Specializing in Density:

Spatial Sorting and the Pattern of Trade*

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Abstract

This paper documents one way that domestic economic geography affects patterns of trade by showing that a country's population distribution is an important source of comparative advantage. We develop a new strategy to estimate both the "population density affinity" of each industry and the "population concentration" of each country. We show that both US states and countries with more concentrated populations disproportionately export in sectors with high population density affinity. The findings are similar using an instrumental variables strategy in which we exploit variation in countries' historical city size distribution to construct instruments for modern population concentration. We rationalize these findings with a model in which sector-specific exports are determined by the distribution of productivity within countries, and show how city-level data can be aggregated to measure determinants of country-level specialization. In the model, countries with higher population-weighted population density specialize in sectors that benefit most from agglomeration. Even conditional on aggregate endowments, our results suggest that the distribution of population within countries and the extent to which population is concentrated in dense cities shape comparative advantage.

JEL codes: F14, F16, R12, R13.

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1 Introduction

Does the distribution of economic activity *within* a country affect what it *exports*? Most analyses of patterns of trade treat countries as unified factor markets or equilibrium "points" in the production space. In this framework, countries are characterized by autarky supply and demand conditions that determine their ability to produce goods at competitive world prices. A growing body of research, however, documents an important interplay between within-country heterogeneity and cross-country trade.[1] While existing work has highlighted the effects of trade on economic geography—the distribution of wages, employment, or economic activity—our focus is on the reverse relationship. This paper hypothesizes that variation across countries in domestic heterogeneity is an important determinant of patterns of cross-country trade.

While this idea is general and a version of it dates back to Courant and Deardorff (1992) and Courant and Deardorff (1993)'s "lumpiness" hypothesis, we take it to data by investigating one particular but central example. A major focus of recent work on economic geography is the observed variation across regions in population density, as well as how urban density differentially boosts the productivity of different industries.[2] This logic suggests that the extent to which a country's population is concentrated in cities might affect not only its domestic productivity, but also its international specialization and the composition of its exports.

If sectors benefit differently from population density, holding all other country-level characteristics constant, countries with a more concentrated population distribution will have a revealed comparative advantage in sectors that benefit disproportionately from agglomeration. Using newly developed measures of industry-level "density affinity" and country-level "population concentration," we argue that urban density is a major determinant of not only the distribution of domestic economic activity, but also international exports.

We first present a model that illustrates how the distribution of factors of production within countries—i.e. having a concentrated versus dispersed population—affects patterns of trade. We assume that sectors vary in the extent to which they benefit from the population density of the location in which production takes place. In the baseline model, we are agnostic about the source of this variation in agglomeration externalities and simply assume that it exists. Countries are composed of cities that are endowed with different sector-neutral productivities. Endogenously, countries with more dispersion in sector-neutral productivity across cities exhibit higher population-weighted density. That is, they end up with a larger share of the population in dense cities.

The theoretical framework provides three key insights. First, motivated by evidence that countries display significant domestic spatial heterogeneity in factor prices, product specialization, and relative productivity (e.g. Porter, 2003; Desmet and Rossi-Hansberg, 2013), our model formalizes the idea that the relevant units of observation for understanding comparative advantage are regions

[1] See, for example, Autor, Dorn, and Hanson (2013), Caliendo, Dvorkin, and Parro (2015), Dix-Carneiro and Kovak (2015), and Ramondo, Rodríguez-Clare, and Saborío-Rodríguez (2016), or the work in progress by Bakker (2018).

[2] On the role of population density in economic geography and spatial sorting see Keesing and Sherk, 1971; Ciccone and Hall, 1996; Duranton and Puga, 2004; Moretti, 2012 and more recently Davis and Dingel, 2014 and Gaubert, 2018. On the impact of density on *sector-specific* productivity and role of density in determining heterogeneity across sectors in spatial sorting, see, for example, Nakamura, 1985; Rosenthal and Strange, 2004; Faggio, Silva, and Strange, 2017.

within countries where production takes place. This is different from most models of comparative advantage, which focus on aggregate country-level characteristics that are taken as given. Second, our model documents how regional data and characteristics can be aggregated to uncover country-level determinants of comparative advantage. For example, the model motivates our use of "population-weighted density" as the country-level summary of within-country heterogeneity in population density. Finally, the model provides theoretical justification for our main empirical framework and result: countries with higher population-weighted density have relatively lower autarky prices in sectors that benefit from agglomeration; hence, their exports exhibit a revealed comparative advantage in these sectors.

The rest of the paper empirically investigates whether the distribution of population within countries is an important determinant of comparative advantage. Our empirical strategy requires two main ingredients: (i) a sector-level causal estimate of "density affinity," or the extent to which production in each sector is disproportionately located in denser locations, and (ii) a country-level estimate of population concentration.

To measure industry-level density affinity, we turn to detailed business location data across US urban areas from the County Business Patterns (CBP) and non-parametrically estimate the extent to which each sector is disproportionately located in denser locations. To account for potential endogeneity in the correlation between density and industry specialization, we use subterranean geological instruments that exogenously shift local density independently from other city-level characteristics. This procedure generates causal estimates of the marginal impact of a change in density on industry-level production. In the end, this procedure yields industry-level measures of density affinity across all 4-digit NAICS manufacturing sectors; the substantial heterogeneity in density affinity that we estimate lends credibility to the modeling assumption that there is significant variation in sector-specific sorting with respect to population concentration.

To measure population-weighted density across regions and countries, we rely on satellite-derived gridded population data from the *LandScan* database.[3] The *LandScan* database incorporates comprehensive country-level census data on the distribution of population, and derives gridded population estimates using "smart interpolation," a multi-layered, asymmetric, spatial modeling approach.[4] These data make it possible to estimate characteristics of the geographic population *distribution* of each country. To measure population-weighted density, we sum population density across grid cells within each country, weighting each cell by its total population. This captures the experienced population density of the average person in the country.

Armed with these estimates, we investigate the relationship between density and comparative advantage. Before turning to cross-country trade, we focus on the exporting patterns of US States. Using the *LandScan* data, we estimate the population-weighted density of each state, and document that denser states indeed export relatively more in "density-loving" sectors.[5] While this result is

[3]The data are available here: https://landscan.ornl.gov/landscan-datasets. We use the 2016 edition of the data set.

[4]For more information, see here https://landscan.ornl.gov/documentation

[5]While some recent studies have attempted to estimate export data at the metropolitan level (see e.g. the database constructed by (Tomer and Kane, 2014)), most trade flows data are still collected at a broader level of aggregation. The lowest level of consistent and exhaustive trade reporting in the United States is the state.

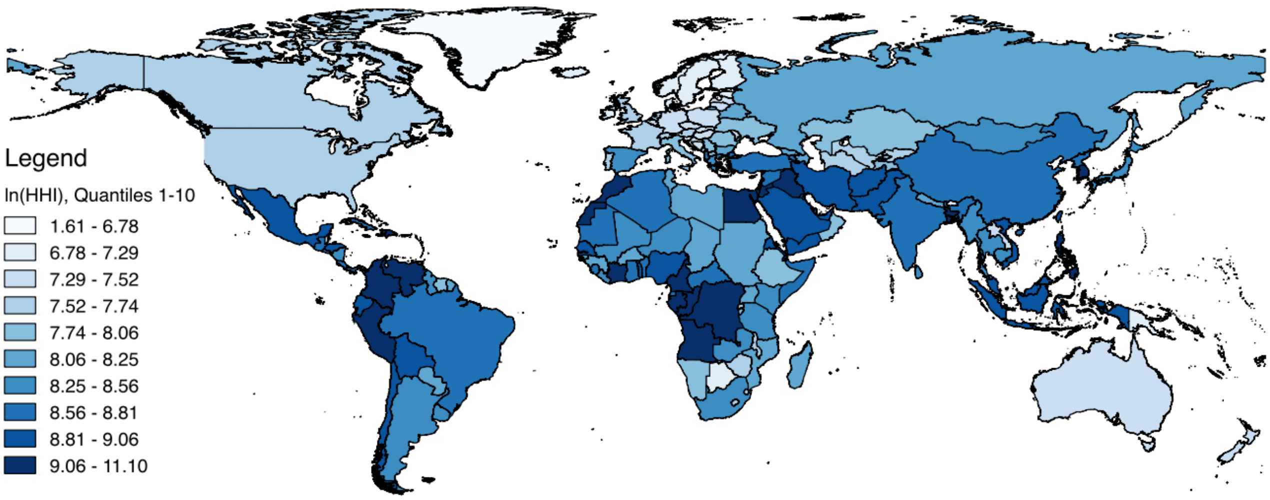


Figure 1: **Population weighted population density across countries (deciles)**. The figure is a map in which countries are color-coded based on their population-weighted density decile. Darker countries have higher population-weighted density.

a preliminary test of our hypothesis, it also validates our density affinity estimates as supply side determinants of sector productivity rather than the product of path dependence, or demand-side forces. That is, our estimates of density affinity from the city-level US data could have been driven by the fact that, for historical or demand-side reasons, certain sectors are over-represented in certain US cities; this does not necessarily imply that there is a systematic relationship between density and sector-level productivity. However, the state-level export results suggests that density-loving sectors are indeed more productive in denser regions within the US.

Next, we investigate the role of density as a source of country-level comparative advantage. Country-level estimates of population weighted density are displayed in the map in Figure 1. Visually, there is substantial variation in density across countries, even within continents and income levels. For example, Finland and Sweden are two of the wealthiest and also two of the least dense countries in the world, by our measure; indeed, both countries have strong revealed comparative advantage in pulp and paper product exports, one of the least density-loving sectors.[6] Within sub-Saharan Africa, Botswana is among the least dense countries while the nearby Democratic Republic of Congo and Djibouti, among the world's poorest countries, are among the densest. Djibouti, meanwhile, exhibits a strong revealed comparative advantage in semiconductors, one of the most density-loving sectors.[7] Finally, the United States has mid-range population-weighted density since it has both very dense cities, as well as a relatively large share of the population living in suburbs, towns, and rural areas. Anecdotally, these countries' export patterns are consistent with our hypothesis.

[6]See Sweden exports in the Atlas of Economic Complexity for HS4 codes 4800-4810, NAICS code: 3221.
[7]See Djibouti exports in the Atlas of Economic Complexity for HS4 code: 8541, NAICS code: 3344.

We find that this pattern is systematic. Countries with higher population-weighted density have a revealed comparative advantage in density-loving sectors. This finding is robust to the inclusion of a broad range of country and industry-level controls, including the skill and capital intensity of each sector, as well as country-level income, skill endowment, specialization in agriculture, and several other controls that might bias the relationship between population-weighted density and a country's composition of exports. The results also remain similar across a range of possible parameterizations of the key independent variable.[8]

To correct for potential reverse causality from trade flows to density (see Krugman and Elizondo, 1996; Ades and Glaeser, 1995), we exploit differences in countries' historical city sizes to construct instruments for modern variation in density. Data on the global distribution of cities and their populations for historical periods were collected by Chandler (1987), and recently digitized by Reba, Reitsma, and Seto (2016). While trade might affect modern economic geography, it is unlikely that modern patterns of trade, which have evolved substantially in recent decades and particularly after the Second World War, affected the *historical* (c. 1900) distribution of cities within countries.[9] Using this identification strategy, the estimated effect of density on trade flows from our baseline results remains virtually unchanged. In our sample of countries, we find that the impact of the within-country population distribution on patterns of trade is comparable to and if anything slightly larger in magnitude than the impact of human or physical capital.

Finally, we investigate potential channels of causality underpinning the relationship density affinity and trade. While our "density affinity" estimates were non-parametric and reduced form, we document a similar pattern to our baseline results when we focus instead on the research and development (R&D) intensity of each industry, consistent with evidence that dense cities facilitate and spur innovation (Duranton and Puga, 2001; Duranton and Puga, 2004). We also document a similar pattern when we focus on the reliance of each industry on immobile natural resources, consistent with the idea that only industries that do not rely on natural resources are free to locate in cities (Ades and Glaeser, 1995). However, the combination of these channels do not fully explain our baseline results, suggesting that additional and unobservable industry-level agglomeration forces are also at play. We also rule out a set of additional possible channels, including skill and capital abundance, as well as the reliance of each industry on service-sector inputs.[10]

Our key finding is that the distribution of population within countries is a key determinant of cross-country specialization and comparative advantage. This study is at the intersection of several broad areas of research. Our theory is most closely related to Courant and Deardorff (1992) and Courant and Deardorff (1993), who argue that patterns of trade come not only from relative factor abundance, but also from factor distribution ("lumpiness"). The potential relevance of "lumpiness" in relative factor endowments for regional specialization has been explored more recently by Debaere (2004), Bernard, Robertson, and Schott (2010), and Brakman and Van Marrewijk (2013). We

[8] The results are also qualitatively identical using either Poisson pseudo maximum likelihood estimation or ordinary least squares.

[9] For a detailed discussion of the evolution of US patterns of trade, see Irwin (2017).

[10] On the relationship between service sector sourcing and economic geography, see Abdel-Rahman and Fujita (1990), Abdel-Rahman and Fujita (1993), Abdel-Rahman (1994), and Abdel-Rahman (1996)

contribute to this literature by using new satellite data to estimate variation across countries in population concentration—one form of factor "lumpiness"—and directly investigating its impact on comparative advantage.

This paper is also related to investigations of the sorting of sectors across cities (most recently Davis and Dingel, 2014; Gaubert, 2018). A range of work has documented that agglomeration benefits some sectors more than others and there is substantial heterogeneity in sector-specific sorting with respect to population density (Nakamura, 1985; Rosenthal and Strange, 2001; Rosenthal and Strange, 2004; Holmes and Stevens, 2004; Ellison, Glaeser, and Kerr, 2010; Faggio, Silva, and Strange, 2017). We extend existing work in this area by developing a reduced-form strategy to estimate industry-specific "density affinities" and, more importantly, investigating the relationship between domestic sorting of production and international trade.

Other work has focused on the impact of within-country trade costs on patterns of trade (Rauch, 1991; Coşar and Fajgelbaum, 2016). A large theoretical literature on patterns of trade arising from agglomeration, initiated by Krugman (1991), has given rise to studies of the stylized interaction between agglomeration and more traditional sources of comparative advantage (Van Marrewijk et al., 1997; Ricci, 1999; Pflüger and Tabuchi, 2016). We suggest that agglomeration may benefit sectors differentially even within manufacturing, and provide evidence that it shapes comparative advantage in cross-country trade.

Finally, our empirical framework builds on existing assessments of sources of comparative advantage across countries; recent empirical analyses that rely on a similar framework but investigate country-level characteristics include Nunn (2007), Chor (2010), Costinot (2009), Bombardini, Gallipoli, and Pupato (2012), and Cingano and Pinotti (2016).

