novel mechanism we propose to account for the stylised facts outlined in section 3 in this section we present several theoretical results for a simplified version of the model discussed in the previous section. In particular in this section we focus attention on a setting featuring 2 symmetric countries, each containing two asymmetric locations. Countries are symmetric in the sense that they have equal populations, and all locations across and within countries have the same land endowments N. Moreover, each country has a more productive location indexed as location 1, which is reflected in lower Pareto shape parameters $\alpha_{c1} < \alpha_{c2}$ and $\alpha_{c'1} < \alpha_{c'2}$. However, city level productivity is equalised across location pairs in the two countries such that $\alpha_{c1} = \alpha_{c'1} = \alpha_1$ and $\alpha_{c2} = \alpha_{c'2} = \alpha_2$. As additional simplifications, we omit from the analysis the idiosyncratic amenity shocks (and hence assume that amenities are homogenous across all locations) and also assume that trade is costless across locations within countries, with the only trade frictions being international trade costs denoted by $\tau > 1$ (in the notation of the previous section $d_{ij} = 1$ if i and j are in the same country, and the $d_{ij} = \tau > 1$ if i and j denote locations in different countries).

With these simplifications in place, both price indices and equilibrium utilities are equalised across all locations in the two countries (due to costless trade and migration within countries, and due to cross-country symmetry). We can therefore choose the composite tradable good as the numeraire and set the tradable price index to 1 in all locations. This yields that the price of capital used to build housing in equilibrium is given by $p_k = \kappa$.

Moreover, in this simplified setting, firms optimal pricing choices lead to each firm choosing two optimal price levels, one for its domestic (national) market and one for the foreign market. These are given by:

$$p_d^i(\psi) = \frac{\sigma}{\sigma - 1} \frac{w_i}{\psi}$$
$$p_x^i(\psi) = \tau p_d^i(\psi)$$

In turn, operational profits derived from serving domestic markets are given by:

$$\pi_d^i(\psi) = \frac{R}{\sigma} \left(\frac{\psi \rho}{w_i} \right)^{\sigma - 1} - w_i f \tag{22}$$

where R denotes the aggreate revenues of the tradable sector in each country. A firm's profits from serving the foreign market are given by

$$\pi_x^i(\psi) = \tau^{1-\sigma} \frac{R}{\sigma} \left(\frac{\psi \rho}{w_i} \right)^{\sigma - 1} - w_i f_x \tag{23}$$

Thus total profits for a firm of productivity ψ at location i that has achieved succesful entry are given by

$$\pi^i(\psi) = \begin{cases} \pi_d^i(\psi) & \text{if} \quad \pi_x^i(\psi) < 0 \\ \pi_d^i(\psi) + \pi_x^i(\psi) & \text{if} \quad \pi_x^i(\psi) > 0 \end{cases} \tag{24}$$

Similarly, firm revenues are given by

$$r_d^i(\psi) = R \left(\frac{\psi \rho}{w_i} \right)^{\sigma - 1}$$
$$r_x^i(\psi) = \tau^{1-\sigma} r_d^i(\psi)$$

With total revenues being given by:

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

Moreover, in equilibrium each location will be characterised by two productivity thresholds: the minimum productivity threshold for successful entry (which we denote ψ_i^*) and the minimum productivity threshold for successful entry into exporting (which we denote ψ_{xi}^*). We also define for each location two average productivity measures: the average productivity of all firms in each location (denoted $\tilde{\psi_i}$) and the average productivity of exporters at each location (denoted $\tilde{\psi_{xi}}$). These are given by:

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

Equilibrium conditions With the preliminaries above, the equilibrium of the simplified model is defined by the set of equilibrium conditions outlined below.

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

$$\pi_d^i(\tilde{\psi_i}) = w_i f k_i(\psi_i^*) \tag{25}$$

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

$$\pi_x^i(\tilde{\psi_{xi}}) = w_i f_x k_i(\psi_{xi}^*) \tag{26}$$

3. Free entry condition

$$\pi^i = \pi_d^i(\tilde{\psi_i}) + p_x^i \pi_x^i(\tilde{\psi_{xi}}) = \frac{w_i f_e}{1-G_i(\psi_i^*)} \tag{27}$$

where $p_x^i = [1-G_i(\psi_{xi}^*)]/[1-G_i(\psi_i^*)]$ is the probability that a firm in location i engages in exporting

4. Spatial equilibrium for workers among pairs of locations i and j within the same country

$$U_i = \frac{v_i}{\kappa^{(1-\gamma)(1-\beta)} r_i^{\gamma(1-\beta)}} = U_j = \bar{U} \tag{28}$$

5. Market clearing for land in each city

$$r_i = \frac{1-\beta}{\beta} \gamma \frac{w_i L_i}{N} \tag{29}$$

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 speak directly to the stylized facts we have documented and are described in the following proposition:

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.

Intuitively, in the more productive city of each country (the city with the lower Pareto shape parameter), the productivity distribution from which local entrants draw exhibits a fat upper tail. As a result, these cities will feature a relatively large number of large and productive firms, 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 and populations in these cities. Moreover, higher local wages will tend to increase the stringency of the selection into entry process in the more productive cities, as low productive firms become more likely to exit without producing in these locations. In turn this endogenous selection mechanism will tend to augment the productivity differences between the firms in the two cities. 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 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:

$$\frac{\psi_{xi}^*}{\psi_i^*} = \frac{\psi_{xj}^*}{\psi_j^*} = \tau \left(\frac{f_x}{f}\right)^{\frac{1}{\sigma-1}} \tag{30}$$

However, in the more productive city, the presence of a fat upper tail implies that a higher mass of firms jumps over the local "Melitz barrier" and becomes 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, with the intensive margin of exporting (i.e. the export intensity of exporters) being constant across space[37]. Taken together, our simple model predicts that more productive cities will be 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

[37]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.

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 observation (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, of geographic policies on international trade, as well as investigate whether trade and geographic policies are complements or substitutes.

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 τ leads to a relative increase in the size of the more productive city in each country, 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 city, as these locations have a higher fraction of firms who are exporters. In turn this leads to an increase in the size of each countries'productive cities at the expense of less productive locations. All in all, trade liberalization increases aggregate productivity both because the firm selection process becomes more stringent in all locations (the productivity threshold for successful entry goes up in all locations) and also because more factors are employed in the more productive city of each country. In turn, this increase in aggregate productivity is reflected in an increase in real wage levels, which leads to an increase in aggregate welfare.

Moving on to the analysis of geographic policy, in the proposition below we characterise the implications of an generalised increase in housing supply elasticities affecting all locations:

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

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 each country's more productive cities, as these locations were more constrained by the scarcity of land and housing. As a result of this mechanism, workers shift in both countries towards the more productive cities. This shift in factors in turn causes an increase in aggregate productivity and an increase in aggregate export intensity (the relative mass of firms shifts to the more productive location, and firms in this location are more likely to become exporters). Moreover, welfare increases both as a direct effect of housing becoming cheaper due to relaxed land use restrictions and as a result of real wages increasing due to increased aggregate productivity.

Finally, our last set of results concerns the patterns of complementarity and substitutability between trade and geographic policies:

Proposition 4. *Depending on model parameters, trade liberalization and planning deregulation may either be complements or substitutes.*

Proof: See appendix

The model predicts a complex pattern of complementarity and substitutability between trade and spatial policies that depends on economic fundamentals. For instance, it can be shown that trade and spatial policies are substitutes if the productivity differences across locations within countries are very large - i.e. the aggregate TFP gains associated with liberalizing land use decline with the level of a country's international economic integration. Intuitively, this is because when productivity differences across cities are very large and international trade costs are low, a large fraction of each country's population is concentrated in the more productive city. This leaves relatively little scope for further reallocation of factors (and hence aggregate productivity increases) in response to planning deregulation. By contrast, if land use constraints are strongly binding (i.e. the consumption share of housing and the importance of land in housebuilding are both very high), and productivity differences across locations within countries are not too great, then spatial policies and trade policies are complements. Intuitively, when land constraints are strongly binding the two locations in each country will tend to be of similar sizes, in spite of their productivity differences, in both the closed and the open economy. However, in the open economy the land use constraints will be more binding on the more productive locations in the open economy, where in the presence of less stringent land use constraints the more productive city would be relatively larger. Thus, in this context, any lessening of land use restrictions would cause a larger reallocation of labour towards the more productive location in the more open economy, leading to a larger increase in TFP. To summarize, whether trade and geographic policies are complements or substitutes depends on fundamentals and remains an empirical question, one that we will explore in detail in section 5.

5 Quantitative Analysis

In this section we take the model to the data. We first present the main features of the estimation procedure. We then show how the model fits our main stylized fact for the Chinese economy. Finally, we provide quantitative results for the effect of (i) trade liberalization and (ii) spatial policies on welfare and productivity.

5.1 Structural Estimation

Functional Forms

The first step to estimate the model is to specify the productivity process. In the model, firms sort perfectly into cities and into exporting according to their raw efficiency z. This produces the stark prediction that small cities have no productive firms nor exporters. Yet, in the data, small cities feature both productive and unproductive firms, and they may produce for the domestic or foreign markets. To accommodate these facts, we modify the baseline model in two ways. First, we introduce a disturbance term in ex-post productivity that varies across firms and cities. This reflects the fact that firms may be more productive in certain locations, for example because they have better knowledge of the local culture and can organize production in a more efficient way. The resulting productivity process features two sources of randomness: raw productivity (z), and a idiosyncratic productivity shock ($\varepsilon_{i,L}$) that varies across firms and cities. In this way, we allow firms to sort imperfectly into cities of different sizes.

We specify the same functional form for ex-post productivity ψ (including agglomeration economies related to the firm's optimal city choice) as Gaubert (2018):

$$\log(\psi_j(z_i, L, s_j)) \quad = \quad a_j \log L + \log(z_i) \left[1 + \log \frac{L}{L_0}\right]^{s_j} + \varepsilon_{i,L} \tag{31}$$

where L_0 denotes the size of the smallest city, and $\{a_j, s_j\}$ are sectoral parameters. Equation (31) shows that ex-post (log) productivity ψ is composed by three terms. The first term ($a_j \log L$) represents the classical agglomeration mechanism: Firms are more efficient when they locate in larger cities. The second term represents the log-modularity between firms' raw efficiency z and (normalized) city size (L/L_0). According to this, firms' raw productivity z and city size L are complementary: Initially more productive (high z) firms benefit relatively more from locating in larger cities (provided that s is greater than zero). Finally, the last term $\varepsilon_{i,L}$ is an idiosyncratic term that varies across firms and cities. Importantly, this term is distributed independently of firm's raw productivity z. Thus, regardless of the level of raw productivity z, firms can still find optimal to locate in smaller cities.

We assume that raw productivity z follows a log-normal distribution with mean zero and variance σ_Z. We restrict the process for $\log z$ to be non-negative to ensure that ex-post productivity ψ increases with city size. Consequently, the distribution for $\log z$ is truncated at zero. Regarding the idiosyncratic term $\varepsilon_{i,L}$, we assume that it is distributed type-I extreme value. We restrict the parameters so that the mean of the process is equal to zero. With this restriction, the distribution is determined solely by the scale parameter β_ε.[38]

In the model, firms become exporters with probability one after the surpass the export productivity threshold. Yet, in the data, not all highly productive firms are exporters. To accommodate this stark prediction of the model, we specify a Pareto distribution for the probability of becoming exporters, as an increasing function of the relative distance of firms' ex-post productivity from the export productivity threshold in each city, $\psi_j^*(L)$:

$$\Pr(\text{Export>0}) = \begin{cases} 1 - \left(\frac{\psi_j(z_i, L, s_j)}{\psi_j^*(L)}\right)^{-\theta}, \text{ with } \theta > 0 & \text{if } \psi_j(z_i, L, s_j) \geq \psi_j^*(L) \\ 0 & \text{otherwise} \end{cases} \tag{32}$$

Note that this parametrization is consistent with more productive firms having a higher probability of becoming exporters. At the same time, this specification relaxes the step-function for export probability by the canonical Melitz's (2003) model. Firms with productivity just above the export productivity threshold have an export probability marginally above zero. The export probability increases continuously until eventually reaching one for high enough productivity levels.

Estimation Procedure

To estimate the model, we use the data from the Chinese Census of Manufacturing (see Section 2, for details). To match the relative size of China in the world economy in 2004, we consider a world with 20 symmetric countries. The estimation is carried out sector-by-sector for each 2-digit manufacturing ISIC industry.[39]

The estimation strategy proceeds in two steps and follows Gaubert (2018). We first calibrate all parameters that can be directly linked to the data $\{\sigma_j, \xi_j, b(1-\eta)/\eta, \tau_j\}$. The elasticity of substitution σ_j is set to match the average 2-digit markup, computed at the the establishment-level using the procedure outlined by De Loecker and Warzynski (2012). The Cobb-Douglas sectoral share ξ_j is computed as the share of each sector's value added within the manufacturing sector. The composite parameter $b(1-\eta)/\eta$ corresponds in the model to the elasticity of wages to city size. This elasticity is equal to the difference between the elasticity of average value-added to city size minus the elasticity of average employment to city size.[40] Thus, we run regressions for the logarithm of average city-level value-added, and the logarithm of average city-level employment as dependent variables, against the logarithm of urban population of the city size, and then subtract the coefficient on log city size from the former regression to the corresponding coefficient on the

[38]The location parameter λ can be recovered explicitly as a function of the scale parameter β_ε. In particular, the restriction $\mathbb{E}(\varepsilon) = 0$ implies that $\lambda = -\gamma\beta_\varepsilon$, where γ is the Euler-Mascheroni constant.

