Specializing in Cities:

Density and the Pattern of Trade*

Antoine Levy† and Jacob Moscona‡

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Abstract

Variation in urban density is a core determinant of patterns of productivity within countries, but does it also shape patterns of trade across countries? We develop a strategy to estimate the extent to which local population density boosts productivity in each industry. Combining these industry-level estimates with fine-grained global population data, we show that both US states and countries with more spatially concentrated ("denser") populations disproportionately export in density-loving sectors. The estimates are similar using an instrumental variables strategy that exploits countries' historical population distributions, and are driven by variation across sectors in the importance of R&D and collaborative/interactive tasks in production. We rationalize these findings with a model in which national export specialization emerges endogenously from the distribution of factors within countries, and show how location-level data can be aggregated to measure country-level specialization. Even conditional on aggregate endowments, the within-country spatial distribution of factors can explain a large share of patterns of trade.

JEL codes: F14, F16, R12, R13.

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†UC Berkeley Haas School of Business, email: levya@mit.edu; website: https://sites.google.com/view/antoine-levy

‡Harvard and J-PAL, email: moscona@fas.harvard.edu; website: https://scholar.harvard.edu/moscona

1. INTRODUCTION

Does the distribution of economic activity *within* countries affect the pattern of trade *across* countries? There is mounting evidence that the distribution of factors within countries—and in particular, urban development—is a key determinant of productivity.[1] Cities are engines of growth and ingenuity, boosting productivity and "magnify[ing] humanity's strengths" (Glaeser, 2011). Density eases search frictions in the labor and product markets, often attracts high-skilled and talented workers, provides large and local consumption markets, and spurs high-tech investment and innovation (e.g. Duranton and Puga, 2004; Moretti, 2012). Thus, urban agglomeration, as well as place-based policies designed to either spur or dampen it, has potentially large effects on regional welfare and inequality (e.g. Kline and Moretti, 2014; Hsieh and Moretti, 2019). While there is a large body of evidence showing that density affects *domestic* productivity and inequality, little is known about whether variation in density and the forms of production that it promotes affect patterns of *international* specialization and trade.

Most analyses of international comparative advantage treat countries as unified factor markets or equilibrium "points" in the production space. In this framework, domestic heterogeneity has little impact on international specialization. An early version of the hypothesis that domestic heterogeneity could affect patterns of trade dates back to Courant and Deardorff (1992), who argue that the "lumpiness" of factor distribution can affect a country's pattern of exports through the lens of a Heckscher-Ohlin model of factor abundance. A key source of domestic heterogeneity is variation across locations in population density. Case-study evidence suggests that density bolsters productivity differentially across industries, some of which end up located at the center of large agglomerations while others end up in smaller cities or sparsely populated areas (e.g., Nakamura, 1985; Rosenthal and Strange, 2004). Thus, the extent to which a country's population is concentrated in dense areas might affect not only local productivity, but also its international specialization.

This paper investigates the extent to which global variation in population density affects patterns of trade. We develop a new strategy to estimate the extent to which local density bolsters production in each industry. Combining this industry-level measure of density affinity with fine-grained data on the global distribution of population density, the key ingredient in urban productivity, we show that denser countries have a strong comparative advantage in density-loving sectors. The findings are largely driven by R&D intensive sectors that rely disproportionately on collaborative and interactive tasks, indicating that these are important intervening mechanisms. While a range of work has analyzed the effect of trade on domestic economic geography, these findings indicate that domestic economic geography also affects patterns of trade.[2]

Model. We first present a model that illustrates how the distribution of factors of production within countries—having a concentrated versus dispersed population—affects patterns of trade. In the

[1] For example, see Keesing and Sherk (1971), Ciccone and Hall (1996), Duranton and Puga (2004), and Moretti (2012) and more recently Davis and Dingel (2014) and Gaubert (2018).

[2] On the impact of trade shocks on domestic economic geography, see, for example: Autor, Dorn, and Hanson (2013), Caliendo, Dvorkin, and Parro (2015), Dix-Carneiro and Kovak (2015), Ramondo, Rodríguez-Clare, and Saborío-Rodríguez (2016), and Bakker (2018)

model, industries vary in the extent to which their productivity is boosted by local population density.[3] Countries are composed of locations endowed with different sector-neutral effective housing productivity. Endogenously, countries with more dispersion in the costs of building dense cities exhibit higher population-weighted density (i.e. a more spatially concentrated population) and have a comparative advantage in sectors that benefit relatively more from local agglomeration.

The theory provides three key insights. First, it motivates our empirical strategy and generates the regression equation used to estimate variation across industries in density affinity. In particular, it shows how location-level data on industry composition, combined with instruments for construction costs, can be used to estimate the key parameter that governs industry-level benefits from population density. Second, it generates a closed-form expression for country-by-industry level exports that is a function of location-specific productivities. While productivity in our model varies across locations, trade data are measured at the country-by-industry level; this aggregation result shows it is possible to link (unobservable) location-level productivity measures to (observable) country-level trade flows. Finally, the model generates a log-linear expression for exports, which is the regression equation we will estimate in the main part of our empirical analysis.