The paper is organized as follows. Section 2 provides a simple formalization of our hypothesis that comparative advantage across countries stems, in part, from the distribution of population within countries. Section 3 describes the data used in the empirical analysis. Section 4 presents our main results and Section 5 concludes.

2 Theoretical Framework

We present a model that illustrates how within-country heterogeneity in productivity can affect a country's pattern of exports across industries. We emphasize how two key ingredients – (i) productivity heterogeneity across a country's locations and (ii) differential returns to agglomeration across industries – can produce patterns of specialization both within and across countries. The theoretical results guide our estimation of the key components of our empirical analysis: industry-level "density affinity" and country-level "population-weighted density," the notion of density that "makes sense" from the perspective of the model at the country level.

2.1 Environment: the closed economy

We study an economy where countries exhibit domestic heterogeneity across inhabited locations, or "cities." A country is defined as a continuum of cities, indexed by $c \in C$, with innate productivity A_c, land area B_c, and equilibrium population L_c. The country's total population is fixed to $\bar{L}$; workers are mobile across regions within a country, but not across borders. The economy consists of J tradable sectors indexed by $j = 1, ..., S$, as well as a non-tradable good specific to each city, "housing" (H_c); housing is the key force of pecuniary congestion in the model. Tradable goods can be shipped from city c to city d, by paying iceberg trade costs $\tau_{c,d} \geq 1$, possibly equal to one (for within-country transactions).

2.1.1 Workers

Workers in city c inelastically supply one unit of labor, earning wage w_c. They derive utility U_c from the consumption of housing and a basket of tradable sectors:

$$U_c(h_c, c_{j=1,...,J}) = (\frac{h_c}{\beta})^{\beta} (\frac{\Pi_{j=1}^{S} (\frac{c_j}{\alpha_j})^{\alpha_j}}{1-\beta})^{1-\beta}$$

where h_c is the worker's housing and c_j, total consumption of sector j, is a CES aggregate of a continuum of varieties indexed by ω:

$$c_j = \left(\int_0^1 c_j(\omega)^{\frac{\sigma-1}{\sigma}} dj \right)^{\frac{\sigma}{\sigma-1}}$$

The price level in each sector j is therefore: $p_j = \left(\int_0^1 p_j(\omega)^{1-\sigma} dj \right)^{\frac{1}{1-\sigma}}$, and the aggregate tradable price level in the country P is: $P = \Pi_{j=1}^{J} p_j^{\alpha_j}$. We assume that $\sigma > 1$, so that within each sector, varieties ω are substitutes. Indirect utility in city c for a worker that supplies a unit of labor is thus: $V_c = \frac{Y_c}{P^{1-\beta} p_{hc}^{\beta}}$. Since utility must be the same for a worker in all cities at some level $V_c = \bar{U} \; \forall \, c$, city-level income Y_c is:

$$Y_c = \bar{U} P^{1-\beta} p_{hc}^{\beta} \tag{2.1}$$

As is standard, income is increasing in the price of housing p_{hc}.

2.1.2 Housing

The supply of land in location c is fixed at B_c; this generates the key pecuniary congestion force in the model. As in Gaubert (2018), atomistic landowners in city c own an amount γ of local land, and produce housing using land and tradable goods, according to the production function:[11]

$$H_c(\gamma) = \gamma^{\xi} (\frac{X_{hc}(\gamma)}{1-\xi})^{1-\xi}$$

Equalizing supply and demand yields equilibrium housing prices in each city:[12]

$$p_{Hc}^{\frac{1}{\xi}} = \beta \frac{L_c Y_c}{B_c P^{\frac{\xi-1}{\xi}}} \tag{2.2}$$

[11]For simplicity, we assume that they divide spending on final goods used as inputs in housing production across the S sectors in the same manner as workers; alternatively, one could model the other input into housing production as migrant labor living at zero cost on rural land and only consuming the final good.

[12]The details are given in Appendix B.

All Ricardian rents accruing to local landowners are fully taxed by the city government and rebated to resident workers as lump-sum transfers T_c, as in Helpman (1998). Thus, disposable income Y_c of a worker in city c is proportional to wage income w_c: $Y_c = w_c + T_c = \frac{w_c}{1-\beta\xi}$. Using the spatial equilibrium condition (2.1), we derive an expression for city-specific wages :

$$w_c = P(1-\beta\xi)\bar{U}^{\frac{1}{1-\beta\xi}}\beta^{\frac{\beta\xi}{1-\beta\xi}}\frac{L_c}{B_c}^{\frac{\beta\xi}{1-\beta\xi}} \propto P \times D_c^{\frac{\beta\xi}{1-\beta\xi}}$$

where D_c is the population density of city c. Consistent with a large literature in urban economics (Glaeser and Gottlieb, 2009), there is a log-linear relationship between local wages and local population density.

2.1.3 Production

To study the impact of density on industrial geography and trade, we turn to the supply side of the economy.[13] For simplicity, labor $L_{jc}(\omega)$ is the only input to production. In each industry j, the output of variety ω in city c, $Q_{jc}(\omega)$, is given by:

$$Q_{jc}(\omega) = \tilde{A}_{jc}L_{jc}(\omega)$$

Each city draws a Ricardian productivity parameter in each sector, $\tilde{A}_{jc}$, from a Fréchet distribution. The unit cost of production for variety ω in sector j and location c is then $\frac{w_c}{\tilde{A}}$. The actual productivity draw $\tilde{A}_{cj}(\omega)$ for a variety of good j in location c has cumulative distribution function:[14]

$$\Pr(\tilde{A}_{cj}(\omega) \leq \tilde{A}) = F_{jc}(\tilde{A}) = \exp(-(\frac{\tilde{A}}{A_{jc}})^{\theta})$$

Here we introduce the key assumption of the model, which allows us to islolate our channel of interest: the relationship between the population distribution and comparative advantage. We assume that a sector's productivity in city c depends on (i) the city's exogenous sector neutral productivity term A_c, (ii) the city's equilibrium population density D_c, and (iii) the extent to which each sector benefits from local density, $\tilde{\eta}_j$. In particular, we let: $A_{jc} = A_c D_c^{\tilde{\eta}_j}$. The sector-specific "density elasticity." $\tilde{\eta}_j$, mediates the relationship between density and sector-specific productivity. This implies that:

$$\Pr(\tilde{A}_{cj}(\omega) \leq \tilde{A}) = \exp(-(\frac{\tilde{A}}{A_c D_c^{\tilde{\eta}_j}})^{\theta})$$

With this formulation, as long as all locations in a country are inhabited, the allocation of labor to any sector in any inhabited city of any country will never be exactly zero.

The variation in η_j across sectors – the extent to which each sector benefits from local agglom-

[13] This section of the model – in particular, determinants of specialization across cities – draws from Michaels, Rauch, and Redding (2013)'s rendition of Costinot, Donaldson, and Komunjer (2011).

[14] We assume the distribution has shape parameter $\theta > \sigma - 1.\theta$, which governs the variance across varieties, is assumed constant across both locations and sectors. As is traditional in supply-driven models of specialization, $\theta > \sigma - 1$ ensures that the CES price index for each sector is well defined.

eration – will be central to our empirical analysis, and is the key modeling assumption. The idea that industries benefit differentially from urban density is backed by substantial evidence (e.g. Nakamura, 1985; Rosenthal and Strange, 2004; Faggio, Silva, and Strange, 2017) and corroborated by our estimates in Section 3 below.[15]

2.1.4 Trade across cities

If we make the (admittedly strong) assumption that trade costs are zero within country,—i.e. for two cities c_n and c'_n in country n, $\tau_{c_n,c'_n} = 1$—cost minimization by consumers in any location d then implies that the share of spending on varieties from location c in sector j must be equal for any locations d in the same country:[16]

$$\pi_{dcj} = \pi_{cj} = \frac{p_{cj} X_{dcj}}{X_{dj}} = \frac{(A_c D_c^{\tilde{\eta}_j})^\theta w_c^{-\theta}}{\sum_{c'} (A_{c'} D_{c'}^{\tilde{\eta}_j})^\theta w_{c'}^{-\theta}} \tag{2.3}$$

where π_{dcj} denotes spending in city d on goods in sector j produced in city c.

2.1.5 Equilibrium

Goods market clearing In the equilibrium of the closed domestic economy, the wage bill in each sector j and city c equals total spending on goods produced in sector j in city c.[17] This generates the tradable goods market clearing condition:

$$w_c L_{jc} = \alpha_j \frac{(A_c D_c^{\tilde{\eta}_j})^\theta w_c^{-\theta}}{\sum_{c'} (A_{c'} D_{c'}^{\tilde{\eta}_j})^\theta w_{c'}^{-\theta}} \sum_d w_d L_d \tag{2.4}$$

In the absence of within-country trade costs, the price index for good j is independent of the location where it is consumed and is proportional to:[18]

$$p_j \propto \Big[\sum_{c'} (A_{c'} D_{c'}^{\tilde{\eta}_j})^\theta w_{c'}^{-\theta} \Big]^{-\frac{1}{\theta}} \propto \Big[\sum_{c'} (A_{c'} D_{c'}^{\tilde{\eta}_j - \frac{\beta\xi}{1-\beta\xi}})^\theta \Big]^{-\frac{1}{\theta}} \tag{2.5}$$

Trade balance requires that tradable spending from all locations on all goods produced in location c

[15] We remain agnostic here about the specific source of sector-specific density affinity; in section 4.4, we explore potential mechanisms, like a lesser reliance on natural resources, local sharing of non-tradable services inputs, or higher innovation intensity.

[16] This is derived in Appendix B. This relies on standard Eaton-Kortum algebra similar to Costinot, Donaldson, and Komunjer (2011) and Michaels, Rauch, and Redding (2013). Given the unbounded nature of the Fréchet distribution, the production structure does not lead to the full specialization of cities in the production of some sectors, which would make the exposition more involved by inducing censoring at the bottom of the sector-city employment density, without adding substantial insight in the model, given that we do not attempt a structural estimation of the parameters

[17] Note that sector j spending coming from location d is equal to the sum of consumer spending ($\alpha_j(1-\beta) Y_d L_d \pi_{jc}$) and intermediate spending by housing producers ($\alpha_j \beta(1-\xi) Y_d L_d \pi_{jc}$), so that total spending in d on j goods produced in c is $\alpha_j(1-\beta\xi) Y_d L_d \pi_{jc} = \alpha_j w_d L_d \pi_{jc}$.

[18] The proportionality coefficients are independent of the sector and city, since θ is assumed constant

is equivalent to the total wage bill in location c:

$$w_c L_c = \sum_j \sum_d \pi_{dcj} \alpha_j (1-\beta\xi) Y_d L_d = \sum_j \alpha_j \pi_{cj} \sum_d w_d L_d = \sum_d w_d L_d \sum_j \alpha_j \pi_{cj} \tag{2.6}$$

Moreover, the housing market must clear in every location, as in Equation (2.2).

Labor market clearing The ratio of labor allocated to sectors j and j' in each city c is given by:

$$\frac{L_{jc}}{L_{j'c}} = \frac{\alpha_j}{\alpha_{j'}} (\frac{p_j}{p_{j'}})^{\theta} D_c^{\theta(\eta_j - \eta_{j'})} \tag{2.7}$$

Total population in a city equals the sum of employment across tradable sectors:

$$\sum_j L_{jc} = L_c \tag{2.8}$$

The labor market clears for the country as a whole:

$$\sum_c L_c = \sum_c \sum_j L_{jc} = \bar{L} \tag{2.9}$$

We can now define the equilibrium of the domestic economy.

Definition 2.1 (Equilibrium)**.** *An equilibrium in the closed economy is defined as an allocation of labor L_{jc} across cities and sectors such that utility is equalized across sites; trading shares satisfy (2.3); labor allocations satisfy (2.7), (2.8) and (2.9); wages satisfy (2.6) and (2.4); tradable prices satisfy (2.5); and housing prices satisfy (2.2).*

2.2 Implications

2.2.1 Within-Country Specialization

We now investigate the domestic sorting of production generated by the model. Double differencing the spending shares (2.3) from any location d across two goods j and j' and two locations c and c' yields:

$$(\frac{\pi_{jc}}{\pi_{j'c}}) / (\frac{\pi_{jc'}}{\pi_{j'c'}}) = \frac{D_c}{D_{c'}}^{\theta(\tilde{\eta}_j - \tilde{\eta}_{j'})} \tag{2.10}$$

While the absolute unit cost of production is increasing in density D_c due to the need to compensate workers with higher nominal wages, as D_c increases costs increase relatively less fast in sectors with higher η_j. Denser cities thus have a comparative advantage in sectors that benefit more from agglomeration.[19] Immediately, this implies:

[19] Introducing decreasing returns at the establishment level, for example related to the use of a fixed factor in production such as management skill or land, would make these cross-cities, within-country comparative advantage results hold in terms of the number of establishments as well, consistent with our empirical results in section 4.

Lemma 2.1. *The share of the labor force employed in higher η_j sectors is relatively larger in denser cities:*

$$(\frac{L_{jc}}{L_{j'c}})/(\frac{L_{jc'}}{L_{j'c'}}) = (\frac{w_c L_{jc}}{w_c L_{j'c}})/(\frac{w_{c'} L_{jc'}}{w_{c'} L_{j'c'}}) = (\frac{\pi_{jc}}{\pi_{j'c}})/(\frac{\pi_{jc'}}{\pi_{j'c'}}) = \frac{D_c}{D_{c'}}^{\theta(\tilde{\eta}_j - \tilde{\eta}_{j'})} \tag{2.11}$$

Equation (2.11) will be key in our empirical estimation of η_j for each sector. We use an exogenous shifter of city-level population density to identify the η_j for each sector from a city-by-sector level regression of local employment on population density, along with city and sector fixed effects (see Section 3.3).

2.2.2 Cross-Country Specialization

Autarky prices As a first step toward understanding the relationship between within-country heterogeneity and patterns of trade, we investigate the implications of the model for the country-by-sector level prices in autarky.