[39]We consider a total of 19 industries. We exclude manufactures of Tobacco products, and merge (i) manufactures of coke, refined petroleum products and nuclear fuel with manufactures of chemicals and chemical products, and (ii) office, accounting and computing machinery with manufactures of electrical machinery.

[40]To see why this is the the case, note that $w(L)l_j(z, L) = (\sigma_j - 1)/\sigma_j r_j(z, L)$, where r represents firm revenues.

latter regression. Finally, the iceberg variable trade cost τ_j is set to match the average export intensity within exporting firms.[41]

In the second stage, we estimate the remaining parameters $\{a_j, s_j, \sigma_Z, \beta_\varepsilon, f_j^e, \theta\}$ through simulated method of moments (SMM). This method compares the objective moments in the data to the moments derived from a simulated economy, for candidate values of the parameters to be estimated. The vector of estimated parameters $\hat{\theta}_{SMM}$ are such that they minimize the weighted distance between the moments in the data ($\mathbf{m}_j$) and the simulated economy ($\hat{\mathbf{m}}_j(\theta_j)$):

$$\hat{\theta}_{j,SMM} = \arg\min_{\theta_j}(\hat{\mathbf{m}}_j(\theta_j) - \mathbf{m}_j)^T W_j(\hat{\mathbf{m}}_j(\theta_j) - \mathbf{m}_j) \tag{33}$$

In equation (33), the matrix W_T weights the vector of moments. We set this matrix to be equal to the inverse of the variance-covariance matrix of the moments. To compute this matrix, we follow Eaton, Kortum, and Kramarz (2011) and compute bootstrapped standard errors of the moments resampling within industry-cities (with replacement) 5,000 artificial economies with the same number of firms as in the Chinese Census of Manufacturing in 2004.

Choice of Moments and Identification

We now discuss the moments we choose to target in the SMM estimation. Table 6 summarizes these moments, together with the parameter each moment aims to identify. The first set of moments relate to $\{a_j\}$. This parameter summarizes classical agglomeration forces: as a_j gets larger, productivity and revenues increase with city size. Accordingly, we define the target moment as the share of value added produced by firms located in cities of different sizes. We construct the moment in the following way. For each sector, we sort cities in terms of population, and define city groups in terms of quartiles of cumulative population (e.g., the first group contains all smallest cities in the economy, until that their population add up to 25 percent of the overall population). Then, we compute four moments as the share of value-added produced by firms located in each of the population quartiles. Thus, the first set of moments match by how much the share of sectoral value added increases with the size of the cities.

The second set of moments relates to $\{s_j\}$, which determines the strength of the complementarity between raw productivity z and city size. To identify this parameter, we seek to match the average value added of firms in relatively large cities. Intuitively, for a given productivity z, the higher is the value of s_j, the stronger is the increase of firm productivity and revenues in city size. Formally, we divide cities in four quartiles by size, and then compute the average value-added of the firms locating in each quartile. We emphasize the top quartile of the city size distribution: differences in s_j will affect relatively more the slope of average value added in relatively large cities,

[41] In the model, the average export intensity conditional on exporting is equal to $\left(1 + \frac{\tau^{\sigma_j - 1}}{(C-1)}\right)^{-1}$.

while it will tend to have a more modest impact in relatively smaller cities.

The third set of moments relate to the scale parameter of the idiosyncratic productivity shock (β_ε). This parameter varies by firm and city size, and it accounts for relatively productive firms locating in small cities. To identify this parameter, we target the average value added of firms in small cities. Through the lens of the model, if average value added in small cities is high, it must be because some highly productive firms are choosing to locate in these cities. Thus, as β_ε increases, we expect the average value added of firms locating in small cities to increase. Formally, this moment is defined analogously to the second set of moments, but with an emphasis on the bottom quartile of the city size distribution.

The fourth set of moments relate to the variance of the truncated log-normal distribution of raw productivity, σ_z. To identify this parameter, we target the top decile of normalized sales across all cities.

Finally, to identify the fixed export cost and the Pareto shape parameter θ, we target the national-level export-related moments. First, to identify the fixed export cost, we target the fraction of firms that are exporters in the data. Intuitively, a higher fixed export cost affects the extensive margin of exporting. As this cost increases, fewer firms will be sufficiently profitable to pay the fixed export cost and participate in export markets. Second, to identify θ, we target the industry-level export intensity, defined as overall exports over sales across all city sizes. Conditional on the fixed export cost, a higher export intensity requires a less disperse exporting probability distribution, leading to a higher level of the shape parameter θ.

Model Fit

The model generally matches the moments in the data well. Table B.6 shows the estimated coefficient for each 2-digit sector, and Table B.7-B.8 compares each data moment to the corresponding moment of the simulated model. Notably, the model replicates the average firm size and the distribution of economic activity across city sizes. Average value-added increases with city size in most sectors (Figure B.4), which in the model occurs due to agglomeration economies and the sorting of most productive firms into larger cities. Similarly, the model fits quite closely the distribution of total employment across quartiles of city size (Figure B.5). Note that the model does not directly target this last moment. Finally, the model fits well the distribution of overall firm-size distribution for most sectors (Figure B.6), which is quite surprising given that the estimation of the model only targets the top decile of the firm size distribution.

To get a sense of how the model fits export-related moments, we estimate the export-size premium implied by the simulated model. This is a non-target statistic that combines information about the estimated productivity distribution and fixed and variable trade costs.[42]

[42] To compute this statistic in the model, we simulate the model using the estimated sectoral parameters. After obtaining draws for intrinsic (z) and idiosyncratic productivity ($\varepsilon_{i,L}$), we solve the firms' location and export decisions

Table 7 shows results for the export-size premium, using the Chinese Census of Manufacturing (columns 1-3) and the simulated model (columns 4-6). Specifically, we estimate a linear regression of firm-employment (in logarithm) against a dummy taking the value one for exporters, controlling for industry (columns 2 and 5) or industry-city fixed effects (columns 3 and 6).[43] Quite remarkably, we obtain similar export-size premiums in the model and data, even though the model does not directly match this moment. Across specifications, the model slightly underestimates the export-size premium, in about 8-11 percent of the premium observed in the data.

5.2 Export Intensity and City Size

We now discuss the model's fit to our main stylized fact, related to the positive relationship between export intensity. This pattern is not directly targeted by our estimation strategy. Thus, our results in this section can be used to evaluate the mechanisms highlighted by the model – firm sorting and agglomeration, plus selection into exporting.

We simulate an economy with 200 equally-spaced city size bins. The support of the city size distribution in the simulated economy resembles the Chinese data described in section 3. Note that although the grid of city sizes is fixed, the effective city size distribution is determined endogenously in the model as a result of sorting and agglomeration forces. For each sector, we draw 20,000 realizations of raw productivity z and 20,000$\times$200 realization of idiosyncratic productivity shocks (one for each potential city size). Then, we solve the firms' problem and determine: (i) optimal city size and (ii) export participation.[44] Conditional on these choices, we solve the general equilibrium problem, taking the effective number of firms in each sector as the equilibrium mass of firms $\{M_j\}$ of the economy. This leads us to the equilibrium values for sectoral prices $\{P_j\}$, aggregate revenues $\{R\}$ and the export productivy threshold $\{\psi^*(L)\}$.[45] Once we obtain these values, we compute revenues and export value, and construct city-level export intensity as the share of aggregate exports to revenues, both defined at the level of city sizes.

Figure 2 shows the main result. It plots (log) export intensity against (log) city size for the model (red-squared symbols) and data (blue-dotted symbols). For both, model and data we plot a

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and the general equilibrium problem. Finally, we use the equilibrium objects and parameters to compute employment, revenues, and exports for each firm.

[43] We do not directly include geographical controls because market access does not vary with city size in the model. Nevertheless, in our most restrictive specification, the industry-city fixed effects account for the average impact of market access on optimal firm size.

[44] In the model, these decisions are independent from each other. Firms' location choice weights the strength of agglomeration economies over ex-post productivity ψ against congestion forces leading to more expensive labor costs. Thus, once firms choose their optimal city, the export decision affects the level of revenues and employment demand.

[45] Unlike the theoretical model, in the empirical model the export productivity thresholds varies with city size. This is directly related to the fact that in the theoretical model, firms sort perfectly into city sizes. As a consequence, there is only one city size featuring both domestic firms and exporters. This city defines the only relevant export productivity threshold. In contrast, in the model with imperfect sorting, all cities may feature exporters. Since labor costs vary across cities, exporting requires a higher productivity threshold in larger cities.

solid line represent the regression line that best fits the data.[46] The model produces a remarkable positive relationship between city size and export intensity: In the model – as in the data – bigger cities are more export-intensive. The regression coefficient is very precisely estimated at a value 0.167 (robust standard error 0.020), accounting for a large portion of the data variation.[47]

One explanation for the weaker relationship estimated by the model compared to the data relates to how the selection-into-exporting mechanism operates. Conditional on productivity, the probability that a firm exports in the model decreases with city size. Firms in larger cities have to pay higher labor costs, which ultimately reduces the probability of generating enough profits to pay the fixed export costs.[48] In contrast, export activity in the data increases with city size, even after controlling for firm-productivity (see columns 2 and 4 in Table 5). Then, unless we introduce an additional force, the model's ability to perfectly fit this dimension of the data is limited.[49]

5.3 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.

5.3.1 Economic Geography and the Effect of Trade Liberalization

We begin comparing the welfare and productivity gains associated with trade openness in our baseline model to a model without geography (e.g. Melitz, 2003). We implement this counterfactual exercise as a symmetrical decline in the variable trade cost τ from prohibitive levels to levels consistent with observed trade flows in all C countries. As τ decreases, firms with realized productivity (i.e., including the effect of agglomeration economies) above the export productivity threshold increase their exports and their share of production sold in foreign markets. Importantly, the decrease in the variable trade cost allows exporters to offer their production 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

[46] In the case of the model, the regression weights each city-size by the number of cities in each bin.

[47] The model overestimates cities' export intensity, particularly for small cities (less than 500 thousand inhabitants). In these cities, the observed average export intensity is 3.3 percent – 40 percent of the value predicted by the model (8.2 percent). In contrast, in large cities (over 5 million inhabitants), the difference between data and model closes to only 1.6 percentage points (12.8 vs. 14.4 percent).

[48] In the statistical model, this holds in expected values because the conditional idiosyncratic productivity shocks $\varepsilon_{i,L}$ are distributed independently of firms' raw productivity z. As a consequence, two firms with the same z may draw very different $\varepsilon_{i,L}$ in large and small cities, leading them to have higher or lower export probability. However, because $\varepsilon_{i,L}$ has mean zero, it will still be true in expectation that – conditional on z – export participation decreases with city size.

[49] One easy way to improve the fit of the model to the data would be to allow the fixed export cost to fall with city size, perhaps reflecting the existence of better productive amenities – such as infrastructure – in larger cities.

of the entry into exporting. All in all, trade liberalization leads to a reallocation of economic activity towards most productive firms, which grow as a result, leading to an increase in aggregate productivity. Welfare also increases as real incomes grow as the aggregate price index decreases.

An important feature of the model is that the matching function between firms and cities does not depend on the degree of openness to trade of the economy. Indeed, optimal city choice only depends on the strength of agglomeration economies compared to congestion costs. Thus, trade liberalization does not induce additional within-firm efficiency gains due to firms moving to larger cities to profit from agglomeration economies. Differences in aggregate productivity will only arise due to reallocation of resources across existing city size bins.

Relative to the model without geography, the magnitude of the effects of trade openness on welfare and productivity in our baseline model may be smaller or larger. In both models, exporters grow relative to non-exporters by the same scaling factor when the economy is opened to trade, such that the relative gains from trade in the two models are driven by the share of firms that become exporters. In turn this is driven by the relative wages (benchmarked against the national average) faced by the firms on the margin of exporting in the two models. If these are higher in our model, then the gains from opening up to trade are smaller in our model (as a smaller fraction of firms become exporters in our model) while if they are lower the converse is true.

To analyze the effect of trade liberalization, we proceed in four steps. First, we compute general equilibrium quantities and values in the full model with geography. For this, we calibrate the land intensity parameter b as in Gaubert (2018), setting the parameter to match the median housing supply elasticity across U.S. cities (see Saiz, 2010). Second, we simulate the baseline economy following the same steps as in section 5.2. Third, we simulate the counterfactual closed economy, where we set τ to a prohibitively high value. This involves recomputing general equilibrium objects, given that in the counterfactual economy, no firm exports. Finally, we compute aggregate TFP and welfare.[50]

Table 8 computes the aggregate productivity and welfare gains from trade liberalization, both in the baseline model and in the model without geography. To simplify comparisons, we normalize productivity and welfare in both models relative to actual open economy. We find that for both, welfare and aggregate productivity, economic geography considerations substantially dampens the effect of trade liberalization policies. Opening the Chinese economy to trade in the model without geography leads to productivity and welfare gains of 30 and 31%, respectively. In contrast, the gains in our model are about one-third lower: Trade liberalization leads to gains of 23 and 24%

[50] For the economy without geography, we proceed in a similar way, but re-estimating a restricted version of the model with the agglomeration parameters, a and s, and the idiosyncratic productivity term $\varepsilon_{i,L}$ equal to zero. We estimate the parameters $\{\sigma_z, f_x, \theta\}$ targeting the top decile of the firm size distribution, the aggregate fraction of exporters and export intensity in each sector. We show the estimated parameters and discuss how this model fits the data in Appendix C.

in welfare and productivity, respectively. This is consistent with exporters locating in relatively larger cities, where operational profits are smaller relative to a model without geography, where firms face a flat wage schedule across cities.

Note that the gains from trade reported in Table 8 most likely overestimate actual gains, because our economy does not consider non-tradable sectors. Nevertheless, to the extent that the non-tradable sector enters aggregate consumption with a Cobb-Douglas weight, mapping our results to a model with a non-tradable sector is straightforward. In this case, the welfare gains from trade can be easily scaled using the expenditure shares of manufacturing and housing. Using the share of manufacturing and housing in 2004 Chinese real GDP leads to welfare gains of 8.8% in the model with geography and 11.6% in the model without geography. This numbers closely match results in Ossa (2015), who estimates gains from trade for China in a multi-sectoral model using a modified version of the sufficient statistic approach by Arkolakis, Costinot, and Rodriguez-Clare (2012).

5.3.2 International Trade and the Effect of Spatial Policies

Our 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 b, which measures the intensity of land use in the housing production function.[51] Changing this parameter affects both housing supply and the cost of labor across cities. In particular, a reduction in the value of b increases the housing supply elasticity, and flattens the wage schedule across city sizes.

In the model, a less restrictive spatial policy lead to a higher level of aggregate productivity. As b decreases, firms have incentives to move (in average) to larger cities. Ultimately, this relocation process generates improvements in aggregate total factor productivity, due to within-firm efficiency gains, and gains from reallocation of resources. On the one side, firms that move to larger cities benefit of larger agglomeration economies, leading to within-firm efficiency gains. On the other side, these firms become larger, and hire relatively more workers. This produces a reallocation of resources within the economy, which reinforces the within-firm effect and leads to additional gains in efficiency.

Relative to the closed economy case, we expect the reduction in land use restrictions to generate a larger effect on aggregate productivity when the economy is open. Most productive firms have a greater weight in the open economy case, because they can export and increase their revenues. This amplifies the impact of the within-firm gains from the closed economy case. In addition, as we discuss in section 4.3, the model predicts that weakening housing supply restrictions increases the fraction of firms that are exporters. This leads to additional gains – relative to a closed economy

[51] 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.

– in the form of reallocation of resources from domestic firms to new exporters.

The property of predetermined city sizes, although convenient analytically for solving the equilibrium of the model, is somehow unrealistic. At least in the short-run, cities grow when the they face increased housing demand. This, in turn, reinforces the within-firm gains and amplifies the overall productivity gains. Thus, when analyzing the general equilibrium effect of policies, we report results a less restrictive interpretation of the model where we allow cities to grow (but the number of cities of each size is fixed).[52]

We proceed in three steps to analyze the effect of changes in b. First, we calibrate the land intensity parameter b. As in Gaubert (2018), we set this parameter to match the median housing supply elasticity across US cities (see Saiz, 2010). Second, we simulate the baseline economy as in section 5.2. Finally, we simulate the various counterfactual economies, where we change the value of b. This involves recomputing: (i) firms' optimal location, (ii) export decision, and (iii) general equilibrium objects. In particular, we vary b so that the housing supply elasticity varies between the 25th and the 75th percentile of the housing supply elasticity across U.S. cities (as defined by Saiz, 2010). Finally, we compute aggregate TFP 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.

Figure 3 plots aggregate TFP against various levels of the housing supply elasticity. In order to simplify comparisons, we compute productivity relative to the level in the baseline economy. Accordingly, when the housing supply elasticity takes the value of the baseline economy (1.75), the value for normalized aggregate TFP is zero. In each panel, we plot the productivity trajectories for the closed (dashed line) and open (solid line) economy cases. Both cases show relatively large changes in aggregate productivity. Taking the economy from the first to the fourth quartile of the housing supply distribution increases aggregate productivity in approximately 10 percent relative to the baseline in the closed economy case. When we compute the same statistic for the open economy, the productivity gains scale up to almost 15 percent. Thus, open economy considerations increases the estimated effectiveness of spatial substantially. In our particular exercise, the effectiveness increases in about 50 percent.[53]

[52]Operationally, the counterfactual exercise involves solving a fixed-point problem: A reduction in b leads firms to move to larger cities. This increases the size of these cities, and their attractiveness in terms of agglomeration economies. This leads to subsequent waves of firms moving to larger cities. This process continues up to the point that congestion costs counterbalance the benefits from agglomeration.

[53]Our estimates are significantly larger than the values estimated by Gaubert (2018) for a closed economy version of the model estimated for France. We note that our estimates are not directly comparable to hers: Gaubert (2018) solves the strict interpretation of the model, with predetermined city sizes. This dampens significantly the productivity response of the economy, as it misses agglomeration gains due to changes in the size of the cities.

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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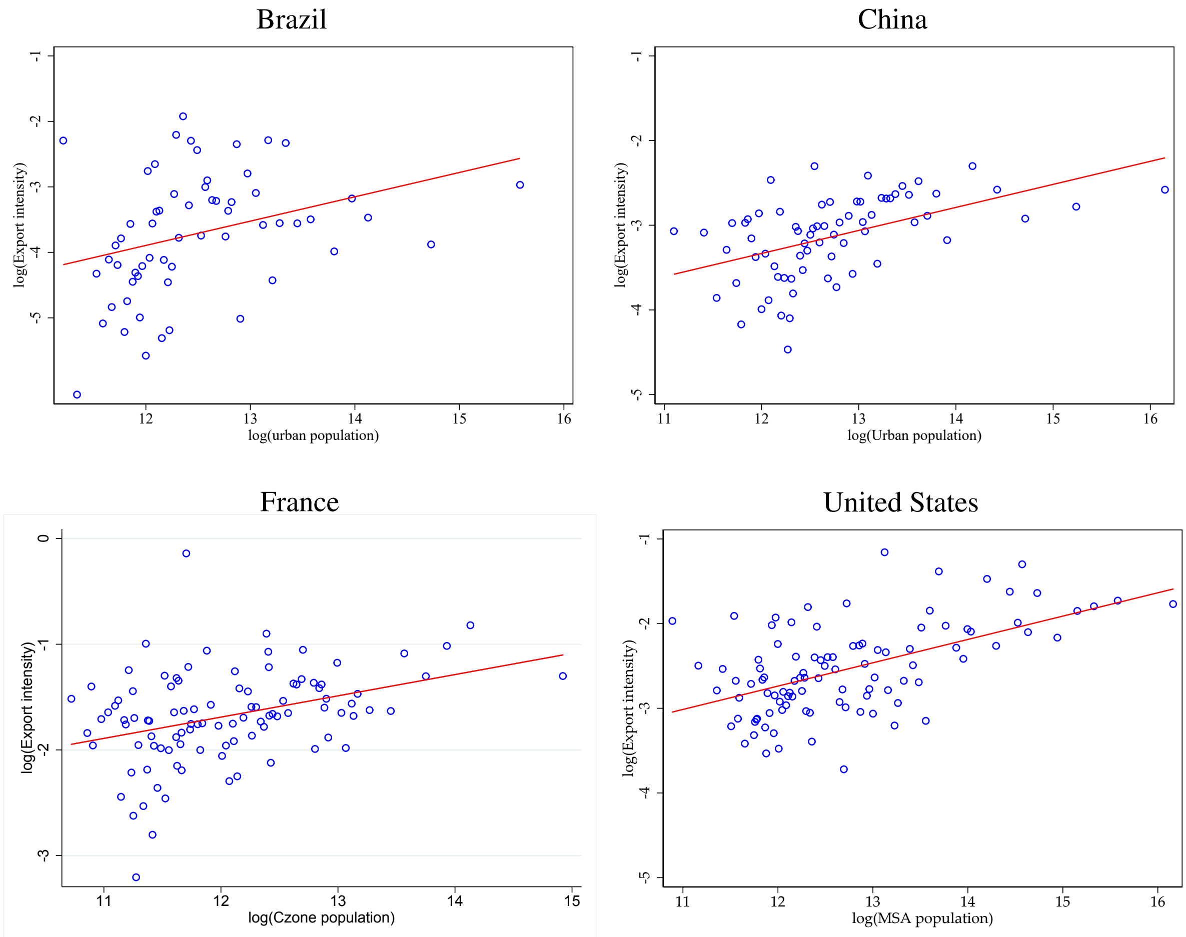
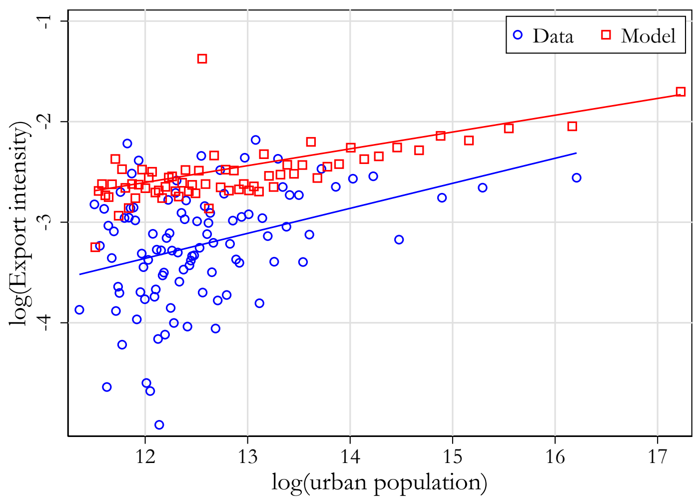
FIGURES

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



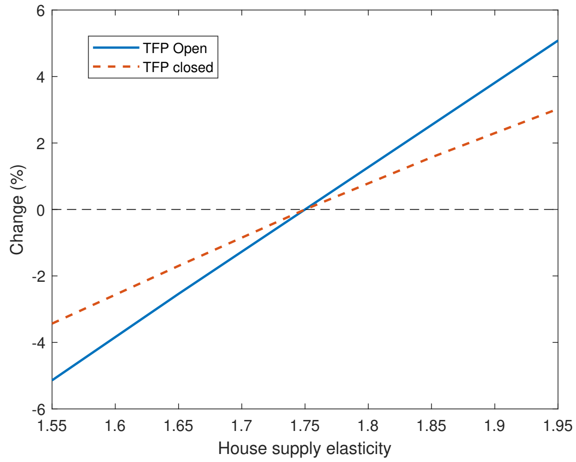
Notes: The figure shows the relationship between city size and export intensity. Cities are defined in terms of metropolitan areas in the cases of China and the United States, and in terms of microregions for the case of Brazil. For all countries, the analysis only considers cities with positive exports and population over 100,000 inhabitants. City-level export intensity is defined as manufacturing exports over manufacturing sales for China; overall exports over manufacturing sales for the United States, and as overall exports over GDP for the case of Brazil.

Figure 2: Export Intensity and City Size in the Baseline Model



Notes: The figure shows the relationship between city size and export intensity predicted by the model. It simulates an economy with 200 city size bins, and 20,000 firms in each sector 2-digit sector. In the simulated economy, we define a log-linear grid over 200 equally spaced city-size bins. The support of the grid of city sizes in the simulated economy resembles the distribution of city sizes in the data. The size of each bubble denotes the number of cities in each city size. The actual number of cities of each size are determined endogenously within the model as a consequence of firms sorting into cities.

Figure 3: Aggregate Productivity Effect of a Reduction in Land Use Restrictions



Notes: The Figure shows the aggregate of aggregate productivity of reducing land-use restrictions. The horizontal shows the housing supply elasticity of the economy, while the vertical axis shows the aggregate TFP response relative to baseline economy. In the model, a less restrictive land use policy is mapped to an increase in the housing supply elasticity. The dashed line shows the closed economy response of aggregate TFP, while the solid line shows the open economy.

TABLES

Table 1: Descriptive Statistics for City Size and Export Intensity Across Datasets

	Population ('000s)				Export Intensity			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Brazil	China	France	U.S.	Brazil	China	France	U.S.
Observations	317	629	210	312	317	629	210	312
Mean	463.0	709.3	258.1	798.8	.0684	.0859	.218	.1131
25th percentile	141.1	182.8	94.6	157.5	.0071	.0215	.136	.0445
50th percentile	203.1	290.3	148.6	277.5	.0358	.0537	.203	.0853
75th percentile	360.7	494.0	287.1	636.6	.0742	.1108	.282	.1370
90th percentile	811.9	918.8	490.1	1,929.2	.1845	.2099	.355	.2250
95th percentile	1,469.3	1,797.8	740.5	3,176.1	.2724	.3028	.410	.3292
Cities without exports	—	—	—	—	20	14	0	0

Notes: The Table analyzes 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 to define metropolitan areas) and the United States; and Commuting Zones for France. For all countries, the analysis only considers cities with positive exports and population over 100,000 inhabitants. City-level export intensity is defined as manufacturing exports over manufacturing sales for China; overall exports over manufacturing sales for the United States, and as overall exports over GDP for the case of Brazil.