Proposition 2.1. *The relative price level of two sectors j and j' in the Home country in autarky can be expressed as:*

$$\log(\frac{p_j}{p_{j'}}) = (\eta_{j'} - \eta_j) \sum_c \omega_{jj',c} \ln(D_c) \tag{2.12}$$

where $\omega_{jj',c}$ are bilateral Sato-Vartia weights (Sato, 1976; Vartia, 1976) across any two goods j and j' in city c, computed from the export shares:

$$\omega_{jj',c} = \Big(\frac{\pi_{cj} - \pi_{cj'}}{\log(\pi_{cj}) - \log(\pi_{cj'})}\Big) \Big/ \Big(\sum_d \frac{\pi_{dj} - \pi_{dj'}}{\log(\pi_{dj}) - \log(\pi_{dj'})}\Big)$$

Proof. See Appendix B. □

Conditional on a fixed distribution of city-level densities D_c, the closed economy price index in sector j relative to j' is lower when $\eta_j > \eta_{j'}$. Stronger agglomeration forces in a sector increase productivity in all cities, and lower equilibrium prices for any distribution of density. Moreover, we have the following corollary:[20]

Corollary 2.1. *Conditional on the vector of $A_{c'}$'s and wages, a more dispersed distribution of D_c across places – defined as second-order stochastic dominance of the density distribution – lowers the price index by more for high η_j sectors than for lower $\eta_{j'}$ sectors.*[21]

A more dispersed population - i.e. greater variation in D_c – implies relatively more variation in sourcing prices across producing locations for higher η_j sectors. Substitution across sourcing cities

[20] We can allow for variation in density, conditional on a vector of innate productivity amenities and wages, for example by allowing for an "outside sector" with $\eta_0 = 0$ to be produced with constant productivity A_{0c} in all cities, and thus to determine nominal wages independently of density, with the price of housing adjusting to equalize utilities for dispersed population densities. In that case, with wages pre-determined, a flatter supply curve for housing (as characterized by a lower share of land in production ξ) would lead to stronger density variation across cities for a given distribution of wages and innate productivity $A_{c'}$.

[21] This follows immediately from Proposition 2.1, since the log is concave and $\theta > 0$. As in Proposition 1 in Redding and Weinstein (2020), this results from substitutability across suppliers (note we assumed $\theta > \sigma - 1 > 0$), making the price index log sub-modular in η_j and $D_{c'}$.

implies lower relative price indices for more "density-loving" sectors in countries with a more dispersed population. This sub-modularity property of price indices in η_j and D_c is at the core of comparative advantage of countries in our global economy.

Comparative Advantage To illustrate the implications of the model for patterns of exports under international trade, we aggregate trade flows at the country level. As in Ramondo, Rodríguez-Clare, and Saborío-Rodríguez (2016), we study the special case of N countries, indexed by i, each composed of a set of regions $c \in C_i$, trading S goods indexed by j. We continue to assume that iceberg trade costs are zero across two regions within any country; we also assume trade costs are symmetric and constant across any two regions in two different countries, $\tau_{cc'} = \tau_{ii'} = \tau_{i'i} = \tau_{c'c}$ for $c \in C_i$, $c' \in C_{i' \neq i}$.

All countries have the same total population $\bar{L} = L_i$ and the same land area $\int_{c \in C_i} B_c = \int_{c \in C_{i'}} B_c$. We let $B_c = 1$ in each city, so that we simplify the model to the case where $L_c = D_c$. We define X_{inj} as exports from country i to country n in industry j, $\tilde{w}_{ij} = \frac{\sum_{c \in C_i} w_c L_{jc}}{\sum_{c \in C_i} L_{jc}}$ as the average wage in sector j in country i, and M_i as country i's aggregate wage bill, $M_i = \tilde{w}_i L_i = \sum_j w_{ij} L_{ij}$. We can then state the following aggregation result:[22]

Proposition 2.2. *Exports of sector j from country i to country n satisfy the following aggregation results*

$$X_{inj} = \alpha_j M_n \frac{T_{ij} w_{ij}^{-\theta} \tau_{ni}^{-\theta}}{\sum_s T_{sj} w_{sj}^{-\theta} \tau_{ns}^{-\theta}}$$

where the country level productivity parameter is:

$$T_{ij} = \Big(\sum_{c \in C_i} (A_c D_c^{\eta_j})^{\frac{\theta}{1+\theta}} (\frac{L_{jc}}{L_{ji}})^{\frac{\theta}{1+\theta}} \Big)^{1+\theta}$$

Moreover, the aggregate wage bill can be expressed as:

$$M_i = \sum_j w_{ij} L_{ij} = \sum_j \Delta_{ij} L_{ij}^{\frac{\theta}{1+\theta}} T_{ij}^{\frac{1}{1+\theta}}$$

where Δ_{ij}, country i's market access in sector j, solves the system of $N \times S$ equations:

$$\Delta_{ij} = \left[\alpha_j \frac{\sum_n M_n \tau_{in}^{-\theta}}{\sum_s \tau_{is}^{-\theta} \Delta_{sj}^{-\theta} L_{sj}^{\frac{1}{1+\theta}} T_{sj}^{\frac{1}{1+\theta}}} \right]^{\frac{1}{1+\theta}}$$

Proof. See Appendix B. □

The country-sector-level parameter T_{ij} in country i and sector j is endogenous to the distribution of employment shares: Proposition 2.1 and Equation (2.11) immediately imply that T_{ij} is relatively higher for high η_j goods in countries with a population more concentrated in a few places, and thus, all else equal, for countries with more variance in sector-neutral productive amenities A_c. Even

[22] This can be seen as a sector-level counterpart to Proposition 1 in Ramondo, Rodríguez-Clare, and Saborío-Rodríguez (2016).

though we assumed all countries have the same total population, the within-country population distribution drives patterns of cross-country trade.

Two-Country Case To build the intuition behind this result, we focus on the the case of two countries, Home and Foreign. First, suppose that Home and Foreign have identical distributions of amenities, A_c and A_c^*. Then there will be cross-city trade both within and across countries, but there will be no apparent pattern of inter-industry trade at the country level. More precisely, the distribution of import shares will be the same for any importing destination across all cities in the two countries. Next, assume the distribution of *sector-neutral* productivity across cities is *more even* in the Foreign country than at Home. By "more even", we mean that the distribution of Foreign productivity is a "utility-preserving spread," an extension of the "mean-preserving spread" concept defined as:

Definition 2.2. *G is a "utility-preserving spread" of G^* if in the closed economy, welfare is the same at Home and in Foreign, $\bar{U} = \bar{U}^*$, but the variance of A_c is higher than the variance of A_c^*.*[23]

This implies, from Equation (2.13), that the distribution of population at Home second-order stochastically dominates the distribution in Foreign; the Generalized Lorenz Curve of population in the Foreign economy lies strictly above the Lorenz curve at Home. By Proposition 2.1, the relative prices of higher η_j goods are lower in the closed Home economy than in the closed Foreign economy. Equation (2.11) implies that the relative share of employment of high η_j sectors is increasing in density, so in the Home country, relatively more workers are active in high η_j sectors than in the Foreign country. Aggregating cross-location trade flows to the country level, the Home country will appear to specialize in goods that have a high η_j's and import goods with lower η_j's. Let the Generalized Lorenz Curve (GLC) of population density be the cumulative distribution function of experienced density, such that $GLC(p)$ is the percentage of the population experiencing a density below the p-th percentile of city-level population densities. Then, in particular, in a two-goods setting with identical shares $\alpha_1 = \alpha_2$:

Corollary 2.2. *Suppose there are two countries, H and F, and two goods j and j' where $\eta_j > \eta_{j'}$ and $\alpha_j = \alpha_{j'}$. The CDF's of location-specific amenities in H and F are G and G^*. If G is a utility-preserving spread of G^*, then the Generalized Lorenz Curve of population-weighted density in H lies strictly below the Generalized Lorenz Curve of population-weighted density in F. Moreover, H is a net exporter of j and F is a net exporter of j'.*

2.2.3 From Theory to Measurement: Population-Weighted Density

One question remains: to link the theory to data, how should we measure the dispersion of D_c at the country-level? The model implies a convenient way to summarize the distribution of city-level densities to a country-level measure. From the equilibrium definition in Section 2.1, the population distribution can be expressed as the labor market clearing (2.9), along with a system of C equations,

[23] One can imagine an experiment with two cities, c_1 and c_2, where initially $A_{c_2} > A_{c_1}$. Then a utility-preserving spread could involve lowering A_{c_1} by ϵ, and increasing A_{c_2} by $\alpha\epsilon$, where α is chosen so that $\bar{V}_0 = \bar{V}'(\alpha)$.

one for each city, that depend on the city-level population-weighted densities, the city-level population weighted amenities, and a constant term:[24]

$$L_c D_c^{\frac{\beta\xi}{1-\beta\xi}} = \sum_j \alpha_j \frac{(A_c D_c^{\tilde{\eta}_j - \frac{\beta\xi}{1-\beta\xi}})^\theta}{\sum_{c'} (A_{c'} D_{c'}^{\tilde{\eta}_j - \frac{\beta\xi}{1-\beta\xi}})^\theta} \sum_d L_d D_d^{\frac{\beta\xi}{1-\beta\xi}} \tag{2.13}$$

Since the supply of housing is partially inelastic (due to the use of local land in housing production), the economy has a unique equilibrium when the maximum sector-level density elasticity ($\eta_{max} = \max_j \eta_j > 0$) is "not too large" relative to the share of land in housing production (ξ); this makes congestion forces strong enough to offset multiple equilibria. When this is the case, as shown in Redding (2016), a location's density D_c is increasing in its productive amenity A_c, since a higher A_c increases the marginal product of labor in any sector, leading to rising nominal wages, population inflows, and land prices, until utility is again equalized. Agglomeration forces, modeled as positive η_j's, reinforce this phenomenon, but do not offset it if they are small enough.

Because equilibrium density D_c is increasing in A_c, at the country level, a greater dispersion of A_c therefore leads to greater equilibrium D_c dispersion. This is driven by workers relocating from lower to higher A_c and D_c locations. The population density distribution in an economy with more dispersed A_c is second-order stochastically dominated by the population density distribution in an economy with less dispersed A_c^* (see Appendix B).

In the special case where total population is held constant,[25] and B_c and A_c are uncorrelated, greater dispersion in the exogenous A_c's increases the variance of density, and thus country-level "population-weighted density":

$$D_i = \int_0^{\max D_c} \frac{L_c^2}{B_c} dH(D_c)$$

While, as discussed below, there are several intuitively appealing features of using this as our county-level parameterization of population concentration, it also follows directly from the model. Population-weighted density is thus the country-level observable counterpart of dispersion in A_c. This is the measure we estimate next in Section 3, and use in the in the causal analysis in Section 4.1.

3 Data and Descriptive Evidence

3.1 Data Sources

Economic Geography in the US Data on economic activity in the US are collected from the 2016 version of the County Business Patterns (CBP) data set. The CBP contains information on employment, establishment counts, and total payroll in each industry and Core-Based Statistical Area (CBSA). We focus on measures at the NAICS 4-digit level, which are less likely to suffer from sup-

[24]Using the sectoral price index (2.5) and the spending shares (2.3), immediately yields that the own share of spending in sector j for any location c π_{ccj} is super-modular in a city's density and a sector η_j, since $p_j \propto (\frac{(A_c D_c^{\tilde{\eta}_j})^\theta}{\pi_{ccj}})^{-\frac{1}{\theta}} w_c$. From the own shares of spending, one can derive an expression for $\bar{V}$ in equilibrium, as in Redding (2016).

[25]In the data, we control flexibly for total population.

pression.[26] We compile data on a range of industry-level characteristics from the latest available year in the NBER-CES Manufacturing Industry Database, including capital intensity, the labor share, and average wages. We also include data from the American Community Survey to control for the age and gender breakdown of the workforce as well as detailed measures of the educational attainment of the workforce in each industry. Raster data displaying the distance to bedrock of each 250m grid cell in the US, which we use to construct the instrument for city-level density, are from the International Soil Reference and Information Centre (ISRIC) *SoilGrid* project.[27]

Trade US State-level international exports from 2016 are collected from the US Census Bureau's USATradeonline database.[28] These data are provided at the NAICS 4-digits level, which is our primary level of analysis across industries. We focus on gross exports flows, as they are the natural counterpart of spending in our theoretical framework. Cross-country trade flows data are obtained from the UN Comtrade Database for all available exporters in 2016, at the HS4 digit level.[29] We map HS4 industries to NAICS-4 industries using the crosswalk developed by Pierce and Schott (2012).

Density Spatial data on global population density are obtained from the *LandScan* Database.[30] These data are calculated by combining existing demographic and census data with remote sensing imagery, and are released as a raster data set composed of one square-kilometer grid cells.[31] The resultant population count is an ambient or average day/night population count. We use the gridded *LandScan* data to compute state and country-level estimates of population-weighted density.

Additional Data To include additional controls in our cross-state and cross-country estimates, we compiled US state-level data on educational attainment, age composition, and worker income from the 2016 American Community Survey estimates. At the country level, we also compiled informa-

[26]We verify that our results are not sensitive to imputation when using interpolation techniques to impute missing employment data in the CBP.

[27]See here: https://www.isric.org/explore/soilgrids.

[28]US state-level data were downloaded from the census API at the following link: `https://usatrade.census.gov/data/`

[29]We verify that our results are not sensitive to dropping exporters that are "small countries", defined as those with population lower than a million.

[30]*LandScan* data can be found here: `https://landscan.ornl.gov` We use the LandScan data product from 2016.

[31]For more information, see here: https://landscan.ornl.gov/documentation. According to *LandScan*:

> ORNL's LandScan is the community standard for global population distribution. At approximately 1 km resolution (30 × 30 degree), LandScan is the finest resolution global population distribution data available and represents an ambient population (average over 24 hours). [...] The LandScan global population distribution models are a multi-layered, dasymetric, spatial modeling approach that is also referred to as a "smart interpolation" technique. In dasymetric mapping, a source layer is converted to a surface and an ancillary data layer is added to the surface with a weighting scheme applied to cells coinciding with identified or derived density level values in the ancillary data. [...] The modeling process uses sub-national level census counts for each country and primary geospatial input or ancillary datasets, including land cover, roads, slope, urban areas, village locations, and high resolution imagery analysis; all of which are key indicators of population distribution. [...] Within each country, the population distribution model calculates a "likelihood" coefficient for each cell and applies the coefficients to the census counts, which are employed as control totals for appropriate areas. The total population for that area is then allocated to each cell proportionally to the calculated population coefficient

tion on educational attainment, urbanization, GDP per capita, and a range of other country-level characteristics from the World Bank's World Development Indicators and International Monetary Fund's World Economic Outlook databases, and measures of country-level capital stocks from the Penn World Tables.

3.2 Estimating State and Country Level Density

Using the *LandScan* data, for both US states and countries, we compute *population-weighted density* (D_i) as:

$$D_i = \sum_{g \in G(i)} \left(L_g \times \frac{L_g}{\sum_{g' \in G(i)} L_{g'}} \right)$$

where g indexes grid cells and $G(i)$ is the set of grid cells in country (or state) i. L_g is the population, according to *LandScan*, in grid cell i. Since all grid cells are the same size, L_g is also the density of grid cell i.[32] This measure is equivalent to weighting the population density of each grid cell in a country or state by its population, and yields a measure of population density that approximates to the expected experienced density of a person in the state or country.[33]

This is our key state and country-level independent variable of interest. Intuitively, this measure captures the concentration of population within a state or country. For a given total population if people are very concentrated in a few cities this measure will be large whereas if people are is dispersed across many less-dense cities or suburban areas, D_i will be small. Figure 1 plots deciles of D_i for each country around the world. There is substantial variation in D_i across countries, both within continents and within income groups.