Table 2: Export Intensity and City size in Brazil, China, France, and the United States

Dependent Variable: City-Level Export Intensity

	Brazil		China		France		United States	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log City Size	.327***	.264***	.339***	.272***	.198***	.183***	.319***	.293***
	(.121)	(.125)	(.0523)	(.0466)	(.047)	(.045)	(.035)	(.035)
Geog. Controls	No	Yes	No	Yes	No	Yes	No	Yes
Mean Dep. Var.:	-3.65	-3.65	-3.14	-3.14	-1.67	-1.67	-2.52	-2.52
R^2	.013	.212	.043	.264	.060	.300	.158	.256
Observations	297	297	615	615	210	210	310	310

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 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 3: Export Intensity and City Size: 2SLS Results for China

Specification:	OLS	RF	FS	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	ln Exp. Intensity	ln Exp. Intensity	ln City Size	ln Exp. Intensity	ln Exp. Intensity	ln Exp. Intensity
ln City Size	0.321***	—	—	0.361**	0.385**	0.380**
	(0.113)			(0.180)	(0.195)	(0.190)
ln City Size	—	—	—	—	—	-0.0732
× Coastal Dummy						(0.289)
ln 1580 Population	—	0.116**	0.321***	—	—	—
		(0.0551)	(0.0487)			
First Stage F-Statistic	—	—	—	43.4	55.9	22.5
Geog. Controls	Yes	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var.	-2.89	-2.89	14.27	-2.89	-3.14	-2.89
R^2	.352	.324	.377	.352	.180	.354
Observations	260	260	260	260	210	260

Notes: This Table examines the effect of city size on export intensity, instrumenting contemporaneous urban population with 1580's population. All regressions are run at the prefecture level, corresponding to the level to which historical population from Bai and Jia (2021) is available. Column 1 reports OLS estimates. Column 2 report the reduced form for log export intensity against city size. The first stage results of the IV regressions are reported in column 3, 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. Column 5 repeats the analysis in column 4, restricting the sample to the subset of prefectures not located in the coast. Finally, column 6 replicates column 4 including an interaction term between city size and a coastal dummy. Robust standard errors (in parentheses). Key: *** significant at 1%; ** 5%; * 10%.

Table 4: 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%	.137**	.060**	69.5%
	(.0455)	(.0113)		(.0421)	(.0180)	
Geog. Controls	Yes	Yes	—	Yes	Yes	—
Mean Dep. Var.:	-1.00	-2.12	—	-1.36	-0.31	—
R^2	.235	0.159	—	.171	.179	—
Observations	615	615	—	210	210	—

Notes: The Table decomposes the overall elasticity between city-level export intensity (total exports over sales) and city size into its across and within industry variation. 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). The sample includes all Chinese metropolitan areas and French commuting zones with at least 250 manufacturing firms. Geographical controls for China and France are described in the notes to Table 2. Robust standard errors in parentheses. Key: *** significant at 1%; ** 5%; * 10%.

Table 5: Export Activity and City Size: Firm-Level Regressions

Dependent Variable: As indicated in table header

	China		France	
	(1)	(2)	(3)	(4)
Dependent Variable:	$\mathbb{I}$(Exports>0)	log(Export Intensity)	$\mathbb{I}$(Exports>0)	log(Export Intensity)
log(City Size)	.0715***	-.0658	.0178**	.0668*
	(.0061)	(.0426)	(.0071)	(.0384)
Geog. Controls	Yes	Yes	Yes	Yes
4-digit Industry FE	Yes	Yes	Yes	Yes
Mean Dep. Var.:	0.262	-2.25	0.751	-2.08
Observations	1,035,664	103,202	194,688	44,276

Notes: The Table analyzes the relationship between city size and firm-level export activity for China and France. Columns 1 and 3 use a categorical variable that takes the value one for firms with strictly positive exports as the dependent variable. Columns 2 and 4 use the logarithm of export intensity as the dependent variable. All regressions are weighted by the sale share of each firm in city-level sales. Cities are defined in terms of metropolitan areas in China and commuting zones for the case of France. The analysis only considers cities with at least 250 manufacturing firms. Geographical controls for China and France are described in the notes to Table 2. Regressions are weighted by firms' total sales shares (within their cities). Standard errors are clustered at the city level. Key: *** significant at 1%; ** 5%; * 10%.

Table 6: Parameters and Target Moments

Parameter	**Moment**
<u>I. Calibrated Parameters</u>	
σ_j	Average sectoral markup (De Loecker & Warzinsky, 2012)
ξ_j	Sectoral value added share
$\frac{b(1-\eta)}{\eta}$	Elasticity of wages to city size
τ_j	Average export intensity across exporting firms
<u>II. Estimated Parameters</u>	
a_j	Share of value added across city sizes
s_j	Average value added across city size (top quartile)
$\nu_{j,Z}$	Top decile firm size distribution
$\nu_{j,R}$	Average value added across city size (bottom quartile)
f_j^e	National Export probability
θ	National export intensity

Notes: The Table summarizes the target moments we use when taking the model to the data. With the exception of the composite parameter $b(1-\eta)/\eta$, all parameters are computed at the level of 2-digit ISIC sectors (revision 3). The quantitative analysis considers a mixed strategy, calibrating parameters that can be directly mapped to particular moments of the data (upper panel), and estimating the remaining parameters (bottom panel) through simulated method of moments.

Table 7: Export size premium

Dependent Variable: Firm Size (log employment)

	Data			Model		
	(1)	(2)	(3)	(4)	(5)	(6)
Export dummy	1.295***	1.225***	1.232***	1.159***	1.134***	1.123***
	(.0038)	(.0039)	(.0040)	(.0024)	(.0023)	(.0024)
Industry FE	no	yes	yes	no	yes	yes
Industry-City FE	no	no	yes	no	no	yes
Observations	947,185	947,185	947,185	948,788	948,788	948,788

Notes: The Table shows the results of estimating an OLS regression of firm size, in terms of the logarithm of labor, against an export dummy variable. All regressions are estimated at the firm-level. Columns 1-3 uses information from the Chinese Census of Manufacturing of 2004, while columns 4-6 uses simulated data from our structural model. We winsorize the top and bottom percentiles of the dependent variable in the data and model to avoid the influence of outliers. Robust standard errors in parentheses. Key: *** significant at 1%; ** 5%; * 10%.

Table 8: Welfare and Productivity Gains from Trade Liberalization

	Model with Geography		Model without Geography	
	Welfare	TFP	Welfare	TFP
Open Economy	1.000	1.000	1.000	1.000
Closed Economy	0.763	0.769	0.686	0.701
Gains from Trade (%)	23.7%	23.1%	31.4%	29.9%

Notes: The Table shows the estimated gains from trade in terms of aggregate welfare and measured total factor productivity (TFP). The model with geography corresponds to the baseline model introduced in section 4. The model without geography corresponds to an constrained version of the baseline model where agglomeration parameters and firm-city specific productivity are restricted to be equal to zero. This alternative model is estimated to match the relevant data moments.

Online Appendix

Cities, Heterogeneous Firms, and Trade

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Nico Voigtländer Yang Yang

A Proof of Equilibrium Existence

The equilibrium is constructed in four steps. First, we solve for the equilibrium subsidy offered by city developers. Second, we show that it pins down how firms match with city sizes within countries, as well as the set of city sizes generated in each country in equilibrium by city developers. Third, general equilibrium quantities are determined in each country by market clearing conditions and free entry conditions in the traded goods sectors, once we know the equilibrium matching functions from step 2. Finally, the city-size distribution within countries is determined by these quantities, using labor-market clearing conditions. In each step, the relevant functions and quantities are uniquely determined; hence, the equilibrium is unique.

Step 1: Equilibrium Subsidies

Lemma 1. *To determine the equilibrium subsidies, we first outline the optimization problem of city developers. City developers revenue comes from fully taxing the profits of local landlords. In turn, housing market clearing in each city implies that total landlord profits in each city are given by:*

$$\pi_H(L) = b(1-\eta)w(L)L \tag{A.1}$$

Thus, a city developer i developing a city of size L faces the following problem:

$$\max \Pi_L = b(1-\eta)w(L)L - \sum_{j=1}^{S} \int_z T_j^i(z,L)\pi_j^o(z,L)1_j(z,l,i)M_j dF_j(z) \tag{A.2}$$

such that

$$1_j(z,L,i) = 1 \text{ if } L = \arg\max \pi^T_{Sub,j}(z,L) \text{ and firm } z \text{ chooses city } i$$
$$1_j(z,l,i) = 0 \text{ otherwise}$$

In this expression, M_j denotes the mass of firms in sector j in each country (which will be the same in all countries by symmetry), $F_j(.)$ is the distribution of raw efficiencies in sector j in each country and $\pi_j^T(z,L)$ is the total profit before subsidy of a firm of efficiency z in sector j, as defined in equation (15) (which again will be the same in all countries by symmetry).

With the above set-up in place, it can be shown that, in equilibrium, city developers offer and firms take-up operational profit subsidies according to the schedule:

$$T_j(z, L) = T_j^* = \frac{\beta(1-\eta)(\sigma_j - 1)}{1-(1-b)(1-\eta)} \tag{A.3}$$

Proof: Competition among city developers means that the revenues raised from attracting any firm and sector category to the city exactly balance out the subsidies offered to that firm and sector combination:

$$\beta(1-\eta)w(L)L_j(z, L) = T_j(z, L)\pi_j^o(z, L) \tag{A.4}$$

where $L_j(z, L)$ represents the total number of workers drawn to the city when attracting a firm of productivity z in sector j in the productive conditions of a city of size L; while the LHS of (A.4) represents the total expenditures on housing of the workers drawn to the city as a result of the firm choosing to locate in the city. This expenditures represent the (marginal) revenue of the city developer from attracting a firm of productivity z in sector j in the productive conditions of a city of size L. If the above equation were not to hold the city developer would either be making losses or positive profits. In the latter case, another developer would have an incentive to start a city of size L and offer subsidies slightly lower than $T_j(z, L)$, draw all firms of productivity z in sector j and make a profit. This can't be the case in equilibrium.

Starting from (A.4) we can obtain the subsidy schedule in (A.3) by noting that the total number of employees drawn to a city when a firm of productivity z in sector j chooses the city is equal to the workforce of the firm plus a multiplier effect brought by the workers purchase of locally produced housing. Thus the number of workers drawn to the city by a firm is related to the firm's equilibrium employment via the equation:

$$l_j(z, L) = [1-(1-b)(1-\eta)]\, L_j(z, L) \tag{A.5}$$

Moreover, to obtain the subsidy schedule established by the above Lemma, we need to note that firm level can be written as:

$$l_j(z, L) = \begin{cases} \frac{(\sigma_j - 1)\pi_j^D(z,L)}{w(L)} & \text{if } z < z_j^*(L) \\ \frac{(\sigma_j - 1)\pi_j^D(z,L)}{w(L)}\left(1 + \frac{C-1}{\tau^{\sigma_j - 1}}\right) & \text{if } z \geq z_j^*(L) \end{cases}$$

which can be equivalently written:

$$l_j(z, L) = \frac{(\sigma_j - 1)\pi_j^o(z, L)}{w(L)} \tag{A.6}$$

Finally substituting (A.5) and (A.6) in (A.4) yields the subsidy schedule established in (A.3). Moreover, substituting the optimal subsidies in (A.3) and the expressions for domestic profits from (12) into (16) yields the following expressions for total profits after subsidies:

$$\pi^T_{Sub,j}(z,L) = \begin{cases} k_{1j}\left(1+T^*_j\right)\left[\frac{\psi(z,L,s_j)}{w(L)}\right]^{\sigma_j-1} E_j P_j^{\sigma_j-1} & \text{if } z < z^*_j(L) \\ k_{1j}\left(1+T^*_j\right)\left[\frac{\psi(z,L,s_j)}{w(L)}\right]^{\sigma_j-1} E_j P_j^{\sigma_j-1}\left(1+\frac{C-1}{\tau^{\sigma_j-1}}\right) - (C-1)Pf^e_j & \text{if } z \geq z^*_j(L) \end{cases} \tag{A.7}$$

where the parameter k_{1j} is given by

$$k_{1j} = \frac{1}{\sigma_j^{\sigma_j}}\left(\sigma_j - 1\right)^{\sigma_j-1}$$

Step 2: Equilibrium City Sizes and the Matching Function

Within each country, the city developers'problem determines the equilibrium city sizes generated in equilibrium. Cities are opened up when there is an incentive for city developers to do so, i.e. when there exists a set of firms and workers that would be better off choosing this city size. Workers are indifferent between all locations within their countries, but firms are not, since their profits vary with city size. Given the equilibrium subsidies offered by city developers, the profit function of a firm with raw productivity z in sector j is given by (A.7).

Note that the firm's problem can be reduced to maximizing the expression in the square brackets in (A.7) which yields the first order condition:

$$\frac{\psi_2(z,L,s_j)L}{\psi(z,L,s_j)} = b\frac{1-\eta}{\eta} \tag{A.8}$$

with $w(L)$ being the wage schedule established by equation (8). There is a unique profit-maximizing city size for a firm of type z in sector j, under the regularity conditions we have assumed. Define the optimal city size as follows:

$$L^*_j(z) = \arg\max_{L\geq 0} \pi^T_{Sub,j}(z,L)$$

Assume that, for some firm type z and sector j, no city of size $L^*_j(z)$ exists. There is then a profitable deviation for a city developer on an unoccupied site to open up this city. It will attract the corresponding firms and workers, and city developers will make a positive profit by subsidizing firms at a rate marginally smaller than $T_j(z,L)$. The number of such cities adjusts so that each city has the right size in equilibrium. This leads to the following lemma, letting $\mathcal{L}$ denote the set of city sizes in equilibrium:

Lemma 2. *The set of city sizes for each country in equilibrium, $\mathcal{L}$, is the set of optimal city sizes for firms.*

Given this set of city sizes, the optimal choice of each firm in every country is fully determined. Define the matching function

$$L_j^*(z) = \arg\max_{L \in \mathcal{L}} \pi_{Sub,j}^T(z, L)$$

It is readily seen that the profit function of the firm (equation (A.7)) inherits the strict log-supermodularity of the productivity function in z and L. Therefore, the following lemma holds.

Lemma 3. *The matching function $L_j^*(z)$ is increasing in z.*

This result comes from a classic theorem in monotone comparative statics (Topkis (1998)). The benefit to being in larger cities is greater for more productive firms and only they are willing in equilibrium to pay the higher wages there. Furthermore, within each country the matching function is fully determined by the firm maximization problem, conditional on the set of city sizes $\mathcal{L}$. As seen from equation (A.7), this optimal choice does not depend on general equilibrium quantities that enter the profit function proportionally for all city sizes. Finally, under the regularity assumptions made on ψ as well as on the distribution of z, $F_j(.)$, the optimal set of city sizes for firms in a given sector and country is an interval (possibly unbounded). The sectoral matching function is invertible over this support. For a given sector, we use the notation $z_j(L)$ to denote the inverse of $L_j^*(z)$. It is increasing in L. The set of city sizes $\mathcal{L}$ available in equilibrium in each country is the union of the sector-by-sector intervals.

Moreover, given the bijection between productivity levels and city sizes within each sector and country in equilibrium, there will be a productivity threshold z_j^* associated with export participation (i.e. for all $z \geq z_j^*$ firms are involved in exporting to all countries, while for $z < z_j^*$ firms are purely domestic). Due to symmetry, these sectoral exporting thresholds z_j^* are the same in all countries.

Step 3: General Equilibrium Quantities

The equilibrium has been constructed up to the determination of the following general equilibrium values. The reference level of wages $\bar{w}$ defined in equation (8) is taken as the numeraire. The remaining unknowns are the aggregate revenues in the traded goods sector in each country E (identical in all countries), the mass of firms M_j in each sector and country (M_j's are the same in all countries due to symmetry), the sectoral price indexes P_j (identical in all countries), and the sectoral exporting thresholds z_j^*.

At the level of each country and sector, aggregate operational profits (ignoring fixed costs of exporting but including subsidies) are given by:

$$\pi^o_{Agg,j} = \int_{z_{min}}^{z_j^*} k_{1j}(1+T_j^*)\left[\frac{\psi(z,L_j^*(z),s_j)}{w(L_j^*(z))}\right]^{\sigma_j-1} E_j P_j^{\sigma_j-1} M_j dF_j(z)$$
$$+\int_{z_j^*}^{z_{max}} k_{1j}(1+T_j^*)\left[\frac{\psi(z,L_j^*(z),s_j)}{w(L_j^*(z))}\right]^{\sigma_j-1} E_j P_j^{\sigma_j-1}\left(1+\frac{C-1}{\tau^{\sigma_j-1}}\right) M_j dF_j(z) \quad \text{(A.9)}$$

which can be rewritten

$$\pi^o_{Agg,j} = k_{1j}(1+T_j^*)E_jP_j^{\sigma_j-1}M_j \underbrace{\left[\int_{z_{min}}^{z_j^*}\left[\frac{\psi(z,L_j^*(z),s_j)}{w(L_j^*(z))}\right]^{\sigma_j-1} dF_j(z) + \int_{z_j^*}^{z_{max}}\left[\frac{\psi(z,L_j^*(z),s_j)}{w(L_j^*(z))}\right]^{\sigma_j-1}\left(1+\frac{C-1}{\tau^{\sigma_j-1}}\right)dF_j(z)\right]}_{S_j(z_j^*)} \quad \text{(A.10)}$$

Having an expression for aggregate operational profits at the sectoral level, it is straightforward to obtain an expression for aggregate revenues at the sectoral level:

$$R^o_{Agg,j} = E_j = \sigma_j k_{1j} E_j P_j^{\sigma_j-1} M_j S_j(z_j^*) \quad \text{(A.11)}$$

We can also derive an expression for the aggregate labor force used in sector j in every country

$$l_{Agg,j} = \int_z \frac{(\sigma_j-1)\pi^o_{Agg,j}}{(1+T_j^*)w(L_j^*(z))} M_j dF_j(z) \quad \text{(A.12)}$$

which can be expanded as

$$l_{Agg,j} = k_{1j}(\sigma_j-1)E_jP_j^{\sigma_j-1}M_j \underbrace{\left[\int_{z_{min}}^{z_j^*}\frac{\psi(z,L_j^*(z),s_j)^{\sigma_j-1}}{w(L_j^*(z))^{\sigma_j}}dF_j(z) + \left(1+\frac{C-1}{\tau^{\sigma_j-1}}\right)\int_{z_j^*}^{z_{max}}\frac{\psi(z,L_j^*(z),s_j)^{\sigma_j-1}}{w(L_j^*(z))^{\sigma_j}}dF_j(z)\right]}_{Emp_j(z_j^*)} \quad \text{(A.13)}$$

Finally, employing the expression for aggregate operational profits derived above we can find an expression for aggregate total profits

$$\pi^T_{Agg,j} = \pi^o_{Agg,j} - M_j\int_{z_j^*}^{z_{max}}(C-1)Pf_j^e dF_j(z)$$
$$\pi^T_{Agg,j} = k_{1j}(1+T_j^*)E_jP_j^{\sigma_j-1}M_jS_j(z_j^*) - M_j\left[1-F_j(z_j^*)\right](C-1)Pf_j^e \quad \text{(A.14)}$$

By the free entry condition we then have that:

$$E(\pi^T) = k_{1j}(1+T_j^*)E_jP_j^{\sigma_j-1}S_j(z_j^*) - \left[1-F_j(z_j^*)\right](C-1)Pf_j^e = Pf_j \quad \text{(A.15)}$$

All in all, within each country, equilibrium is defined by the system of equations (A.16) to (A.19):

$$k_{1j}(1+T_j^*)\left[\frac{\psi(z,L_j^*(z_j^*),s_j)}{\left((1-\eta)L_j^*(z_j^*)\right)}\right]^{\sigma_j-1}E_jP_j^{\sigma_j-1}\frac{1}{\tau^{\sigma_j-1}}=f_j^eP\ \ \forall j\in 1,\ldots,S \tag{A.16}$$

$$P\left\{f_j+(C-1)\left[1-F_j(z_j^*)\right]f_j^e\right\}=k_{1j}(1+T_j^*)E_jP_j^{\sigma_j-1}S_j(z_j^*)\ \ \forall j\in 1,\ldots,S \tag{A.17}$$

$$1=\sigma_jk_{1j}P_j^{\sigma_j-1}M_jS_j(z_j^*)\ \ \forall j\in 1,\ldots,S \tag{A.18}$$

$$N=\sum_{j=1}^{S}k_{1j}(\sigma_j-1)E_jP_j^{\sigma_j-1}M_jEmp_j(z_j^*)+N(1-b)(1-\eta) \tag{A.19}$$

where (A.16) comes from the definition of z_j^*, (A.17) comes from a re-writing of the zero profit condition in (A.15), (A.18) is a rewriting of (A.11), while (A.19) is a national labor market clearing condition.

This system of $3S+1$ equations characterizes the general equilibrium in each country. Given the symmetry of the countries, the same general equilibrium quantities apply for each country (in particular trade balance ensures that expenditures on all tradables are the same in each country). Inverting this system of $3S+1$ equations gives the $3S+1$ unknowns (for each country, but these quantities have the same values for all countries): P_j the price index for sector j in each country, M_j, the mass of firms that enters in sector j in each country, and z_j^*, the exporting threshold for each country, for all $j\in\{1,...,S\}$. It also gives E, the aggregate revenues in the traded goods sector in each country by performing the substitution $E_j=\xi_jE$ in the equations above.

Step 4: Equilibrium City-Size Distribution

Within each country, the city developers'problem and the firms'problem jointly characterize (1) the set of city sizes that necessarily exist in equilibrium and (2) the matching function between firm type and city size. Given these, the city-size distribution is pinned down by the national labor market clearing conditions. The population living in a city of size smaller than any L in each country must equal the number of workers employed by firms in that country that have chosen to locate in these same cities, plus the workers hired to build housing. Thus, $\forall L>L_{min}$

$$\int_{L_{min}}^{L}uf_L(u)du=\sum_{j=1}^{S}M_j\int_{z_j(L_{min})}^{z_j(L)}l_j(z,L_j^*(z))dF_j(z)+(1-b)(1-\eta)\int_{L_{min}}^{L}uf_L(u)du \tag{A.20}$$

where $L_{min}=\inf\mathcal{L}$ is the smallest city size.

Differentiating this with respect to L and dividing by L on both sides gives the city size density

($f_L(L)$ is not normalized to sum to 1):

$$f_L(L) = k_2 \frac{\sum_{j=1}^{S} M_j 1_j(L) l_j(z_j(L), L) f_j(z_j(L)) \frac{\partial z_j(L)}{\partial L}}{L} \tag{A.21}$$

where $k_2 = \frac{1}{1-(1-b)(1-\eta)}$ is a constant and $1_j(L) = 1$ if sector j has firms in cities of size L and 0 otherwise. The equilibrium distribution of city sizes $f_L(.)$ is uniquely determined by equation (A.21), hence the following lemma:

Lemma 4. $f_L(.)$ *is the unique equilibrium of this economy in terms of the distribution of city sizes within countries. Note that this distribution is the same for all countries (due to symmetry).*

Note that for each city size, the share of employment in each sector can be computed using the same method, now sector by sector (and country by country). For a given city size, the average sectoral composition over all cities of a given size L is determined by the model. On the other hand, the model is mute on the sectoral composition of any individual city of size L, which is irrelevant for aggregate outcomes. This comes from the fact that agglomeration externalities depend on the overall size of the city, and not on its sectoral composition.

This step completes the full characterization of the unique equilibrium of the economy.

B Additional Figures and Tables

B.1 Additional Empirical Results for China

B.1.1 City-Industry Level Results

In this section, we replicate the city-level analysis in the main text at the industry-city level. In doing so, we restrict our attention to the case of China. Results for France are not reported, but they are qualitatively similar. For each industry j (at the 4-digit ISIC level), we run versions of the equation:

$$y_{jc} = \alpha_j + \beta_j \log(UrbanPopulation)_c + \gamma X_c + \varepsilon_{jc} \tag{A.22}$$

where y denote different outcomes for export activity defined at the city-industry level, and X_j corresponds to the set of geographical controls we use in Table 2. We run this equation industry-by-industry, and also pooling industries while allowing for industry fixed-effects. Note that in this last case, the coefficient β_j is restricted to be homogeneous across industries. In all regressions, we only include information for cities with positive exports (but allow industries to have zero exports in any given city).

Table B.1: Export Activity and City Size: Pooled Industry-City Level Regressions

	——Export Intensity ——		——$\mathbb{I}$(Exports>0) ——	
	(1)	(2)	(3)	(4)
log City Size	0.011***	0.011***	0.113***	0.120***
	(0.0007)	(0.0006)	(0.0018)	(0.0018)
Geographical Controls	yes	yes	yes	yes
4-digit Industry FE	no	yes	no	yes
Mean Dependent Variable	0.054	0.054	0.234	0.234
R^2	0.040	0.159	0.127	0.219
Observations	45,355	45,355	45,355	45,355

Notes: The Table shows the results of estimating A.22 at the city-industry level. Regressions 1-3 uses export intensity as dependent variable. Columns 4-6 uses dependent variable a categorical variable that takes the value one for positive exports. Regressions in columns 1 and 4 are run at the city level, for comparability with results in Table B.1. Cities are defined in terms of Metropolitan Areas. The analysis only considers cities with population over 100,000 inhabitants. Geographical controls include a dummy variable for cities located in coastal areas, and the log of the linear distance between the city center and the nearest port. Robust standard errors in parentheses. Key: *** significant at 1%; ** 5%; * 10%.