3.3 Estimating Sector-Specific Density Affinity

Using industry-by-city level data from the US County Business Patterns (CBP), we estimate the agglomeration elasticity of each tradable manufacturing sector; our estimation follows directly from the model's Equation 2.11. Because our focus is cross-country trade, and manufactured goods account for the bulk of international exports, we emphasize the existence of substantial within-manufacturing differences in density affinity.

We compute a "density-elasticity" for each industry by estimating the following equation:

$$y_{cj} = \alpha_c + \gamma_j + \sum_j \eta_j \cdot \left(\ln D_c \cdot \mathbb{I}_j \right) + \epsilon_{cj} \tag{3.1}$$

wjere c indexes cities and j indexes sectors. y_{cj} is the (log of the) number of employees, number of establishments, or first quarter aggregate payroll in industry j and location (city) c. α_c and γ_j are city

[32] Since grid-cells have an area of one square kilometer (so that the population L_g of a grid-cell is also its density, and $N_{G(i)}$ is also the total area of the country), this is equivalent to computing:

$$D_i = \text{Population Weighted Density} = \frac{(\text{Mean Density})^2 + (\text{SD of Density})^2}{\text{Mean Density}}$$

[33] See Wilson (2012) for a justification of the use of population-weighted density by the United States Census Bureau.

and sector fixed-effects, respectively; D_c is population density at the level of the Core Based Statistical Area (CBSA). $\mathbb{I}_j$ is an indicator that equals one for sector j.

The coefficients of interest are the density elasticities, η_j, the key source of industry-level variation in the model (see Equation 2.11). These elasticities capture the extent to which each industry tends to be more or less represented in denser locations.

Since CBSA-level density is likely correlated with a range of other city-level characteristics that might affect industry sorting, it is difficult to interpret the η_j's at face value. To circumvent this issue, we construct an instrument for CBSA-level density in order to estimate the causal effect of a marginal change in CBSA-level density on industry-specific production. Our instrument is the (log of the) average distance of each CBSA to subterranean bedrock. By exogenously shifting density, we estimate the response of industry specialization to density alone, capturing the causal effect of a marginal chage in city-level density on industry-level production.

Lower distance to bedrock in a location eases the land constraint, and can be interpreted as increasing the available share of land B_c in our theoretical framework; construction often requires a foundation in bedrock and is more difficult when bedrock is deep (Schuberth, 1968; Landau and Condit, 1999).[34] The first stage relationship correlation between CBSA-level density and the log of the distance to bedrock is shown in Figure 2. The correlation coefficient is highly statistically significant (t-statistic = 8.07) suggesting that, consistent with the mechanical impact of distance to bedrock on construction, CBSA-level variation in subterranian bedrock systematically shifts equilibrium population density. The necessary identification assumption is that distance to subterrenian bedrock only affects industry sorting through its impact on ease of construction and hence population density.[35]

Industries with the highest and lowest estimate of density elasticities are listed in Table 1. Since we have six versions of the density elasticities—using employment, establishments, and payroll, estimated using either OLS or IV-2SLS—we report the ten industries with the highest and lowest first principal component of all six elasticity estimates. However, the set of industries is very similar for each elasticity individually. While many of these sectors are intuitive and commonly associated with production in dense cities, in the case of the top sectors, or production away from large cities, in the case of the bottom sectors, they also do not map clearly onto common determinants of comparative advantage. The top of our list features both skill-intensive industries (e.g. Semi-conductor and Other Electronic Component Manufacturing) and industries at the bottom end of the skilled labor requirement distribution (e.g. Bakeries and Tortilla Manufacturing). The same is true for capital intensity.[36] Indeed, the first principal component of our elasticities is not significantly correlated with capital intensity, several measures of skill intensity, or the age or gender breakdown of employment. This suggests that our analysis is not just capturing well-understood determinants of comparative

[34] Recent research has suggested the use of underlying geologic characteristics to provide exogenous sources of variation in land supply availability and estimate its economic effects (Rosenthal and Strange, 2008; Saiz, 2010; Duranton and Turner, 2018) However, most of the existing research has focused on within-city variation in geological features to instrument for urban shape, rather than cross-metropolitan areas variation.

[35] While this assumption seems likely, we also verify that the results are similar after controlling for other ground and soil characteristics (e.g. characteristics of soil content, agricultural suitability, etc.).

[36] Moreover, motor vehicle manufacturing and navigational equipment manufacturing are both at the top of Nunn (2007)'s list of contract intensive industries, but are at opposite ends of our list.

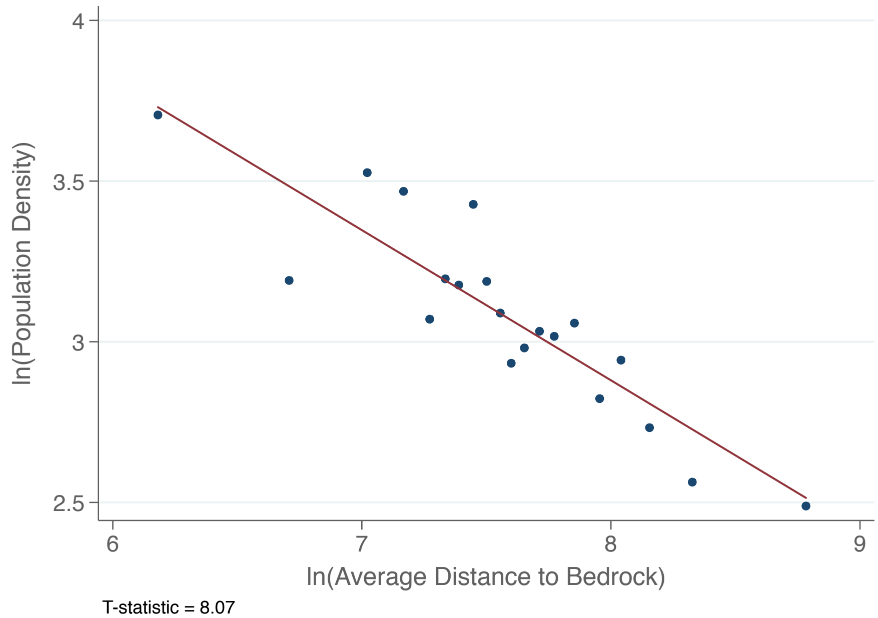


Figure 2: **Distance to Bedrock and Population Density.** The figure is a binned scatter plot. It reports the correlation between log of distance to bedrock and log of population density at the CBSA level. The t-statistic is 8.07.

advantage, something that we verify in more detail empirically in the next sections.

Figure 3 shows the distribution of establishments in the top and bottom ten sectors listed in Table 1 across the US. For each CBSA c and sector j, we compute:

$$\text{Representation}_{cj} = \Big(\frac{\sum_{j\in \text{T,B}} \text{Establishments}_{cj}}{\sum_j \text{Establishments}_{cj}}\Big) \Big/ \Big(\frac{\sum_c \sum_{j\in \text{T,B}} \text{Establishments}_{cj}}{\sum_c \sum_j \text{Establishments}_{cj}}\Big)$$

where T and B are the set of ten highest and lowest η_j sectors respectively. This normalization captures the over- or under-representation of top or bottom sectors in city c by normalizing the share of city c manufacturing establishments that belong to $j \in T/B$ by the overall share of manufacturing establishments that belong to $j \in T/B$ in the US. Otherwise, larger sectors would appear highly represented everywhere, and all sectors would appear well represented in larger cities.

Figure 3a shows the geographic distribution of low-η_j sectors; they are disproportionately located in Upper Midwest and Central and Northern Plains regions (purple-shaded regions). High-η_j sectors,displayed in Figure 3b, are disproportionately located on the East and West coasts, as well as in cities in Texas and parts of the Midwest. There is significant variation within regions and states as well. Indeed, almost all states have locations in which both high and low η_j sectors are disproportionately produced.

Discussion Our baseline empirical results do not take a strong stance on industry-specific characteristics driving variation in the ”density affinity” of manufacturing industries. Existing estimates of

Table 1: The Ten Most and Least Density Elastic Industries

(1) First PC, η_j	(2) NAICS Code	(3) Industry Name	(4) First PC, η_j	(5) NAICS Code	(6) Industry Name
3.077139	3342	Communications Equipment Manufacturing	-1.719853	3325	Hardware Manufacturing
2.931949	3344	Semiconductor and Other Electronic Component Manufacturing	-1.941343	3161	Leather and Hide Tanning and Finishing
2.815478	3345	Navigational, Measuring, Electromedical, and Control Instruments Manufacturing	-2.293531	3114	Fruit and Vegetable Preserving and Specialty Food Manufacturing
2.754001	3327	Machine Shops; Turned Product; and Screw, Nut, and Bolt Manufacturing	-2.347334	3331	Agriculture, Construction, and Mining Machinery Manufacturing
2.673068	3222	Converted Paper Product Manufacturing	-2.607069	3361	Motor Vehicle Manufacturing
2.618597	3231	Printing and Related Support Activities	-2.749151	3112	Grain and Oilseed Milling
2.464373	3118	Bakeries and Tortilla Manufacturing	-2.819922	3274	Lime and Gypsum Product Manufacturing
2.299636	3371	Household and Institutional Furniture and Kitchen Cabinet Manufacturing	-3.013974	3221	Pulp, Paper, and Paperboard Mills
2.258956	3219	Other Wood Product Manufacturing	-3.192425	3111	Animal Food Manufacturing
2.190134	3121	Beverage Manufacturing	-4.159338	3122	Tobacco Manufacturing

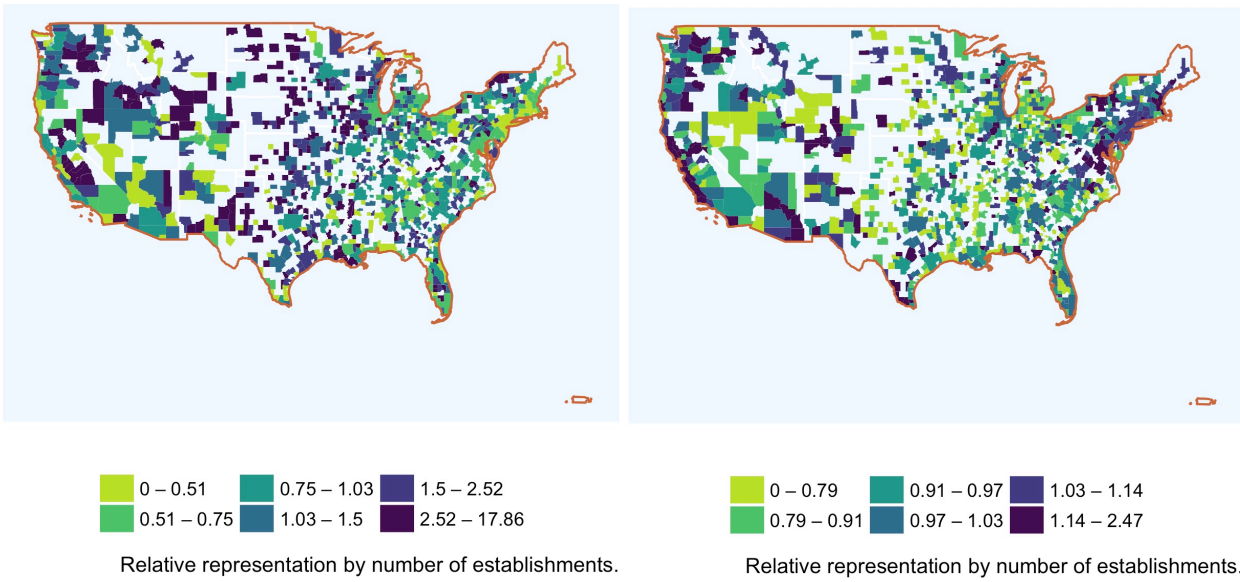
Notes: The density elasticity measure is the first principal component from our six elasticity estimates for each sector.

the impact of urban agglomeration on productivity find substantial variation across sectors, and our results corroborate this (Shefer, 1973; Nakamura, 1985; Rosenthal and Strange, 2004; Faggio, Silva, and Strange, 2017). Recent work has proposed industry-level variables that determine the extent to which sectors benefit from agglomeration and production in denser cities; these include education and skill requirements (Davis and Dingel, 2014) or capital intensity (Gaubert, 2018). An important distinction between most recent work and our estimates is that we restrict attention to tradable manufacturing sectors; therefore, the fact that high-skilled services, for example, are disproportionately located in cities is outside the scope of our analysis.

An alternative source of density affinity is the intensive use of differentiated local services (Abdel-Rahman and Fujita, 1990; Abdel-Rahman and Fujita, 1993; Abdel-Rahman, 1994; Abdel-Rahman, 1996). In this framework, density facilitates the production of non-tradable services (e.g. (Clark, 1945), and hence service-reliant sectors sort into dense cities. Anecdotally, many large companies justify their relocation in large cities by their readily available diversity of services producers.[37] Some manufacturing sectors may locate in dense cities because of their improved ability to efficiently source from non-tradable sectors in the larger local market.

Another potential determinant of variation in density affinity is the extent to which each sector relies on raw materials (e.g. minerals, agriculture) as inputs. Sectors that rely on immobile natural

[37] See Bruce Nollop, Wall Street Journal - The Experts, April 25, 2016: *"As companies focus on their core competencies, they can benefit greatly from cities' networks of service providers"*.



(a) Low η_j Sectors

(b) High η_j Sectors

Figure 3: **Representation of Low- and High- η_j Sectors Across US Cities.** Both (a) and (b) are US CBSA-level maps. (a) displays the relative representation of low-η_j sectors, the ten sectors with the lowest first principal component of our six density elasticity estimates. (b) displays the relative representation of high-η_j sectors, the ten sectors with the lowest first principal component of our six density elasticity estimates. These sectors are listed in Table 1

resources might be less able to locate in cities and reap the benefits of agglomeratinon (Ades and Glaeser, 1995); locating in urban centers for these sectors would mean paying high transportation costs on inputs. Finally, dense cities might be particularly productive places for innovation and R&D (e.g. Duranton and Puga, 2004). If this is the case, the density affinity measure might be capturing the extent to which each sector benefits from innovation and the role of R&D in the production process. We investigate the potential contribution of these mechanisms in Section 4.4.