Table B.1 shows the results when we pool industries and cities. In columns 1-3 we explore the overall variation in export intensity, within and across industries. We avoid applying logarithms to the ratio of exports to output as in the previous sub-section, because the issue of zeros in exports at the industry-city level becomes endemic. For comparability with Table 2, we show the estimated export intensity semi-elasticity using aggregate city-level information (column 1). The estimated coefficient is positive and significant at the 1% level, as in Table 2. Then, in columns 2-3 we show results defining export intensity at the city-industry level. As it can be seen, the estimated coefficient for city size is largely unaffected by the inclusion of industry fixed effects: It varies from .0139 (no industry FE) to .133 (with industry FE). These values are also in the ballpark of the coefficient we estimate with city-level information in column 1. The stability of the coefficient on log city size in columns 1-3 suggests that the positive correlation between export intensity and city size reflect to an important extent, variation occurring within industries.

In columns 4-6 we explore whether is more likely to observe positive industry-level exports in larger cities. For this, we define a categorical variable that takes the value one for industries with strictly positive exports, and use it as the dependent variable in (A.22). Columns 4-6 of Table B.1 show the results. In column 4 we show results for aggregate city-level export intensity. The estimated coefficient suggest that doubling the city size increases the likelihood of positive export in 5.5 percentage points. Then, in columns 5-6 we show results using data aggregated at the city-industry level, with and without fixed effects, respectively. In both cases, the coefficients are positive and statistically significant at the 1% level. As in the case of overall export intensity, the coefficients on the log city size is remarkably stable when we include industry fixed-effects. The point estimates suggest that doubling city size increases the probability of positive export in 11.2-11.8 percentage points.

To check the robustness of the pooled results, we run specification (A.22) industry-by-industry. Table B.2 summarizes the results for the 118 four-digit ISIC industries.[1] Column 1 shows results using export intensity, and column 2 when using a categorical variable for the probability of positive exports. As it can be seen in the first row of Table B.2, in both cases the average semi-elasticity is close to the average effect estimated in Table B.1. More importantly, the bottom part of Table B.2 shows a positive coefficient for practically all industries at different confidence levels. In the case of export intensity, in two-third of the industries export intensity increases with city size at least at the 10% level (column 1). For the case the case of the probability of positive industry-level exports, in over 97% of industries the probability of positive export increases with city size at the 10% level. All this evidence is reassuring for our results in Table B.1, and suggests that the patterns we found before are also observed within industries.

[1]We exclude 5 industries with activity in less than 100 cities out of the total of 1,178 cities in our sample.

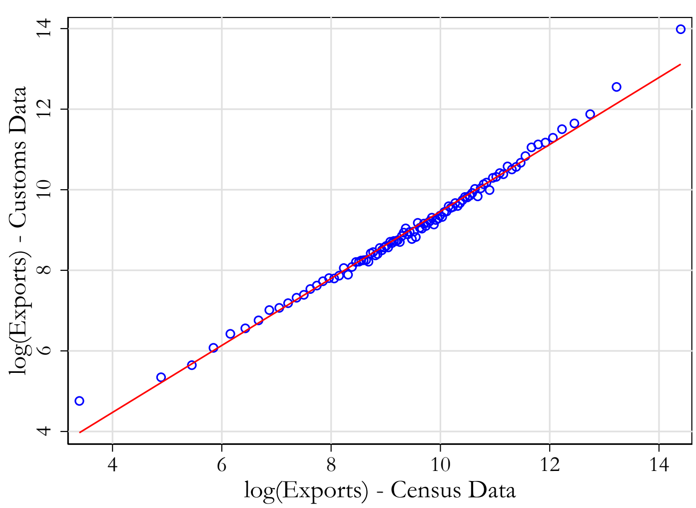
Table B.2: Export Activity and City Size: Pooled Industry-City Level Regressions

	(1)	(2)
Dependent Variable	Export intensity	Export Probability
Mean	0.0120	0.1202
5th percentile	-0.0012	0.0398
10th percentile	-0.0002	0.0604
25th percentile	0.0033	0.0828
Median	0.0085	0.1241
75th percentile	0.0192	0.1535
90th percentile	0.0294	0.1843
95th percentile	0.0345	0.1923
% [t-stat>0.000]	88.6	99.2
% [t-stat>1.645]	49.6	95.9
% [t-stat>1.960]	44.7	95.1
% [t-stat>2.326]	36.6	91.1

Notes: The Table shows the results of estimating A.22 industry-by-industry. Column 1 uses export intensity as dependent variable, while column 2 a categorical variable that takes the value one for positive exports as dependent variable. The analysis only considers cities with positive exports and population over 100,000 inhabitants. Geographical controls include a dummy variable for cities located in coastal areas, and the log of the linear distance between the city center and the nearest port. Robust standard errors in parentheses. Key: *** significant at 1%; ** 5%; * 10%.

B.1.2 Additional Robustness Checks

Figure B.1: 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.

Table B.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 2 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 B.4: Export intensity and City Size: Further Robustness for China Checks

	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			
Overall MA population	0.225***	615	yes	yes	MA
	(0.0556)	0.248			
2000 Census Urban MA population	0.297***	615	yes	yes	MA
	(0.0436)	0.280			
Customs exports, Urban Population	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			
Overall MA population, Full control set	0.234**	329	yes	yes	Prefecture
	(0.1140)	0.249			
Customs exports, Urban Prefectures	0.290***	322	yes	yes	Prefecture
	(0.1103)	0.244			

Notes: The Table replicates results in Table 2 under different controls, agglomeration measures, and city definitions. All regressions include the same set of geographical controls than Table 2, and two dummies for cities located in Special Economic Zones (SEZ) and Coastal Development Areas (CDA), which are intended to promote exports and overall economic activity in selected areas. For all regressions, the dependent variable corresponds to the natural logarithm of export intensity, computed as the ratio of city-level exports and sales, computed over all Chinese manufacturing firms in 2004.

B.2 Additional Empirical Results for France

Table B.5: Export Activity and City Size: Additional Specifications for France

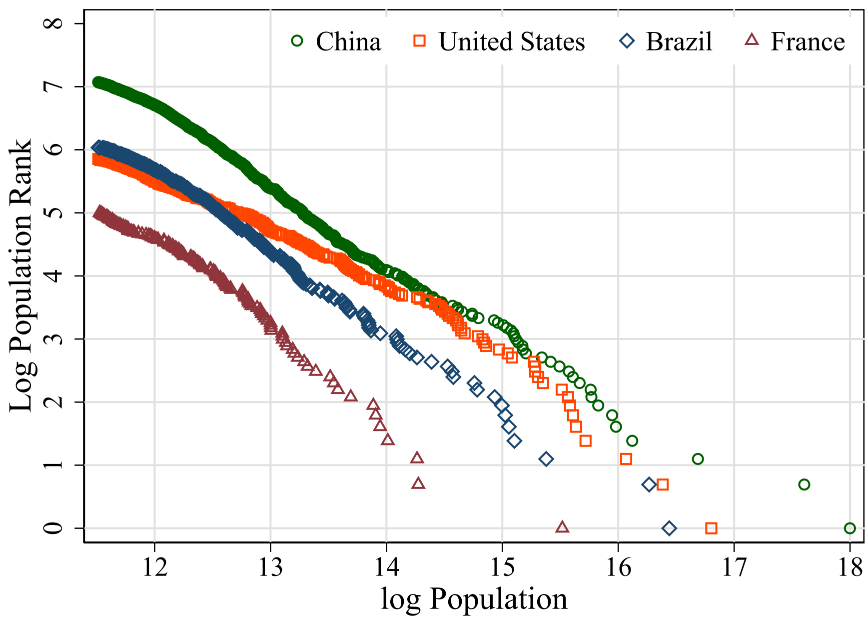
	Historical IV	Single location	Plant level	All sectors
	(1)	(2)	(3)	(4)
log City Size	.115*	.173***	.157***	.177***
	(.06002)	(.05572)	(.04318)	(.03916)
Geographical Controls	yes	yes	yes	yes
Mean Dep. Var.:	-1.68	-1.72	-1.45	-2.46
R^2	.215	.280	.238	.210
Instrument	log City Size in 1876	-	-	-
Effective F stat	120.4	-	-	-
Observations	208	161	183	304

Notes: The Table replicates results in Table 2 using historical population as instrument for current population (column 1) and for different samples and definitions of firms (columns 2-4). The Effective F-Statistic for the 2SLS regression (column 1) corresponds to the weak-instrument test of Montiel Olea and Pflueger (2013). The critical value for a maximum bias of 5% is 37.4. 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 or establishments. 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%.

B.3 City Size Distribution in the Data and the Model

Figure B.2 shows, the city size distribution for Brazil, China, France, and the United States. The Figure shows that the United States has a relatively lower density of small cities than Brazil, China and France.

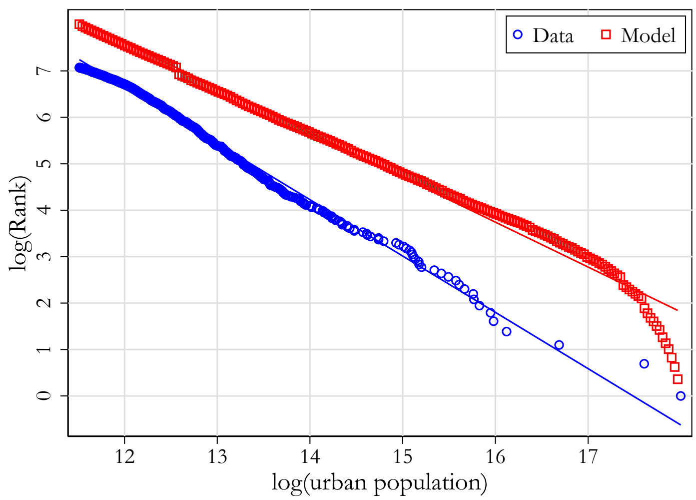
Figure B.2: City Size Distribution in China, United States and Brazil



Notes: The figure shows the distribution of city size – measured in terms of population. It plots the logarithm of each city's ranking against its corresponding population (in logarithms). Cities in China and the United States are defined in terms of metropolitan areas, and as microregions in the case of Brazil (see section 2 for details). For all countries, the figure only considers cities with population over 100,000 people.

Figure B.3 plots the the city size distribution estimated by the model. For this, we compute the number of cities that endogenously arise in each city size bin once the model is simulated. As can be seen, the city-size is well-approximated by a linear regression. The estimated coefficient of the related population-rank regression is -1.004 (robust standard error 0.021), suggesting that the city-size distribution follows Zipf's law. Compared with the actual city-size distribution in China, we observe that the model predicts a higher proportion of large cities and a lower proportion of small cities than the data. This may be due to additional mobility frictions, such as migration restrictions (Au and Henderson, 2006) not explicitly explored by our model.

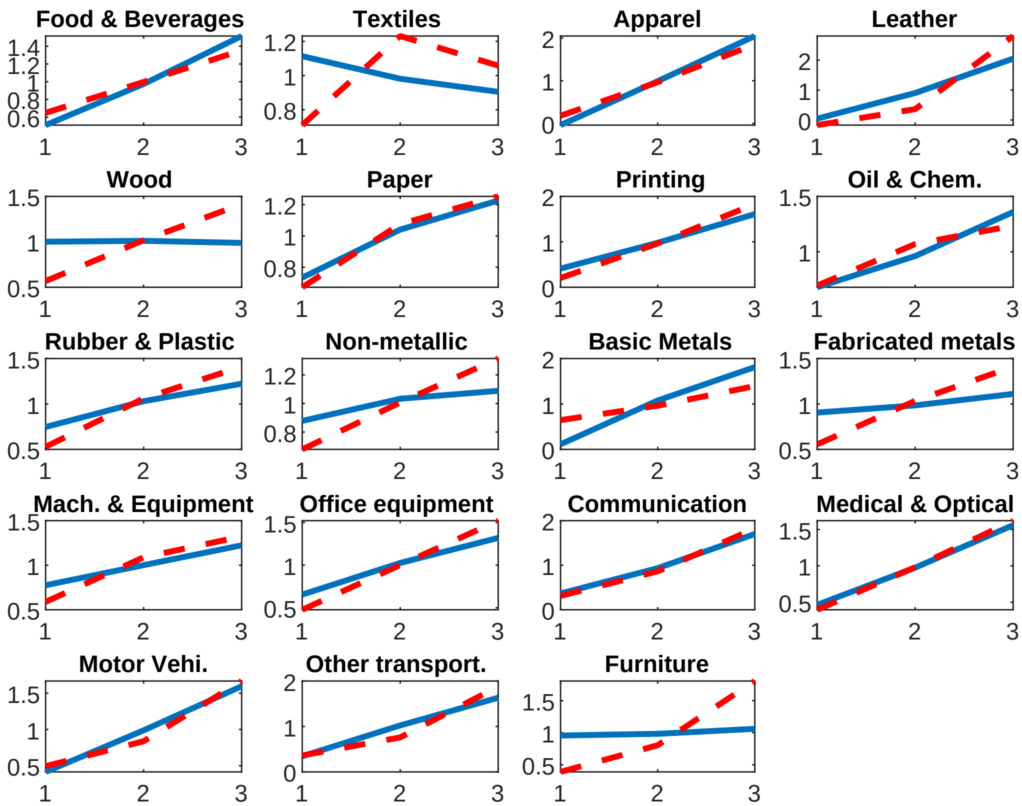
Figure B.3: City Size Distribution: Model vs. Data



Notes: The figure compares the city size distribution implied by the estimated model with the Chinese data. For both, model and data, the figure plots the logarithm of urban population for each city against its corresponding ranking (in logarithms). Cities are defined in terms of metropolitan areas (see section 2 for details). The analysis only considers cities with population above 100,000 people.

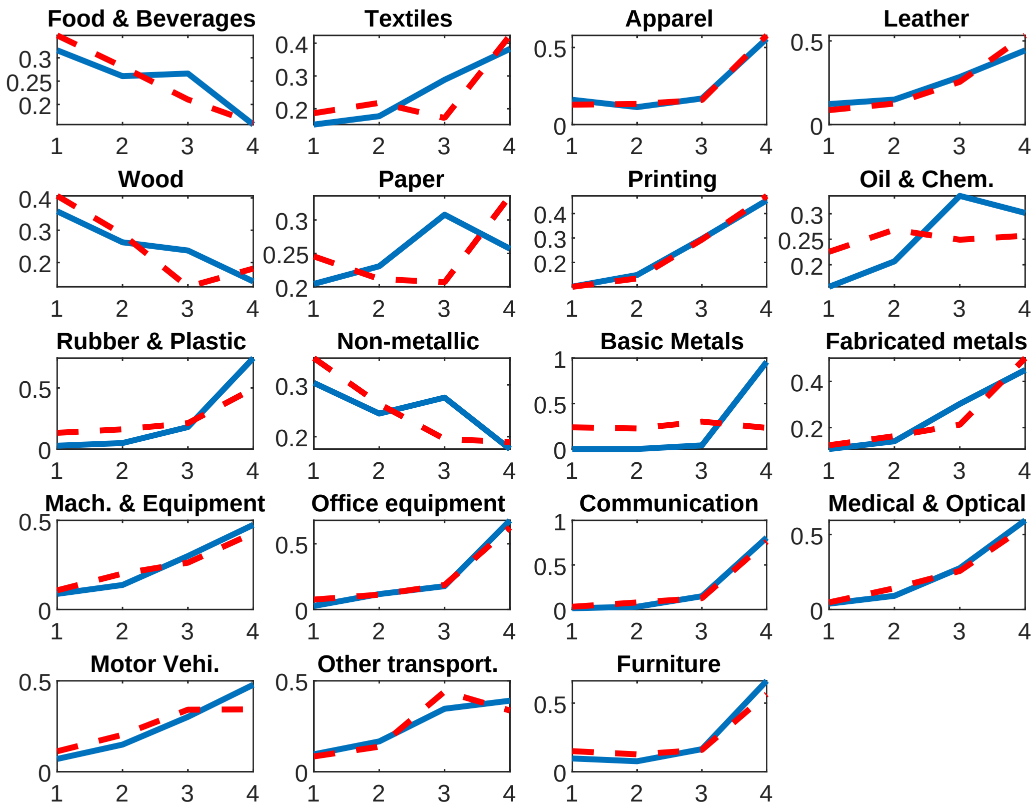
B.4 Model Fit

Figure B.4: Average value added by city size



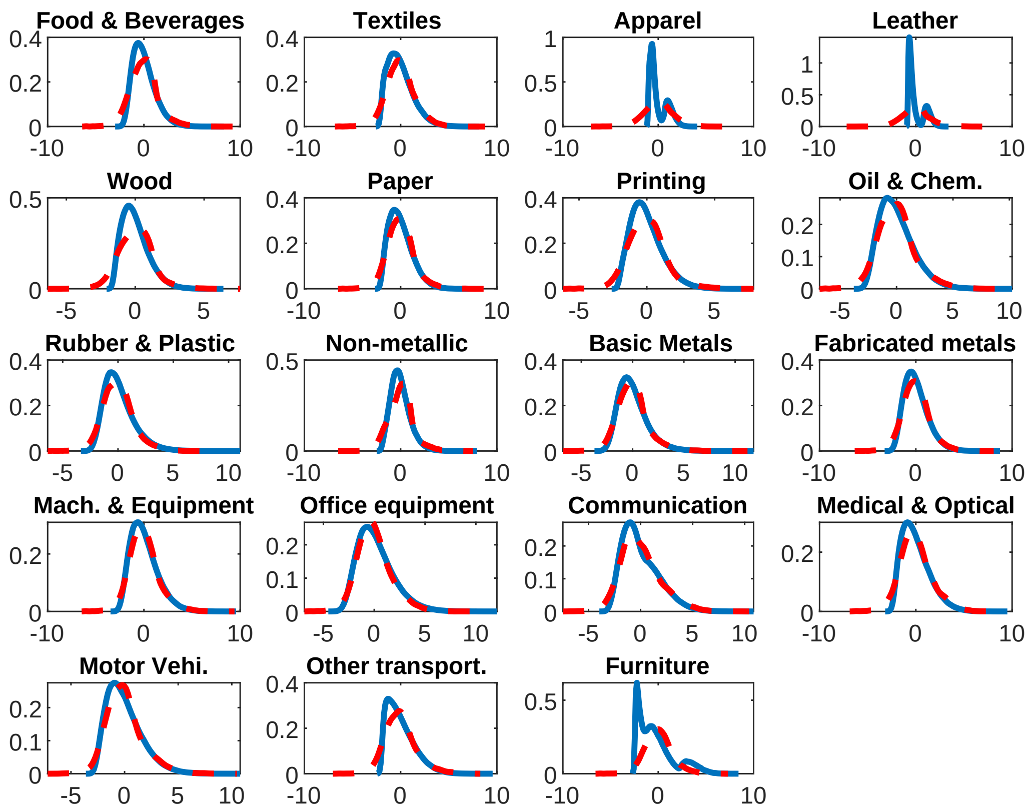
Notes: The figure shows the fit of the model (blue, solid line) to the observed (red, dashed line) average value added by city size in the Chinese manufacturing sector. Average value added is normalized by the average value added across all city sizes.

Figure B.5: Share of total value added by city quartile



Notes: The figure shows the fit of the model (blue, solid line) to the observed (red, dashed line) employment share in each quartiles of city size in the Chinese manufacturing sector. The model does not directly target the employment distribution across city sizes.

Figure B.6: Firm size distribution



Notes: The figure shows the fit of the model (blue, solid line) to the observed (red, dashed line) log-revenue distribution in the Chinese manufacturing sector. The model only targets the top decile of the distribution of revenues in each sector.

Table B.6: Estimated Coefficients

		s		σ_z		σ_R		A		θ		f_x †	
ISIC	INDUSTRY	Coeff.	St.dev.	Coeff.	St.dev.	Coeff.	St.dev.	Coeff.	St.dev.	Coeff.	St.dev.	Coeff.	St.dev.
15	Food and beverages	0.371	(0.044)	0.137	(0.012)	0.084	(0.014)	-0.008	(0.003)	0.204	(0.006)	0.165	(0.058)
17	Textiles	0.133	(0.118)	0.058	(0.026)	0.128	(0.026)	0.108	(0.16)	0.147	(0.037)	0.004	(0.004)
18	Apparel	0.589	(0.111)	0.019	(0.002)	0.013	(0.001)	0.086	(0.033)	4.425	(0.767)	1.863	(0.657)
19	Leather products	0.141	(0.196)	0.006	(0.055)	0.019	(0.002)	0.097	(0.162)	4.980	(0.028)	2.115	(0.694)
20	Wood (except furniture)	0.253	(0.158)	0.100	(0.019)	0.131	(0.016)	0.078	(0.013)	0.084	(0.009)	0.035	(0.020)
21	Paper	0.072	(0.015)	0.098	(0.02)	0.187	(0.013)	0.089	(0.001)	0.031	(0.004)	0.002	(0.001)
22	Publishing & printing	0.387	(0.067)	0.087	(0.02)	0.069	(0.023)	0.086	(0.005)	0.013	(0.001)	0.005	(0.005)
23-24	Petroleum and fuel;	0.269	(0.103)	0.181	(0.031)	0.195	(0.057)	0.034	(0.018)	0.293	(0.013)	0.083	(0.026)
25	Rubber & plastics	0.435	(0.167)	0.205	(0.04)	0.021	(0.051)	0.264	(0.116)	0.024	(0.014)	0.000	(0.000)
26	Non-metallic mineral	0.768	(0.29)	0.240	(0.057)	0.080	(0.101)	0.015	(0.031)	0.045	(0.003)	0.065	(0.022)
27	Basic metals	0.309	(0.232)	0.194	(0.034)	0.015	(0.026)	0.429	(0.174)	4.934	(0.103)	0.908	(0.367)
28	Fabricated metal	0.243	(0.032)	0.178	(0.024)	0.133	(0.028)	0.141	(0.009)	0.038	(0.002)	0.000	(0.000)
29	Machinery and equipment	0.328	(0.083)	0.202	(0.056)	0.184	(0.096)	0.102	(0.006)	0.038	(0.004)	0.001	(0.001)
30-31	Office, accounting,	0.320	(0.376)	0.268	(0.021)	0.102	(0.063)	0.265	(0.033)	0.041	(0.017)	0.000	(0.000)
32	Radio, television and	0.591	(0.197)	0.190	(0.03)	0.168	(0.083)	0.104	(0.085)	0.964	(0.929)	0.766	(0.783)
33	Medical, precision and	0.173	(0.098)	0.144	(0.025)	0.442	(0.042)	0.104	(0.003)	0.079	(0.004)	0.007	(0.004)
34	Motor vehicles, trailers	0.276	(0.12)	0.149	(0.059)	0.300	(0.117)	0.039	(0.071)	0.091	(0.016)	0.005	(0.002)
35	Other transport	0.032	(0.06)	0.015	(0.023)	0.378	(0.048)	0.094	(0.011)	0.087	(0.003)	0.008	(0.002)
36	Furniture	0.273	(0.025)	0.204	(0.032)	0.023	(0.011)	0.293	(0.062)	1.288	(2.474)	0.934	(1.052)

Notes: The Table shows the parameters for the model presented in section 4 estimated for the Chinese manufacturing sector in 2004. The quantitative analysis considers a mixed strategy, calibrating parameters that can be directly mapped to particular moments of the data (upper panel), and estimating the remaining parameters (bottom panel) through simulated method of moments. †: As a share of median domestic profits.

Table B.7: Model Fit: Targeted Moments

		Average Value Added by City Size						VA Share by City Quartiles						Export		Export	
		Small Cities		Medium Cities		Large Cities		Bottom Quartile		Top Quartile		Size Distribution		Participation		Intensity	
ISIC	INDUSTRY	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model
15	Food and beverages	0.926	0.655	1.423	1.257	1.932	1.863	0.290	0.260	0.230	0.193	0.100	0.101	0.060	0.059	0.058	0.059
			(0.071)		(0.077)		(0.103)		(0.021)		(0.039)		(0.004)		(0.001)		(0.005)
17	Textiles	0.831	1.257	1.440	1.271	1.237	1.302	0.145	0.105	0.509	0.515	0.100	0.096	0.182	0.178	0.119	0.175
			(0.195)		(0.023)		(0.218)		(0.048)		(0.167)		(0.002)		(0.001)		(0.006)
18	Apparel	0.075	0.081	0.399	0.501	0.765	1.131	0.110	0.107	0.620	0.651	0.100	0.095	0.310	0.309	0.190	0.440
			(0.128)		(0.02)		(0.094)		(0.008)		(0.017)		(0.003)		(0.004)		(0.016)
19	Leather products	-0.052	0.009	0.111	0.539	0.861	1.214	0.091	0.087	0.504	0.520	0.100	0.097	0.276	0.276	0.085	0.430
			(0.011)		(0.011)		(0.018)		(0.002)		(0.006)		(0.004)		(0.002)		(0.004)
20	Wood (except furniture)	0.383	0.692	0.684	0.684	0.951	0.717	0.372	0.307	0.236	0.190	0.100	0.098	0.097	0.094	0.073	0.132
			(0.075)		(0.028)		(0.089)		(0.057)		(0.071)		(0.003)		(0.003)		(0.003)
21	Paper	0.676	0.852	1.081	1.060	1.260	1.244	0.213	0.160	0.403	0.338	0.100	0.099	0.043	0.043	0.012	0.015
			(0.034)		(0.033)		(0.063)		(0.017)		(0.022)		(0.003)		(0.002)		(0.002)
22	Publishing & printing	0.166	0.277	0.785	0.751	1.494	1.365	0.072	0.067	0.519	0.546	0.100	0.102	0.024	0.017	0.004	0.015
			(0.151)		(0.029)		(0.09)		(0.006)		(0.082)		(0.003)		(0.002)		(0.003)
23-24	Petroleum and fuel;	1.295	1.106	1.993	1.745	2.303	2.248	0.139	0.120	0.399	0.367	0.100	0.099	0.081	0.081	0.043	0.042
	Chemical products		(0.013)		(0.075)		(0.048)		(0.005)		(0.053)		(0.002)		(0.001)		(0.004)
25	Rubber & plastics	0.520	0.741	1.044	1.039	1.388	1.494	0.118	0.022	0.521	0.791	0.100	0.102	0.091	0.085	0.033	0.055
			(0.195)		(0.159)		(0.168)		(0.038)		(0.199)		(0.001)		(0.002)		(0.013)
26	Non-metallic mineral	0.631	0.625	0.935	0.780	1.221	0.982	0.283	0.242	0.278	0.227	0.100	0.100	0.046	0.045	0.030	0.044
	products		(0.202)		(0.049)		(0.084)		(0.041)		(0.01)		(0.002)		(0.003)		(0.003)
27	Basic metals	1.118	0.454	1.664	0.719	2.413	1.740	0.189	0.000	0.295	0.977	0.100	0.101	0.054	0.053	0.037	0.034
			(0.594)		(0.278)		(0.165)		(0)		(0.015)		(0.003)		(0.001)		(0.003)
28	Fabricated metal	0.499	0.982	0.929	1.096	1.268	1.202	0.103	0.070	0.548	0.551	0.100	0.099	0.102	0.094	0.045	0.098
	products		(0.094)		(0.035)		(0.143)		(0.026)		(0.079)		(0.004)		(0.004)		(0.003)
29	Machinery and equipment	0.808	0.969	1.495	1.242	1.816	1.705	0.079	0.072	0.508	0.540	0.100	0.100	0.083	0.081	0.035	0.043
			(0.084)		(0.081)		(0.128)		(0.014)		(0.058)		(0.003)		(0.002)		(0.004)
30-31	Office, accounting,	0.629	1.010	1.321	1.631	2.006	2.193	0.053	0.017	0.686	0.677	0.100	0.099	0.140	0.138	0.040	0.228
	computing, electrical mach.		(0.203)		(0.038)		(0.125)		(0.02)		(0.062)		(0.002)		(0.005)		(0.038)