4 Empirical results: Density and Trade

4.1 Estimation Framework

We now examine the impact of within-country population distribution on patterns of trade. We investigate whether population-weighted density, D_i, is a systematic source of comparative advantage. The primary estimating equation is:

$$\text{Exports}_{ij} = \alpha_i + \gamma_j + \beta \cdot \eta_j^{IV} \cdot \ln(D_i) + X_{ij}'\Gamma + e_{ij} \tag{4.1}$$

where i indexes states or countries and j indexes sectors. The unit of observation is a country (or state) by sector pair. The dependent variable is total exports in sector j from state or country i. The independent variable of interest is an interaction term between (i) IV estimates of sector-level density affinity (η_j^{IV}) and (ii) log of state or country-level population weighted density ($\ln(D_i)$). The density affinity of all NAICS-4 sectors were estimated using Equation (3.1) and the instrumental variables strategy outlined in Section 3.3. All specifications include sector and state or country fixed effects; we also include a range of controls that vary at the state-by-sector or country-by-sector level (X'_{ij}) chosen to absorb potential omitted variables. Finally, in Section 4.3.1 we propose an instrumental variables strategy that exploits variation in countries' historical city size distribution as shifters of modern population density.

The coefficient of interest is β. If $\beta > 0$, it implies that countries with greater population-weighted density have a revealed comparative advantage in "density-loving" sectors. This framework follows the "regression-based index" of comparative advantage summarized in French (2017), as used, among others, by Nunn (2007) or Bombardini, Gallipoli, and Pupato (2012). Following Silva and Tenreyro (2006), we use the Poisson pseudo-maximum likelihood (PPML) estimator as our baseline specification, but show throughout that results are similar using OLS.[38]

4.2 State-Level Estimates

The over-representation of some manufacturing sectors in dense areas in the United States might stem from either local supply or local demand conditions. Our hypothesis focuses on the supply side, by suggesting that denser cities are relatively more efficient in the production of "density-loving" industries. If this is the case, dense areas within the US should not only attract relatively more employment and production in these industries, but also export significantly more of them internationally.

Thus, as a first test of our hypothesis that regions with greater population-weighted density specialize in the export of density-loving industries, we estimate Equation (4.1) at the US state level.[39] Even across US states, there is substantial variation in the pattern of population distribution. Moreover, while many models of international trade consider the entire US as a single "point" or observation, different parts of the US specialize in vastly different industries (see e.g. Irwin (2017) for a long-term perspective).

Table 2 presents estimates of Equation (4.1) at the state-by-sector level.[40] Panel A reports Poisson maximum likelihood estimates while Panel B reports OLS estimates with log of exports as the outcome variable. Across specifications, we find that the coefficient of interest is positive and statistically significant, suggesting that US states with greater population-weighted density have a comparative advantage in density-loving industries.

Column 1 presents the coefficient of interest when only $\eta_j^{IV} \times \ln(D_i)$ – the interaction between state-level population weighted density and industry-level density affinity – is included on the right

[38]As shown by Fally (2015), the Poisson pseudo-maximum likelihood estimation method has the additional benefit of ensuring that predicted trade flows satisfy the "adding up" constraint implicit in gravity models of trade.

[39]While some recent studies have attempted to estimate export data at the metropolitan level (see e.g. the database constructed by Tomer and Kane (2014)), most trade flows data are still collected at a broader level of aggregation. The smallest level of consistent and exhaustive trade reporting in the United States is the state.

[40]We restrict the sample to manufacturing industries only because of the far better coverage of the County Business Patterns in these sectors, in order to focus on tradable goods, and to avoid results being driven by agricultural exports from low-density states.

Table 2: State-Level Trade, Baseline Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent Variable is Total Exports from the State-Sector						
Strategy for estimation of density affinity:	η_j computed using industry-level employment					η_j computed using industry-level number of establishments	
	Panel A: Outcome Variable is Total Exports (Thousands), PML Model						
D_i x η_j	0.612***	0.539***	0.563***	0.437***	0.538***	3.508***	3.241***
	(0.145)	(0.117)	(0.201)	(0.0917)	(0.199)	(0.541)	(0.660)
	Panel B: Outcome Variable is log(Exports), OLS Model						
D_c x η_j	0.146*	0.129*	0.142*	0.120*	0.124	0.864**	0.839**
	(0.0734)	(0.0725)	(0.0738)	(0.0685)	(0.0793)	(0.358)	(0.363)
R-squared	0.756	0.758	0.757	0.758	0.760	0.756	0.760
Factor Intensity Controls	No	Yes	No	No	Yes	No	Yes
State Level Controls	No	No	Yes	No	Yes	No	Yes
Industry Level Controls	No	No	No	Yes	Yes	No	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
States	50	50	50	50	50	50	50
Observations	4,182	4,132	4,182	4,132	4,132	4,182	4,132

Notes: The unit of observation is a state-by-sector pair. The coefficient of interest is the coefficient on an interaction between state-level population weighted density and sector-level density affinity computed using the bedrock IV and city-level employment in columns 1-5 and estalishments in columns 6-7. Panel A reports Poisson pseudo-maximum likelihood estimates while Panel B reports OLS estimates. All specifications include state and sector fixed effects, along with other controls listed at the bottom of each column. Standard errors, clustered at the state level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively

hand side (along with state and industry fixed effects). The remaining specifications investigate the robustness of this baseline result to the inclusion of additional controls.

In order to address the concern that the results are driven by state-level differences in education and comparative advantage in high-skill industries, in column 2 we include a series of interactions between state-level educational attainment and sector-level skill demand. In particular, we separately interact the share of people in each state who have achieved a (i) high school degree, (ii) a bachelors degree, and (iii) a graduate degree, with the share of people employed in each sector (i) that have a high school degree or (ii) that have at least a college degree. The inclusion of these six interactions has little effect on our coefficient of interest.

In column 3, we control for a series of state-level variables interacted η_j^{IV} in order to investigate whether the baseline result is driven by some omitted state-level characteristic. These controls include (log of) the median household income; (log of) state-level population; the share of inhabitants with high school, bachelor, and graduate degree; and the share of young people, aged 18-30. It is possible, for example, that denser states are also just wealthier and that this drives the correlation in column 1. However, the coefficient of interest remains similar after including these state-level controls.

In order to address the potential for omitted industry-level characteristics, in column 4 we control for a series of industry-level characteristics interacted with $\ln(D_i)$. These covariates, computed for each manufacturing industry in the US, are the value of installed capital per worker, (log of) the average employee compensation, the share of workers with at least a college degree, the average age of employees, and the gender breakdown of employment.

In column 5 we include all 17 controls mentioned thus far and again, the coefficient of interest remains very similar. It does, however, lose statistical significance in Panel B when we use an OLS regression model and log of exports as the outcome variable; this is driven by a larger standard error rather than a decline in coefficient magnitude.

In columns 6-7 we repeat the specifications from columns 1 and 5—the specifications without any controls and the specification with all controls—and construct the "density affinity" measure using industry-level establishment data rather than employment data. The number of establishments is a potentially less noisy measure of industry-level production across space than employment, and moreover is never suppressed in the CBP data. Reassuringly, in both columns 6 and 7 and in both Panels A and B, our coefficient of interest is positive and highly significant.

This first set of results demonstrates that US states that exhibit a more spatially concentrated population export relatively more in sectors whose production is concentrated in denser metropolitan areas. According to our estimates, a one-standard deviation increase in the density interaction in the fully controlled specification increases the dependent variable by 0.139 standard deviations when computed using the elasticity with respect to employment and 0.295 when computed using the elasticity with respect to establishments. While natural, these results suggest that the distribution of population may affect not only the economic geography of a region, but also its international industrial specialization.

Sensitivity and Robustness In Table A1 we further test the sensitivity of the baseline result by estimating a series of additional specifications. Each coefficient reported in Table A1 is the result from a separate regression. First, we consider the robustness of the result to alternative measures of η_j. While for our baseline results, we primarily focused on a version of η_j^{IV} computed from city-level employment data, we also compute η_j^{IV} using city-level establishment and payroll data. Rows 1-3 of Table A1 reproduce the baseline results using versions of η_j^{IV} computed using employment, establishments, or payroll data; the coefficient of interest is qualitatively very similar across specifications. In column 2, we add the full set of controls from Table 2 to the right side of the regression and again the coefficients of interest are similar.

Yet another way we can compute the independent variable of interest is to calculate the η_j using OLS, rather than IV, estimates of Equation (3.1). While we prefer our IV strategy because there are likely many city-level characteristics that are correlated with density and might influence the sorting of production, for clarity we report the full set of specifications from rows 1-3 using η_j's computed using OLS instead of IV-2SLS. These specifications tell a very similar story. All 12 coefficients presented in Table A1 are statistically significant at below the 1% level.

Finally, while in the baseline results, we exclude state-industry pairs with zero exports, the estimates are very similar if we include the zeroes. These results are reported in Table A2 and are reassuring since they imply that are results are not driven by the omission of observations with no trade.

4.3 Country-Level Estimates

We now turn to the main results of the paper: the relationship between density and patterns of cross-country trade. Estimates of (4.1) in which the units of observation are country-industry pairs are reported in Table 3. Panel A presents Poisson maximum likelihood estimates while Panel B reports estimates from an OLS model. The coefficient of interest in a specification without controls is presented in column 1; it is positive and highly significant. Countries with a more concentrated population distribution—the darker countries in Figure 1—have a revealed comparative advantage in density-loving sectors.

Columns 2-6 investigate the robustness of the result to the inclusion of a series of controls in order address potential concerns due to omitted variable bias. In column 2, we control for traditional determinants of comparative advantage , including capital and skill intensity (Romalis, 2004).[41] Since data on the country-level capital stock is only available for 90 countries, the sample size of the regression is reduced; nevertheless, the coefficient of interest is almost exactly identical.

In column 3 we control for a series of country-level characteristics interacted with the sector-level density elasticity measure, η_j^{IV}. These are included to account for the fact that population-weighted density is potentially related to other country-level characteristics that may affect comparative advantage. In particular, we control for (the log of) country-level total population, educational attainment, urbanization, the share of population employed in agriculture, the share of population employed in service production, (log of) per capita GDP (PPP adjusted), and a rule of law index, all interacted with η_j^{IV}. Again, the coefficient of interest is very similar after the inclusion of these controls and remains highly statistically significant.[42]

Next, we investigate the robustness of the result to the inclusion of sector-level controls. Analogous to the concern that there is an omitted country-level variable that might bias the result, we might be concerned that our the η_j^{IV} capture some industry-level characteristic that is omitted from the specification in column 1. To address this, we control for the same industry-level controls as in Table 2, interacted with country-level measures of population-weighted density D_i. Reassuringly, the coefficient of interest is again very similar after the inclusion of these controls.

In column 5, we include all controls mentioned thus far on the right-hand side of the regression. Due to missing covariates, the sample size is reduced to 83 countries, yet the coefficient of interest remains positive and highly significant.

This first set of country-level results suggests that the distribution of population within countries is a potentially important determinant of comparative advantage and patterns of trade. Our esti-

[41] In particular, we interact country-level capital stock (as drawn from the Penn World Tables) with an industry's average level of capital intensity obtained from the NBER-CES Manufacturing database. We also interact measures of educational attainment at the country level with our estimates of the skill intensity of an industry in US data computed from the share of high school and college attainment of workers in the industry in the American Community Survey data.

[42] Moreover, the coefficient of interest is also similar if only individual country-level controls or smaller sets of country-level controls are included on the right-hand side, but to conserve space we do not report these specifications.

Table 3: Country-Level Trade, Baseline Estimates

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable is Total Exports from the Country-Sector				
	Panel A: Outcome Variable is Total Exports (Thousands), PML Model				
D_i x η_j	0.456***	0.464***	0.757***	0.462***	0.765***
	(0.111)	(0.110)	(0.0849)	(0.0710)	(0.0731)
	Panel B: Outcome Variable is log(Exports), OLS Model				
D_i x η_j	0.104**	0.105**	0.288***	0.122***	0.262***
	(0.0487)	(0.0524)	(0.0645)	(0.0454)	(0.0627)
R-Squared	0.814	0.796	0.793	0.816	0.797
Factor Intensity Controls	No	Yes	No	No	Yes
Country Level Controls	No	No	Yes	No	Yes
Industry Level Controls	No	No	No	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Countries	134	90	107	134	83
Observations	10,464	7,241	8,542	10,332	6,674

Notes: The unit of observation is a country-by-sector pair. The coefficient of interest is the coefficient on an interaction between country-level population weighted density and sector-level density affinity computed using the bedrock IV and city-level employment. Panel A reports Poisson pseudo-maximum likelihood estimates while Panel B reports OLS estimates. All specifications include country and sector fixed effects, along with other controls listed at the bottom of each column. Standard errors clustered at the country level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

mates from column 2, when only factor endowment controls are included, imply that a one standard deviation increase in the density interaction increases the outcome variable by 0.113 standard deviations. This is slightly larger in magnitude than the coefficient on the capital interaction, which implies a standardized beta coefficient of 0.109.[43] When we include the full set of controls on the right hand side, the coefficient of interest increases and implies a beta coefficient on the density interaction of 0.276.

Sensitivity and Robustness We present a series of robustness tests to assess the sensitivity of the baseline estimates. First, in Table A3 we reproduce all baseline results after including continent-by-industry fixed effects. This specification compares the comparative advantage of countries within the same continent that have different population distributions; it was motivated by the fact that, visually, there is some variation across continents in population-weighted density (see Figure 1). The results remain very similar and, if anything, are more precisely estimated after the inclusion of these additional fixed effects.

[43] Interestingly, our estimates of the magnitudes of comparative advantage due to factor endowments is very similar to Nunn (2007), who estimates a beta coefficient on an analogous capital interaction of 0.105.

We next report a series of specification checks that are analogous to the state-level tests reported in Table A1; these are displayed in Table A4. We report estimates from versions of the baseline regression equation that use all possible strategies to compute sector-level density affinity. The only difference from the state-level robustness tests is that we add additional columns, columns 3-4, in which we exclude countries at the bottom end of the population and income distribution. The lowest income countries likely also have lower quality data and the smallest or poorest countries might have extreme values of either density or trade values. The country-level results are very similar across specifications, suggesting that the baseline results are not driven by the details of our variable. Of the 24 specifications presented in Table A4, the coefficient of interest loses statistical significance in only one case (Row 4, Column 2).[44]

Finally, the results are very similar if we include country-industry pairs with zero exports. These results are reported in columns 3-4 of Table A2 and are very similar to our baseline estimates.

4.3.1 Endogeneity

This section proposes an instrument for country-level population-weighted density and reports instrumental variable estimates of our baseline specification. The goal of introducing an instrument is to make sure that the baseline results are not driven by reverse causality. That is, it is possible that the composition of a country's exports has feedback effects and shapes its economic geography; we would then find a positive coefficient on our density interaction, but it would be incorrect to interpret the relationship as evidence for density as a source of comparative advantage. To rule out the possibility that our results capture the effect of trade on economic geography, we use characteristics of countries' city size distribution in 1900 to construct instruments for economic geography today. While characteristics of a country's historical population distribution predict its modern population distribution, it seems unlikely that modern patterns of trade, which developed largely after World War II, had a direct effect on city sizes in 1900 (Irwin, 2017).