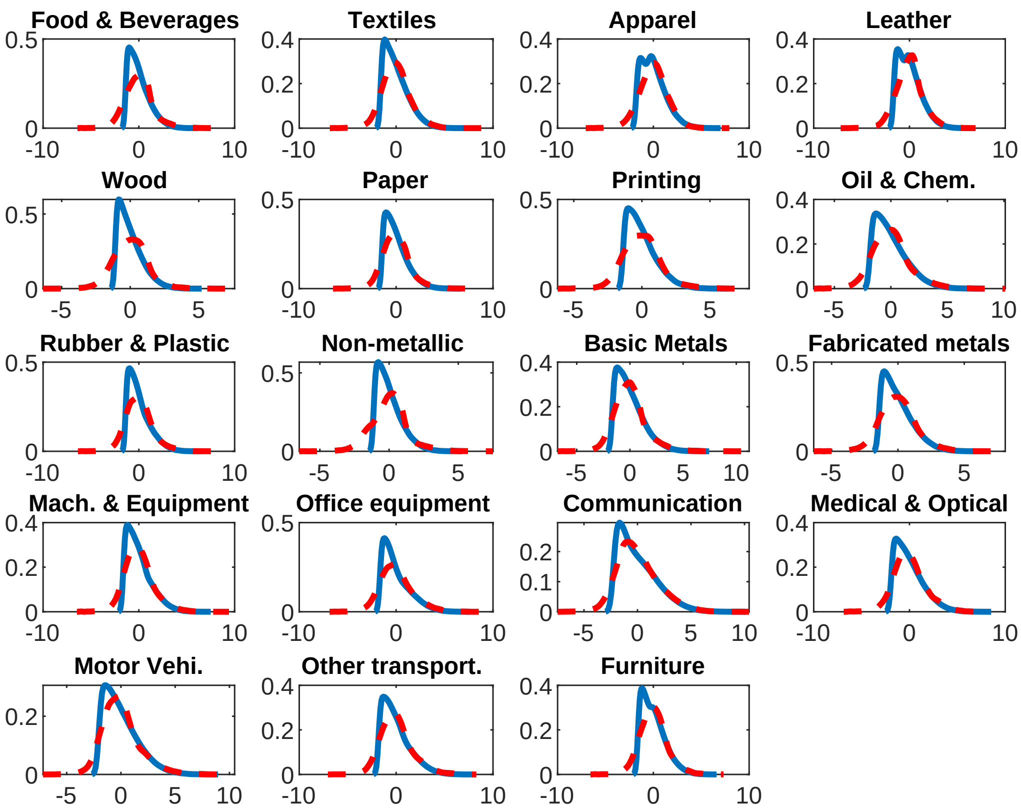
Table B.8: Model Fit: Targeted Moments (continued)

		Average Value Added by City Size						VA Share by City Quartiles				Top Decile Firm		Export		Export	
		Small Cities		Medium Cities		Large Cities		Bottom Quartile		Top Quartile		Size Distribution		Participation		Intensity	
ISIC	INDUSTRY	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model
32	Radio, television &	0.423	0.441	1.169	1.301	2.476	2.640	0.012	0.008	0.821	0.814	0.100	0.096	0.254	0.257	0.044	0.365
	communication equipment		(0.077)		(0.184)		(0.264)		(0.004)		(0.047)		(0.005)		(0.004)		(0.073)
33	Medical, precision &	0.443	0.515	1.095	1.194	1.808	1.908	0.031	0.029	0.644	0.646	0.100	0.094	0.160	0.159	0.031	0.216
	optical instruments		(0.111)		(0.061)		(0.016)		(0.004)		(0.025)		(0.002)		(0.003)		(0.003)
34	Motor vehicles, trailers	0.889	0.797	1.506	1.791	2.996	2.894	0.047	0.043	0.505	0.625	0.100	0.101	0.098	0.099	0.024	0.029
	& semi-trailers		(0.151)		(0.093)		(0.064)		(0.014)		(0.077)		(0.002)		(0.004)		(0.002)
35	Other transport	0.506	0.505	1.060	1.581	2.622	2.480	0.072	0.072	0.416	0.453	0.100	0.096	0.098	0.098	0.019	0.066
	equipment		(0.052)		(0.073)		(0.068)		(0.008)		(0.016)		(0.002)		(0.002)		(0.001)
36	Furniture	0.267	0.774	0.552	0.758	1.239	1.110	0.138	0.055	0.565	0.729	0.100	0.099	0.221	0.207	0.132	0.285
			(0.61)		(0.485)		(0.3)		(0.052)		(0.188)		(0.003)		(0.014)		(0.100)
	Average	0.580	0.671	1.089	1.102	1.687	1.654	0.134	0.097	0.485	0.545	0.100	0.099	0.127	0.125	0.055	0.146

Notes: The Table summarizes the moments targeted by the parameter of the model when taking the model to the data. With the exception of the composite parameter $b(1-\eta)/\eta$, all parameters are computed at level of 2-digit ISIC sectors (revision 3). The quantitative analysis considers a mixed strategy, calibrating parameters that can be directly mapped to particular moments of the data (upper panel), and estimating the remaining parameters (bottom panel) through simulated method of moments.

C Model without Geography

Figure C.7: Firm size distribution



Notes: The figure shows the fit of the model (blue, solid line) to the observed (red, dashed line) log-revenue distribution in the Chinese manufacturing sector. The model only targets the top decile of the distribution of revenues in each sector.

Table C.9: Estimated Coefficients

		σ_z		θ		f_x †	
ISIC	INDUSTRY	Coeff.	St.dev.	Coeff.	St.dev.	Coeff.	St.dev.
15	Food and beverages	0.217	(0.005)	1.491	(0.031)	0.052	(0.004)
17	Textiles	0.147	(0.005)	0.998	(0.031)	0.028	(0.005)
18	Apparel	0.230	(0.005)	0.116	(0.080)	0.000	(0.000)
19	Leather products	0.214	(0.011)	0.205	(0.096)	0.000	(0.001)
20	Wood (except furniture)	0.156	(0.007)	1.030	(0.026)	0.056	(0.005)
21	Paper	0.241	(0.005)	1.772	(0.065)	0.062	(0.008)
22	Publishing & printing	0.156	(0.004)	1.441	(0.033)	0.102	(0.011)
23-24	Petroleum and fuel;	0.436	(0.010)	1.731	(0.143)	0.022	(0.006)
25	Rubber & plastics	0.155	(0.003)	1.372	(0.021)	0.091	(0.006)
26	Non-metallic mineral	0.341	(0.007)	1.516	(0.055)	0.061	(0.005)
27	Basic metals	0.153	(0.003)	1.827	(0.050)	0.087	(0.011)
28	Fabricated metal	0.217	(0.007)	1.056	(0.038)	0.037	(0.005)
29	Machinery and equipment	0.426	(0.009)	2.031	(0.053)	0.088	(0.008)
30-31	Office, accounting,	0.295	(0.017	1.264	(0.041)	0.142	(0.022)
32	Radio, television and	0.771	(0.048)	1.290	(0.099)	0.046	(0.013)
33	Medical, precision and	0.778	(0.031)	0.916	(0.134)	0.029	(0.007)
34	Motor vehicles, trailers	0.630	(0.019)	1.627	(0.221)	0.014	(0.005)
35	Other transport	0.367	(0.008)	1.839	(0.063)	0.092	(0.012)
36	Furniture	0.292	(0.018)	0.329	(0.095)	0.004	(0.005)

Notes: The Table shows the parameters for the model presented in section 4 estimated for the CHinese manufacturing sector in 2004. The quantitative analysis considers a mixed strategy, calibrating parameters that can be directly mapped to particular moments of the data (upper panel), and estimating the remaining parameters (bottom panel) through simulated method of moments. †: As a share of median domestic profits.

Table C.10: Model Fit: Targeted Moments

		Top Decile Firm Size Distribution		Export Participation		Export Intensity	
ISIC	INDUSTRY	Data	Model	Data	Model	Data	Model
15	Food and beverages	0.100	0.100	0.060	0.060	0.092	0.091
			(0.003)		(0.002)		(0.003)
17	Textiles	0.100	0.100	0.182	0.182	0.266	0.268
			(0.004)		(0.005)		(0.009)
18	Apparel	0.100	0.100	0.310	0.311	0.475	0.478
			(0.003)		(0.005)		(0.011)
19	Leather products	0.100	0.101	0.276	0.277	0.467	0.465
			(0.002)		(0.005)		(0.013)
20	Wood (except furniture)	0.100	0.099	0.097	0.098	0.192	0.193
			(0.003)		(0.002)		(0.007)
21	Paper	0.100	0.101	0.043	0.044	0.065	0.067
			(0.003)		(0.002)		(0.006)
22	Publishing & printing	0.100	0.100	0.024	0.024	0.070	0.069
			(0.002)		(0.001)		(0.005)
23-24	Petroleum and fuel;	0.100	0.099	0.081	0.081	0.067	0.066
	Chemical products		(0.004)		(0.004)		(0.008)
25	Rubber & plastics	0.100	0.101	0.091	0.091	0.199	0.203
			(0.003)		(0.003)		(0.013)
26	Non-metallic mineral	0.100	0.099	0.045	0.046	0.087	0.086
	products		(0.002)		(0.003)		(0.006)
27	Basic metals	0.100	0.101	0.054	0.055	0.066	0.066
			(0.004)		(0.003)		(0.003)
28	Fabricated metal	0.100	0.099	0.102	0.102	0.192	0.191
	products		(0.002)		(0.003)		(0.014)
29	Machinery and equipment	0.100	0.102	0.083	0.083	0.168	0.168
			(0.003)		(0.003)		(0.007)
30-31	Office, accounting,	0.100	0.098	0.140	0.140	0.495	0.498
	computing, electrical mach.		(0.002)		(0.005)		(0.013)
32	Radio, television &	0.100	0.098	0.254	0.255	0.495	0.493
	communication equipment		(0.003)		(0.006)		(0.012)
33	Medical, precision &	0.100	0.099	0.160	0.161	0.337	0.338
	optical instruments		(0.004)		(0.003)		(0.023)
34	Motor vehicles, trailers	0.100	0.100	0.098	0.098	0.073	0.071
	& semi-trailers		(0.002)		(0.003)		(0.013)
35	Other transport	0.100	0.101	0.098	0.100	0.208	0.210
	equipment		(0.003)		(0.004)		(0.007)
36	Furniture	0.100	0.099	0.221	0.219	0.475	0.467
			(0.003)		(0.005)		(0.011)
	Average	0.100	0.100	0.128	0.128	0.236	0.236

Notes: The Table summarizes the moments targeted by the parameter of the model when taking the model to the data. With the exception of the composite parameter $b(1-\eta)/\eta$, all parameters are computed at level of 2-digit ISIC sectors (revision 3). The quantitative analysis considers a mixed strategy, calibrating parameters that can be directly mapped to particular moments of the data (upper panel), and estimating the remaining parameters (bottom panel) through simulated method of moments.