We determined the location and population of cities around the world in 1900 using historical data collected by Chandler (1987), and recently digitized by Reba, Reitsma, and Seto (2016).[45] While we are unable to compute a direct measure of population-weighted density in 1900 analogous to our contemporary D_i, we construct an intuitively similar measure from the city level data. High D_i corresponds to having a high city population concentrated in a relatively small number of cities. For each country, we therefore compute the total population across all cities in the Chandler data (p_i^{1900}), as well as the inverse number of cities (c_i^{1900}). We include both, as well as their interaction ($p_i^{1900} \cdot c_i^{1900}$), interacted with η_j, as excluded instruments. We expect $p_i^{1900} \cdot c_i^{1900} \cdot \eta_j$ to be positively correlated with $D_i \cdot \eta_j$, the endogenous variable, since a high value of $p_i^{1900} \cdot c_i^{1900}$ implies that in 1900 the country had high overall city population concentrated in a small number of cities.

[44]The fact that the estimated coefficient magnitudes decline in rows 4-6 when we add controls is intuitive. In these rows, the η_j estimates used to construct the independent variable were computed using OLS; variation in η_j therefore likely captures sector-specific sorting based on characteristics that are correlated with density, and not necessarily density itself. Therefore, when we include our broad set of industry and country-level controls, the estimated effect is attenuated since these controls capture variation that was unobservable in our city-level regressions.

[45]1900 was chosen because it is the oldest year with broad and global coverage.

In particular, the first stage estimating equation is:

$$(\eta_j^{IV} \cdot \ln(D_i)) = \zeta \cdot c_i^{1900} \cdot \eta_j^{IV} + \xi \cdot p_i^{1900} \cdot \eta_j^{IV} + \phi \cdot p_i^{1900} \cdot c_i^{1900} \cdot \eta_j^{IV} + \alpha_i + \gamma_j + +X_{ij}'\Gamma + e_{ij} \tag{4.2}$$

and we hypothesize that $\phi > 0$. Countries with a high historical urban population concentrated in a small number of cities should—if the logic of the instrument is correct—have higher population-weighted density today. All specifications include country and industry fixed effects. X_{ij}' is a vector of controls that varies at the country-by-industry level; for example, since p_i^{1900} (total urban population in 1900) will likely be mechanically correlated with modern population, we control for modern (log of) country population interacted with η_j.

Instrumental variables estimates of Equation (4.1) are presented in Table 4. Panel A presents IV-2SLS estimates; first stage estimates of Equation (4.2) and OLS estimates of Equation (4.1) are reported in Panels B and C respectively. Our baseline estimate is reported in column 1. Reassuringly, in the first stage specification reported in Panel B, we find that $\phi > 0$ while the direct effects of p_i^{1900} and c_i^{1900} are both negative.

The IV-2SLS coefficient is positive and significant, supporting the argument that density is a source of comparative advantage and that our baseline estimates are not driven by reverse causality. The IV estimate, however, is larger in magnitude than the OLS estimate. One explanation for this is that the IV estimate is capturing a particular local average treatment effect. For example, it could be the case that countries whose modern economic geography is highly correlated with economic geography in 1900 are also countries that industrialized early, and are very specialized in industries that fit their population distribution. This would generate IV estimates that are larger than OLS, since the the instrument captures variation across countries whose specialization is very responsive to their population distribution.

Another possible explanation, as noted above, is that variation in the instruments is correlated with the error term in the second stage regression. Indeed, the instruments are constructed from historical population data and likely capture variation in total population and not only variation in D_i. Following the control strategy in our baseline results, in column 2 we include an interaction term between the (log of) present day population and η_j^{IV} as a control. The IV coefficient is smaller in magnitude in column 2 and more precisely estimated. While it remains larger than the OLS estimate, it is no longer statistically distinguishable.

A potential concern with using the Chandler data is that data quality and coverage are likely different for different sets of countries. In particular, it is likely of lower quality for smaller and lower income countries, which might be more likely to have cities excluded from the data. To make sure this is not driving the result, in columns 3-4 and 5-6 we repeat the specifications from columns 1-2 after dropping countries in the bottom 10% of the population and income distribution respectively. Reassuringly, our estimates remain very similar. The results are also similar if we drop countries in the bottom 20 or 25% of the distribution (not reported).

While it seems unlikely that urban geography in 1900 was caused by modern patterns of trade, it is nevertheless a possibility that historical urban geography affected modern determinants of com-

Table 4: Country-Level Trade, IV Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable is Total Exports from the State-Sector					
	Full Sample		Excluding Bottom 10% by Population		Excluding Bottom 10% by Income	
	Panel A: IV-2SLS Estimates					
D_i x η_j	0.517**	0.279**	0.411**	0.319***	0.404**	0.214**
	(0.236)	(0.117)	(0.196)	(0.116)	(0.185)	(0.0894)
ln(population) x η_j		-0.0895**		-0.0434		-0.0887**
		(0.0366)		(0.0407)		(0.0346)
	Panel B: First Stage Estimates					
(p_i, 1900) x (c_i, 1900) x η_j	0.787**	1.021***	0.797**	1.091***	1.119***	1.153***
	(0.344)	(0.312)	(0.338)	(0.345)	(0.382)	(0.356)
p_i, 1900 x η_j	-0.614***	-0.728***	-0.634***	-0.766***	-0.705***	-0.787***
	(0.213)	(0.180)	(0.211)	(0.189)	(0.227)	(0.192)
c_i, 1900 x η_j	-8.705**	-10.54***	-8.782**	-11.36***	-12.43***	-11.83***
	(3.868)	(3.497)	(3.807)	(3.868)	(4.304)	(3.998)
R-Squared	0.095	0.463	0.115	0.474	0.127	0.527
K-P F-Statistic	8.533	27.145	9.104	24.904	9.176	28.569
	Panel C: OLS Estimates					
D_i x η_j	0.134**	0.196***	0.169***	0.181***	0.129**	0.198***
	(0.0624)	(0.0709)	(0.0608)	(0.0676)	(0.0635)	(0.0719)
ln(population) x η_j		-0.0753**		-0.0175		-0.0861**
		(0.0334)		(0.0344)		(0.0332)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Countries	86	86	77	77	78	78
Observations	7022	7022	6281	6281	6379	6379

Notes: The unit of observation is a country-by-year pair. Panel A reports IV-2SLS estimates, Panel B reports first stage estimates, and Panel C reports OLS estimates. The coefficient of interest is the coefficient on an interaction between country-level population weighted density and sector-level density affinity computed using the bedrock IV and city-level employment. p is the log of the total urban population in 1900 and c is the inverse number of cities. All specifications include country and sector fixed effects, along with other controls listed at the bottom of each column. Sample restrictions are noted in the column header. The Kleibergen-Paap F-statistic for each first stage regression is reported at the bottom of Panel B. Standard errors clustered at the country level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

parative advantage other than D_i. If elements of countries' historical economic geography influence modern determinants of comparative advantage though channels other than features of modern economic geography, it would be a violation of the exclusion restriction. Nevertheless, the robustness of our result to the battery of controls and specifications in the previous section, as well as the broadly similar results using these historical instruments, indicates that density is a potentially important causal determinant of patterns of trade.

4.4 Mechanisms: What drives density affinity?

We next turn to potential mechanisms underpinning the baseline results. While in the main specification we relied on a reduced-form measure of industry-level "density affinity," in this section we explore which industry characteristics potentially underlie the baseline estimates. First, some recent work has highlighted the greater skill and level of human capital in cities (Davis and Dingel, 2014). It is worth noting that in the baseline specification, we were careful to control flexibly for the potential role of variation in skill or education, both across sectors and across countries. In column 1 of Table 5, we report the coefficient on the interaction between population-weighted density and the share of employment in each industry in the US with a college degree. The coefficient on this interaction is statistically insignificant; we also find no evidence that education is driving the result if we break the industry-level education measure into a larger number of discrete bins (not reported). Thus, we do not find strong evidence that our estimate of comparative advantage are driven by cross-industry heterogeneity in education.

Another potential determinant of our density affinity measure is the extent to which each sector relies on differentiated local services. Population density might facilitate the productive provision of services and scetors that rely more on local services may therefore benefit disproportinoately from density (Abdel-Rahman and Fujita, 1990; Abdel-Rahman and Fujita, 1993; Abdel-Rahman, 1994; Abdel-Rahman, 1996). Our estimates lend some support to this hypothesis. Within the United States, we find that manufacturing industries in which services comprise a large share of total intermediate inputs tend to locate in denser areas.[46] When we turn to the trade data, however, service reliance does not explain the export patterns of high-η_j sectors (column 2). The coefficient on the interaction between population-weighted density and industry-level service intensity is in fact negative and far from statistically significant.

Certain industries may locate away from dense cities if they rely on immobile natural resources (e.g. Ades and Glaeser, 1995). These sectors might be less able to benefit from urban externalities and variation in natural resource dependence across industries might drive our variation in density affinity. Anecdotally, the sectors at the bottom of our "density affinity" list seem to be those that source extensively from natural resources (see Table 1). To investigate this, we compute the share of natural resource inputs for each manufacturing sector using the US input-output tables. The coefficient on the interaction term between population-weighted density and industry-level natural resource dependence is negative and significant (column 3 of Table 5), suggesting that indeed denser countries export less in sectors that rely on natural resources. This is consistent with the idea that resource-reliant sectors optimally locate away from urban centers and that dense countries hence are disproportionately productive in industries that do not rely on natural resources.

A final potential mechanism is the role of research and development (R&D) in production. Industries rely differentially on R&D expenditure and innovation in the production process. If cities facilitate innovation (e.g. Duranton and Puga, 2001; Duranton and Puga, 2004), then sectors that rely disproportionately on R&D might be especially productive in dense cities. Therefore, our baseline

[46] We compute each sector's non-tradable input share from the Bureau of Labor Statistics input-output tables.

Table 5: Exploring Potential Mechanisms

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable is Total Exports from the Country-Sector					
η_j computed using industry-level:					Total Emp.	Number of Est.
D_i x η_j					0.875***	2.282***
					(0.171)	(0.494)
D_i x (Share Employment College Educated)$_j$	0.996				1.989	-1.484
	(1.944)				(1.538)	(1.954)
D_i x (Services Input Share)$_j$		-0.646			-0.592	-0.444
		(0.620)			(0.443)	(0.497)
D_i x (Nat. Resource Input Share)$_j$			-1.575**		-0.599	-1.186**
			(0.652)		(0.430)	(0.559)
D_i x (R&D per Worker)$_j$				0.0844**	0.0743**	0.0705*
				(0.0378)	(0.0370)	(0.0387)
D_i x (Share STEM Workers)$_j$				1.124**	1.290**	0.804
				(0.525)	(0.527)	(0.493)
Country Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,437	8,437	8,437	8,333	8,333	8,333

Notes: The unit of observation is a country-by-sector pair. All specifications include country and sector fixed effects, along with other controls listed at the bottom of each column. Sector-level density affinity computed using the bedrock IV and city-level employment (columns 5) or city-levelemployment (column 6). Additional interactions included in each regression are noted on the left side of the table. Standard errors clustered at the country level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

estimates might be capturing the role of density in facilitating R&D. To investigate this, for each sector we compile data on (i) R&D spending per worker and (ii) the share of employees in science, technology, engineering, and mathematical (STEM) fields from the Brookings Advanced Industries database.[47] Again, we include an interaction term between both measures and country-level density in our baseline country-level estimating equation; the estimates are reported in column 4 of Table 5. Both interactions are positive and statistically significant, suggesting that density may play a role in facilitating R&D and that denser places specialize in the export of R&D intensive sectors.

Does the combination of these channels explain our baseline estimates? In columns 5-6, we include all variables from columns 1-4 of Table 5 on the right hand side of the regression, along with the industry-level reduced form density affinity interacted with population-weighted density. If our proposed mechanisms fully explained the baseline results, we would expect the coefficient on the density affinity variable to be zero. However, it remains positive and statistically significant, whether density-affinity is measured using US employment data (column 5) or data on establishments (col-

[47] See here: https://www.brookings.edu/research/americas-advanced-industries-what-they-are-where-they-are-and-why-they-matter/

umn 6). Thus, we find suggestive evidence that (i) the role of cities in facilitating R&D and (ii) heterogeneity in industry-specific natural resource dependence are important channels; however, they do not fully explain our baseline results, suggesting that additional and un-observed industry characteristics are also at play. Uncovering industry-level characteristics that drive sorting with respect to density strikes us as a potentially interesting area for additional exploration.

5 Conclusion

This paper argues that some countries "specialize in density": in the language of the factor endowment literature, countries that exhibit an abundance of dense cities export relatively more in "dense-city-intensive sectors." Most analysis of sources of comparative advantage in international trade have emphasized aggregate variation in country-level endowments or production technologies. Our theory and empirical results, however, suggest that even when two countries look identical in the aggregate, they may still specialize in vastly different industries because the domestic distribution of factors of production is a key determinant of comparative advantage.

Within the United States, we uncover substantial heterogeneity in the density-affinity of tradable sectors. While some sectors are disproportionately located in large cities, others are more frequently found in small cities or suburban areas. We find that US States and countries with higher population-weighted density – that is, with a more concentrated population – export relatively more in sectors with high density affinity. The results are robust to the inclusion of a battery of controls and are similar using an instrumental variables strategy that exploits variation in countries' historical city size distribution.

While the impact of trade on sub-national regions is increasingly well understood, the impact of economic geography and domestic heterogeneity on patterns of trade has been less well documented. The goal of this study is to explore one facet of this relationship, and to show that domestic economic geography can itself be a key driver of international trade flows.

References

Abdel-Rahman, Hesham and Masahisa Fujita (1990). "Product variety, Marshallian externalities, and city sizes". In: *Journal of regional science* 30.2, pp. 165–183.

Abdel-Rahman, Hesham M (1994). "Economies of scope in intermediate goods and a system of cities". In: *Regional Science and Urban Economics* 24.4, pp. 497–524.

— (1996). "When do cities specialize in production?" In: *Regional Science and Urban Economics* 26.1, pp. 1–22.

Abdel-Rahman, Hesham M and Masahisa Fujita (1993). "Specialization and diversification in a system of cities". In: *Journal of Urban Economics* 33.2, pp. 189–222.

Ades, Alberto F and Edward L Glaeser (1995). "Trade and circuses: explaining urban giants". In: *The Quarterly Journal of Economics* 110.1, pp. 195–227.

Autor, David, David Dorn, and Gordon H Hanson (2013). "The China syndrome: Local labor market effects of import competition in the United States". In: *American Economic Review* 103.6, pp. 2121–68.

Bakker, Jan David (2018). "International trade and regional inequality". In: *CEPREMAP Working Paper* 1806.

Bernard, Andrew B, Raymond Robertson, and Peter K Schott (2010). "Is Mexico a lumpy country?" In: *Review of International Economics* 18.5, pp. 937–950.

Bombardini, Matilde, Giovanni Gallipoli, and Germán Pupato (2012). "Skill dispersion and trade flows". In: *American Economic Review* 102.5, pp. 2327–48.

Brakman, Steven and Charles Van Marrewijk (2013). "Lumpy countries, urbanization, and trade". In: *Journal of International Economics* 89.1, pp. 252–261.

Caliendo, Lorenzo, Maximiliano Dvorkin, and Fernando Parro (2015). *The impact of trade on labor market dynamics*. Tech. rep. National Bureau of Economic Research.

Chandler, Tertius (1987). *Four thousand years of urban growth: an historical census.* Lewiston New York St. Davids University Press 1987.

Chor, Davin (2010). "Unpacking sources of comparative advantage: A quantitative approach". In: *Journal of International Economics* 82.2, pp. 152–167.

Ciccone, Antonio and Robert E Hall (1996). "Productivity and the Density of Economic Activity". In: *The American Economic Review* 86.1, pp. 54–70.

Cingano, Federico and Paolo Pinotti (2016). "Trust, firm organization, and the pattern of comparative advantage". In: *Journal of International Economics* 100, pp. 1–13.

Clark, Colin (1945). "The economic functions of a city in relation to its size". In: *Econometrica: Journal of the Econometric Society*, pp. 97–113.

Coşar, A Kerem and Pablo D Fajgelbaum (2016). "Internal geography, international trade, and regional specialization". In: *American Economic Journal: Microeconomics* 8.1, pp. 24–56.

Costinot, Arnaud (2009). "On the origins of comparative advantage". In: *Journal of International Economics* 77.2, pp. 255–264.

Costinot, Arnaud, Dave Donaldson, and Ivana Komunjer (2011). "What goods do countries trade? A quantitative exploration of Ricardo's ideas". In: *The Review of economic studies* 79.2, pp. 581–608.

Courant, Paul N and Alan V Deardorff (1992). "International Trade with Lumpy Countries". In: *Journal of Political Economy*, pp. 198–210.

— (1993). "Amenities, nontraded goods, and the trade of lumpy countries". In: *Journal of Urban Economics* 34.2, pp. 299–317.

Davis, Donald R and Jonathan I Dingel (2014). *The comparative advantage of cities*. Tech. rep. National Bureau of Economic Research.

Debaere, Peter (2004). "Does lumpiness matter in an open economy?: Studying international economics with regional data". In: *Journal of international Economics* 64.2, pp. 485–501.

Desmet, Klaus and Esteban Rossi-Hansberg (2013). "Urban accounting and welfare". In: *American Economic Review* 103.6, pp. 2296–2327.

Dix-Carneiro, Rafael and Brian K Kovak (2015). “Trade liberalization and the skill premium: A local labor markets approach”. In: *American Economic Review* 105.5, pp. 551–57.

Duranton, Gilles and Diego Puga (2001). “Nursery cities: Urban diversity, process innovation, and the life cycle of products”. In: *American Economic Review* 91.5, pp. 1454–1477.

— (2004). “Micro-foundations of urban agglomeration economies”. In: *Handbook of regional and urban economics*. Vol. 4. Elsevier, pp. 2063–2117.

Duranton, Gilles and Matthew A Turner (2018). “Urban form and driving: Evidence from US cities”. In: *Journal of Urban Economics* 108, pp. 170–191.

Ellison, Glenn, Edward L Glaeser, and William R Kerr (2010). “What causes industry agglomeration? Evidence from coagglomeration patterns”. In: *American Economic Review* 100.3, pp. 1195–1213.

Faggio, Giulia, Olmo Silva, and William C Strange (2017). “Heterogeneous agglomeration”. In: *Review of Economics and Statistics* 99.1, pp. 80–94.

Fally, Thibault (2015). “Structural gravity and fixed effects”. In: *Journal of International Economics* 97.1, pp. 76–85.

French, Scott (2017). “Revealed comparative advantage: What is it good for?” In: *Journal of International Economics* 106, pp. 83–103.

Gaubert, Cecile (2018). “Firm sorting and agglomeration”. In: *American Economic Review* 108.11, pp. 3117–53.

Glaeser, Edward L and Joshua D Gottlieb (2009). “The wealth of cities: Agglomeration economies and spatial equilibrium in the United States”. In: *Journal of economic literature* 47.4, pp. 983–1028.

Helpman, Elhanan (1998). “The size of regions”. In: *Topics in public economics: Theoretical and applied analysis*, pp. 33–54.

Holmes, Thomas J and John J Stevens (2004). “Spatial distribution of economic activities in North America”. In: *Handbook of regional and urban economics*. Vol. 4. Elsevier, pp. 2797–2843.

Irwin, Douglas A (2017). *Clashing Over Commerce: A History of US Trade Policy*. University of Chicago Press.

Keesing, Donald B and Donald R Sherk (1971). “Population density in patterns of trade and development”. In: *The American Economic Review* 61.5, pp. 956–961.

Krugman, Paul (1991). “Increasing returns and economic geography”. In: *Journal of political economy* 99.3, pp. 483–499.

Krugman, Paul and Raul Livas Elizondo (1996). “Trade policy and the third world metropolis”. In: *Journal of development economics* 49.1, pp. 137–150.

Landau, Sarah Bradford and Carl W Condit (1999). *Rise of the New York skyscraper: 1865-1913*. Yale University Press.

Michaels, Guy, Ferdinand Rauch, and Stephen J Redding (2013). “Task Specialization in US Cities from 1880 to 2000”. In: *Journal of the European Economic Association*.

Moretti, Enrico (2012). *The new geography of jobs*. Houghton Mifflin Harcourt.

Nakamura, Ryohei (1985). “Agglomeration economies in urban manufacturing industries: a case of Japanese cities”. In: *Journal of Urban economics* 17.1, pp. 108–124.

Nunn, Nathan (2007). "Relationship-specificity, incomplete contracts, and the pattern of trade". In: *The Quarterly Journal of Economics* 122.2, pp. 569–600.

Pflüger, Michael and Takatoshi Tabuchi (2016). "Comparative Advantage and Agglomeration of Economic Activity". In: 10273.

Pierce, Justin R and Peter K Schott (2012). "A concordance between ten-digit US Harmonized System Codes and SIC/NAICS product classes and industries". In: *Journal of Economic and Social Measurement* 37.1, 2, pp. 61–96.

Porter, Michael (2003). "The economic performance of regions". In: *Regional studies* 37.6-7, pp. 549–578.

Ramondo, Natalia, Andrés Rodríguez-Clare, and Milagro Saborío-Rodríguez (2016). "Trade, domestic frictions, and scale effects". In: *American Economic Review* 106.10, pp. 3159–84.

Rauch, James E (1991). "Comparative Advantage, Geographic Advantage and the Volume of Trade". In: *The Economic Journal* 101.408, pp. 1230–1244.

Reba, Meredith, Femke Reitsma, and Karen C Seto (2016). "Spatializing 6,000 years of global urbanization from 3700 BC to AD 2000". In: *Scientific data* 3, p. 160034.

Redding, Stephen J (2016). "Goods trade, factor mobility and welfare". In: *Journal of International Economics* 101, pp. 148–167.

Redding, Stephen J and David E Weinstein (2020). "Measuring Aggregate Price Indices with Taste Shocks: Theory and Evidence for CES Preferences". In: *The Quarterly Journal of Economics* 135.1, pp. 503–560.

Ricci, Luca Antonio (1999). "Economic geography and comparative advantage:: Agglomeration versus specialization". In: *European Economic Review* 43.2, pp. 357–377.

Romalis, John (2004). "Factor proportions and the structure of commodity trade". In: *American Economic Review* 94.1, pp. 67–97.

Rosenthal, Stuart S and William C Strange (2001). "The determinants of agglomeration". In: *Journal of urban economics* 50.2, pp. 191–229.

— (2004). "Evidence on the nature and sources of agglomeration economies". In: *Handbook of regional and urban economics*. Vol. 4. Elsevier, pp. 2119–2171.

— (2008). "The attenuation of human capital spillovers". In: *Journal of Urban Economics* 64.2, pp. 373–389.

Saiz, Albert (2010). "The geographic determinants of housing supply". In: *The Quarterly Journal of Economics* 125.3, pp. 1253–1296.

Sato, Kazuo (1976). "The ideal log-change index number". In: *The Review of Economics and Statistics*, pp. 223–228.

Schuberth, Christopher J (1968). *The geology of New York City and environs*. Published for the American Museum of Natural History [by] Natural History Press.

Shefer, Daniel (1973). "Localization economies in SMSA'S: a production function analysis". In: *Journal of Regional Science* 13.1, pp. 55–64.

Silva, JMC Santos and Silvana Tenreyro (2006). "The log of gravity". In: *The Review of Economics and statistics* 88.4, pp. 641–658.

Tomer, Adie and Joseph Kane (2014). "Mapping freight: the highly concentrated nature of goods trade in the United States". In: *Global Cities Initiative Working Paper*.

Van Marrewijk, Charles et al. (1997). "Producer services, comparative advantage, and international trade patterns". In: *Journal of International Economics* 42.1-2, pp. 195–220.

Vartia, Yrjö O (1976). "Ideal log-change index numbers". In: *Scandinavian Journal of statistics*, pp. 121–126.

Wilson, Steven G (2012). *Patterns of metropolitan and micropolitan population change: 2000 to 2010*. US Department of Commerce, Economics and Statistics Administration, US …

Appendices

A Appendix Figures and Tables

Table A1: State-Level Trade, Alternative Specifications

	(1)	(2)
	Dependent Variable is Total Exports (Thousands)	
η_j computed using:		
Employment, IV	0.612***	0.538***
	(0.145)	(0.199)
Establishments, IV	3.508***	3.241***
	(0.541)	(0.660)
Payroll, IV	0.335***	0.295***
	(0.0753)	(0.111)
Employment, OLS	0.788***	0.459***
	(0.236)	(0.172)
Establishments, OLS	2.650***	1.766***
	(0.462)	(0.401)
Payroll, OLS	0.504***	0.307***
	(0.169)	(0.117)
All Controls	No	Yes
State FE	Yes	Yes
Industry FE	Yes	Yes
Observations	4,182	4,132

Notes: The unit of observation is a state-by-sector pair. Each coefficient is an estimate from a separate regression. The coefficient of interest is the coefficient on an interaction between state-level population weighted density and sector-level density affinity using the strategy listed on the left side of the table. All reported specifications are Poisson pseudo-maximum likelihood estimates and include state and sector fixed effects, along with other controls listed at the bottom of each column. Standard errors clustered at the state level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

Table A2: Baseline Results Including Observations with No Exports

	(1)	(2)	(3)	(4)
	US State-Level		Country-Level	
Outcome Variable:	Exports	Exports (asinh)	Exports	Exports (asinh)
Model:	PML	OLS	PML	OLS
$D_i \times \eta_j$	0.612***	0.425**	0.456***	0.167**
	(0.145)	(0.169)	(0.111)	(0.0720)
State FE	Yes	Yes	-	-
Country FE	-	-	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	4,250	4,250	11,122	11,122
R-squared		0.709		0.823

Notes: The unit of observation is a state-industry pair (columns 1-2) or a country-industry pair (columns 3-4). . The coefficient of interest is the coefficient on an interaction between state- or country-level population weighted density and sector-level density affinity computed using the bedrock IV and city-level employment. In columns 1 and 3, the outcome variable is total exports and in columns 2 and 4, it is the inverse hyperbolic sine of total exports. Observations with zero exports are included in the estimation. Standard errors clustered at the state (columns 1-2) or country (columns 3-4) level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

Table A3: Country-Level Trade, Including Continent $\times$ Industry Fixed Effects

	(1)	(2)	(3)	(4)	(5)
	Dependent Variable is Total Exports from the Country-Sector				
	Panel A: Outcome Variable is Total Exports (Thousands), PML Model				
D_i x η_j	0.412**	0.403**	0.486***	0.380***	0.491***
	(0.191)	(0.181)	(0.163)	(0.0986)	(0.158)
	Panel B: Outcome Variable is log(Exports), OLS Model				
D_i x η_j	0.139**	0.186**	0.342***	0.179***	0.381***
	(0.0667)	(0.0770)	(0.0757)	(0.0627)	(0.0826)
R-Squared	0.837	0.820	0.821	0.837	0.822
Factor Intensity Controls	No	Yes	No	No	Yes
Country Level Controls	No	No	Yes	No	Yes
Industry Level Controls	No	No	No	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Industry x Continent FE	Yes	Yes	Yes	Yes	Yes
Countries	134	90	107	134	83
Observations	10,464	7,159	8,542	10,332	6,674

Notes: The unit of observation is a country-by-sector pair. The coefficient of interest is the coefficient on an interaction between country-level population weighted density and sector-level density affinity computed using the bedrock IV and city-level employment. Panel A reports Poisson pseudo-maximum likelihood estimates while Panel B reports OLS estimates. All specifications include country and continent-by-sector fixed effects, along with other controls listed at the bottom of each column. Standard errors clustered at the country level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

Table A4: Country-Level Trade, Alternative Specifications

	(1)	(2)	(3)	(4)
	Dependent Variable is Total Exports (Thousands)			
Sample:	Full Sample		Excluding countries with pop < 1 million	Excluding bottom 10% income
η_j computed using:				
Employment, IV	0.456***	0.774***	0.457***	0.456***
	(0.111)	(0.0720)	(0.111)	(0.111)
Establishments, IV	1.594***	1.836***	1.594***	1.594***
	(0.361)	(0.262)	(0.362)	(0.361)
Payroll, IV	0.248***	0.401***	0.248***	0.248***
	(0.0640)	(0.0408)	(0.0640)	(0.0640)
Employment, OLS	0.292**	0.135	0.292**	0.292**
	(0.147)	(0.0881)	(0.147)	(0.147)
Establishments, OLS	0.793**	0.480**	0.792**	0.792**
	(0.329)	(0.225)	(0.329)	(0.328)
Payroll, OLS	0.224**	0.105*	0.224**	0.224**
	(0.0985)	(0.0580)	(0.0987)	(0.0984)
All Controls	No	Yes	No	No
Country FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	10,464	6,674	9,277	9,515

Notes: All reported coefficients are from regressions at the country-by-sector level. Each coefficient is an estimate from a separate regression. The coefficient of interest is the coefficient on an interaction between country-level population weighted density and sector-level density affinity computed using the strategy listed on the left hand side of each row. All reported specifications are Poisson pseudo-maximum likelihood estimates and include country and sector fixed effects, along with other controls listed at the bottom of each column. Sample restrictions are noted in the column header. Standard errors clustered at the country level, are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

B Derivations and proofs

B.1 Housing market

Out of nominal disposable income Y_c, a worker in city c spends a constant share $p_{hc}h_c = \beta Y_c$ on the non-tradable good produced in city c, and a constant share $(1-\beta)Y_c = X_c$ on the basket of tradable sectors, with sub-shares $\alpha_j X_c = p_j c_j^c$ on each sector j. Each landowner faces a price p_{hc} for housing and a cost of P for the numeraire input. Each landowner then uses an amount $X_{hc}(\gamma) = \gamma(1-\xi)(\frac{p_{Hc}}{P})^{\frac{1}{\xi}}$ of tradable inputs, and aggregate housing supply is: $H^s(c) = B_c(\frac{p_{Hc}}{P})^{\frac{1-\xi}{\xi}}$. Equalizing supply and demand yields equilibrium housing prices in each city (equation 2.2):

$$p_{Hc}^{\frac{1}{\xi}} = \beta \frac{L_c Y_c}{B_c P^{\frac{\xi-1}{\xi}}}$$

Landowners in a city receive proceeds from real estate sales $\beta Y_c L_c$, out of which they spend $PX_{hc} = (1-\xi)\beta Y_c L_c$ on the final good, while accruing rents $r_c B_c = \xi\beta Y_c L_c$. r_c is defined as the Ricardian rent per unit of land, increasing in local population density and local disposable income. Using the spatial equilibrium condition and the fact that all land rents are fully rebated to local workers, we have:

$$Y_c = \bar{U} P^{1-\beta} p_{hc}^{\beta} = \bar{U} P^{1-\beta} (\frac{\beta L_c Y_c}{B_c P^{\frac{\xi-1}{\xi}}})^{\beta\xi} = \bar{U} P^{1-\beta\xi} (\beta \frac{L_c}{B_c} Y_c)^{\xi\beta}$$

and thus

$$w_c = P(1-\beta\xi)\bar{U}^{\frac{1}{1-\beta\xi}} \beta^{\frac{\beta\xi}{1-\beta\xi}} \frac{L_c}{B_c}^{\frac{\beta\xi}{1-\beta\xi}} \propto P \times D_c^{\frac{\beta\xi}{1-\beta\xi}}$$

B.2 Comparative advantage of cities

Cost minimization by consumers in any location d implies, in the absence of trade costs and using standard Eaton-Kortum algebra (Costinot, Donaldson, and Komunjer, 2011; Michaels, Rauch, and Redding, 2013):

$$p_{dj}(\omega) = \min\{p_{dcj}(j); c \in C\}$$

The probability that the unit cost is less than p for variety ω of good j produced in c is:

$$F_{jc}(p) = \mathbb{P}(\frac{w_c}{\tilde{z}} < p) = 1 - e^{-\left(\frac{\frac{w_c}{p}}{A_c D_c^{\tilde{\eta}_j}}\right)^{\theta}}$$

The probability that the minimal cost for variety ω of good j is less than p is thus:

$$F_j(p) = 1 - (\Pi_{c\in C}(1 - F_{jc}(p)) = 1 - e^{-\sum_{c'}(A_{c'} D_{c'}^{\tilde{\eta}_j})^{\theta} w_{c'}^{-\theta} p^{\theta}}$$

and the probability that location c is the lowest cost supplier for variety ω for location d is:

$$\mathbb{P}(\frac{w_c}{\tilde{z}_{jc}} \leq \min\{p_{dcj}(j); c \in C\}) = \frac{A_c D_c^{\tilde{\eta}_j})^{\theta} w_c^{-\theta}}{\sum_{c'}(A_{c'} D_{c'}^{\tilde{\eta}_j})^{\theta} w_{c'}^{-\theta}}$$

From the Fréchet distribution assumption and the Constant Elasticity of Substitution structure on demand allocation within good j, standard algebra then implies that the share of spending on varieties from location c in sector j must be equal across all locations d:[48]

$$\pi_{dcj} = \pi_{cj} = \frac{p_{cj} X_{dcj}}{X_{dj}} = \frac{(A_c D_c^{\tilde{\eta}_j})^{\theta} w_c^{-\theta}}{\sum_{c'} (A_{c'} D_{c'}^{\tilde{\eta}_j})^{\theta} w_{c'}^{-\theta}} \tag{B.1}$$

where π_{dcj} denotes spending in city d on goods in sector j produced in city c, equation 2.3 in the model.

B.3 Proposition 2.1

The derivation borrows from the definition of the unified price index in Redding and Weinstein (2020). Using spending shares 2.3, and the definition of the price index 2.5, we obtain:

$$\frac{\pi_{cj}}{\pi_{cj'}} = (\frac{P_j}{P_{j'}})^{\theta} \frac{(A_c D_c^{\tilde{\eta}_j})^{\theta} w_c^{-\theta}}{(A_c D_c^{\tilde{\eta}_{j'}})^{\theta} w_c^{-\theta}}$$

Re-expressing and taking logs on both sides:

$$\frac{\log(\frac{P_j}{P_{j'}}) - (\eta_{j'} - \eta_j)\log(D_c)}{\log(\frac{\pi_{cj}}{\pi_{cj'}})} = \frac{1}{\theta}$$

Multiplying both sides by $\pi_{cj} - \pi_{cj'}$, and using that in autarky $\sum_{c \in C} \pi_{cj} = 1$, summing over all cities c and rearranging yields the Sato-Vartia relative price:

$$\sum_{c \in C} \Big(\frac{\pi_{cj} - \pi_{cj'}}{\log(\pi_{cj}) - \log(\pi_{cj'})} \Big) \log(\frac{P_j}{P_{j'}}) = (\eta_{j'} - \eta_j) \sum_{c \in C} \Big(\frac{\pi_{cj} - \pi_{cj'}}{\log(\pi_{cj}) - \log(\pi_{cj'})} \Big) D_c$$

and, rearranging, we obtain the "Sato-Vartia" relative price expression in proposition 2.1.

B.4 Population density dispersion

Because equilibrium density D_c is increasing in A_c, at the country level, greater dispersion of A_c therefore leads to greater equilibrium D_c dispersion, as workers reallocate from lower to higher-A_c, higher-D_c locations. The population density distribution in an economy with more dispersed A_c is second-order stochastically dominated by the population density distribution in an economy with less dispersed A_c^* (see B).

Formally, suppose there are two countries, H and F, and define $H(d)$ as the share of the total

[48] Given the unbounded nature of the Fréchet distribution, the production structure does not lead to the full specialization of cities in the production of some sectors, which would make the exposition more involved by inducing censoring at the bottom of the sector-city employment density, without adding substantial insight in the model, given that we do not attempt a structural estimation of the parameters

population living in cities with density below d in H, the high-amenity-dispersion economy:

$$H(d) = \frac{\sum_{c \in C} L_c \mathbb{1}(\frac{L_c}{B_c} \leq d)}{\bar{L}}$$

Let $H^*(d)$ be its counterpart in F. Then, for any d, we have:

$$\int_0^d H(s)ds \geq \int_0^d H^*(s)ds$$

For any percentile p, there is a corresponding density threshold $H^-1(p) = d$. Let the Generalized Lorenz Curve (GLC) of population density be the function:

$$GLC(p) = \int_0^p H^{-1}(q)dq, \text{ for } p \in [0,1]$$

Integration by parts yields:

$$GLC(p) \leq GLC^*(p) \forall p$$

The GLC of density in a country with a higher dispersion of population lies strictly below that of a country with a more concentrated distribution of population. Note that we have, by a change of variable:

$$GLC(p) = \frac{\sum_{c \in C} \frac{(L_c)^2}{B_c} \mathbb{1}(H(\frac{L_c}{B_c}) \leq p)}{\bar{L}}$$

B.5 Proposition 2.2

We assume, as in Ramondo, Rodríguez-Clare, and Saborío-Rodríguez (2016), that iceberg trade costs are nil within a country, and symmetric (at the country-level) across any two locations in two different countries. The proof follows the structure of Ramondo, Rodríguez-Clare, and Saborío-Rodríguez (2016), extended to a case with many sectors.

We obtain a natural extension of equation 2.4 in a world of many countries, namely that for any city c in country i, the wage bill in sector j satisfies:

$$w_c L_{jc} = \alpha_j \sum_n \frac{(A_c D_c^{\tilde{\eta}_j})^\theta w_c^{-\theta} \tau_{in}^{-\theta}}{\sum_s \sum_{c' \in C_s} (A_{c'} D_{c'}^{\tilde{\eta}_j})^\theta w_{c'}^{-\theta} \tau_{sn}^{-\theta}} \sum_{d \in C_n} w_d L_d \tag{B.2}$$

We rewrite equation (B.2) as:

$$w_c = ((\frac{A_c D_c^{\tilde{\eta}_j})^\theta}{L_{jc}})^{\frac{1}{1+\theta}} \Delta_{ij} \tag{B.3}$$

where Δ_{ij} is a country-sector level variable indexing market access in sector j and country i:

$$\Delta_{ij}^{1+\theta} = \alpha_j \sum_n \frac{\tau_{in}^{-\theta}}{\sum_s \sum_{c' \in C_s} (A_{c'} D_{c'}^{\tilde{\eta}_j})^\theta w_{c'}^{-\theta} \tau_{sn}^{-\theta}} \sum_{d \in C_n} w_d L_d \tag{B.4}$$

We can use the fact that:

$$\sum_{d \in C_n} w_d L_d = \sum_{d \in C_n} \sum_k w_d L_{dk}$$

and equation (B.2) to re-express Δ_{ij}:

$$\Delta_{ij}^{1+\theta} = \alpha_j \sum_n \frac{\tau_{in}^{-\theta} \sum_{d \in C_n} \sum_k L_{kd} \left(\left(\frac{A_d D_d^{\tilde{\eta}_k})^\theta}{L_{dk}} \right)^{\frac{1}{1+\theta}} \Delta_{nk}}{\sum_s \sum_{c' \in C_s} (A_{c'} D_{c'}^{\tilde{\eta}_j})^\theta w_{c'}^{-\theta} \tau_{sn}^{-\theta}}$$

$$\Delta_{ij}^{1+\theta} = \alpha_j \sum_n \frac{\tau_{in}^{-\theta} \sum_k \Delta_{nk} L_{nk}^{\frac{\theta}{1+\theta}} \sum_{d \in C_n} (A_d D_d^{\tilde{\eta}_k})^{\frac{\theta}{1+\theta}} (\frac{L_{kd}}{L_{nk}})^{\frac{\theta}{1+\theta}}}{\sum_s \tau_{sn}^{-\theta} \Delta_{sj}^{-\theta} L_{js}^{\frac{\theta}{1+\theta}} \sum_{c' \in C_s} (A_{c'} D_{c'}^{\tilde{\eta}_j})^{\frac{\theta^2}{1+\theta}} (\frac{L_{jc'}}{L_{js}})^{\frac{\theta}{1+\theta}}} \tag{B.5}$$

where $L_{nk} = \sum_{d \in C_n} L_{dk}$. We define the following objects, that depend on the equilibrium distribution of population within a country:

$$T_{ij} = \Big(\sum_{c \in C_i} (A_c D_c^{\eta_j})^{\frac{\theta}{1+\theta}} (\frac{L_{jc}}{L_{ji}})^{\frac{\theta}{1+\theta}} \Big)^{1+\theta} \tag{B.6}$$

$$M_i = \sum_j \Delta_{ij} L_{ij}^{\frac{\theta}{1+\theta}} T_{ij}^{\frac{1}{1+\theta}} \tag{B.7}$$

Note then that we can re-express equation (B.5) as a system of equations in M_n, T_{sj}, Lsj, and Δ_{sj}:

$$\Delta_{ij}^{1+\theta} = \alpha_j \frac{\sum_n M_n \tau_{in}^{-\theta}}{\sum_s \tau_{is}^{-\theta} \Delta_{sj}^{-\theta} L_{sj}^{\frac{1}{1+\theta}} T_{sj}^{\frac{1}{1+\theta}}} \tag{B.8}$$

We make note that M_i corresponds to the total tradable wage bill in a country:

$$\sum_{c \in C_i} w_c L_c = \sum_{c \in C_i} \sum_j w_c L_{cj} = \sum_j \Delta_{ij} L_{ij}^{\frac{\theta}{1+\theta}} T_{ij}^{\frac{1}{1+\theta}} = M_i \tag{B.9}$$

We now use fact (B.9) to derive the bilateral export flows from country i to country n in sector j, by using the fact that exports of good j from any city $c \in C_i$ to any city $d \in C_n$ are given by:

$$x_{cdj} = \alpha_j w_d L_d \frac{(A_c D_c^{\tilde{\eta}_j})^\theta w_c^{-\theta} \tau_{in}^{-\theta}}{\sum_s \tau_{sn}^{-\theta} \sum_{c' \in C_s} (A_{c'} D_{c'}^{\tilde{\eta}_j})^\theta w_{c'}^{-\theta}}$$

Summing over cities, using (B.5), (B.7) and (B.6), yields, after rearranging:

$$X_{inj} = \sum_{c \in C_i} \sum_{d \in C_n} x_{cdj} = \alpha_j M_n \tau_{in}^{-\theta} \frac{\Delta_{ij}^{-\theta} T_{ij}^{\frac{1}{1+\theta}} L_{ij}^{\frac{\theta}{1+\theta}}}{\sum_s \Delta_{sj}^{-\theta} T_{sj}^{\frac{1}{1+\theta}} L_{sj}^{\frac{\theta}{1+\theta}}} \tag{B.10}$$

We next derive the average wage in country i and sector j:

$$w_{ij} = \frac{\sum_{c \in C_i} w_c L_{cj}}{\sum_{c \in C_i} L_{cj}}$$

by using equation (B.2), again summing over all cities in country i and using the same manipulations:

$$w_{ij} = \frac{\sum_n X_{inj}}{\sum_{c \in C_i} L_{cj}} = \frac{\sum_n X_{inj}}{L_{ij}} = \alpha_j \frac{\sum_n M_n \tau_{in}^{-\theta} \Delta_{ij}^{-\theta} T_{ij}^{\frac{1}{1+\theta}} L_{ij}^{-\frac{1}{1+\theta}}}{\sum_s \Delta_{sj}^{-\theta} T_{sj}^{\frac{1}{1+\theta}} L_{sj}^{\frac{\theta}{1+\theta}}} \tag{B.11}$$

and, using the system (B.8) and substituting, we obtain:

$$w_{ij} = \Delta_{ij} (\frac{T_{ij}}{L_{ij}})^{\frac{1}{1+\theta}} \tag{B.12}$$

Plugging (B.12) into equation (B.10) yields proposition 2.2.