Measurement. To measure industry-level density affinity, we rely on a within-country prediction of the model and turn to detailed business location data across US urban areas from the County Business Patterns (CBP) to 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, and consistent with the source of density heterogeneity in our theoretical framework, we use subterranean geological instruments that shift local density by easing vertical construction costs and constraints. This generates causal estimates of the marginal impact of population 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 of significant variation in sector-specific sorting with respect to population density.

To measure population-weighted density across regions and countries, we rely on satellite-derived gridded population data from the *LandScan* database. *LandScan* incorporates comprehensive country-level census data on the distribution of population, and derives gridded population estimates using "smart interpolation," a multi-layered, dasymetric, spatial modeling approach. These data make it possible to directly calculate 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 worker in the country and measures the concentration of population across space.

Country-level estimates of population weighted density are displayed in the map in Figure 1. 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

[3] In the baseline model, we are agnostic about the source of this variation in agglomeration externalities across sectors.

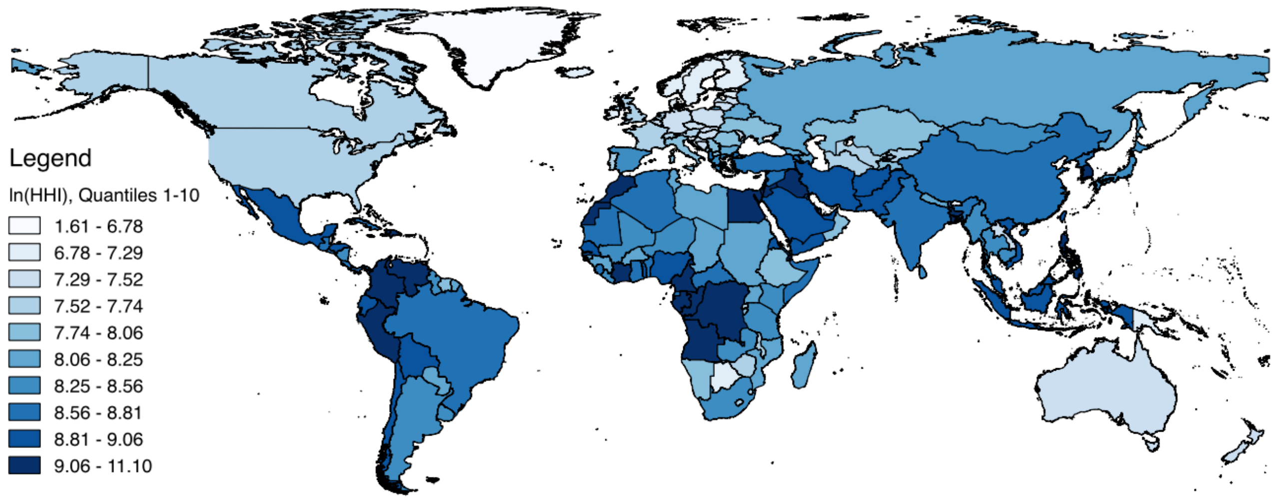


Figure 1: **Population weighted population density across countries (deciles)**. The figure is a map in which countries are color-coded based on their population-weighted density decile. Darker countries have higher population-weighted density.

pulp and paper product exports, one of the least density-loving sectors by our measure.[4] 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.[5] 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.

Results. Before turning to cross-country trade, we first focus on US states and investigate whether variation in density affect their export patterns across industries. 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.[6] While this result is a preliminary test of our hypothesis, it also validates our density affinity measures as supply side determinants of sector productivity, rather than the product of path dependence or demand-side forces. That is, our estimates of industry-level density affinity could have been driven by the fact that certain sectors are over-represented in certain US locations for historical or demand-side reasons; in this case, we would not expect them to correlate with productivity in more vs. less dense states. 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. We

[4]See Sweden exports in the Atlas of Economic Complexity for HS4 codes 4800-4810, NAICS code: 3221.

[5]Indeed, Djibouti, exhibits a strong revealed comparative advantage in semiconductors, one of the most density-loving sectors. See Djibouti exports in the Atlas of Economic Complexity for HS4 code: 8541, NAICS code: 3344.

[6]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.

show that 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 interacted 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 other covariates that might bias the relationship between density and exports. The results are also similar across a range of possible parameterizations of the density affinity measure; either including or excluding observations with zero trade; and using either OLS or Poisson-PML estimators.

To correct for potential reverse causality from trade flows to country-level density (see Krugman and Elizondo, 1996; Ades and Glaeser, 1995), we exploit differences in states' and countries' *historical* population distributions to construct instruments for modern density. Data on the historical distribution of cities and their populations were collected by Chandler (1987), and recently digitized by Reba, Reitsma, and Seto (2016). While patterns of trade might shape modern economic geography, it is unlikely that modern patterns of trade, which have evolved substantially in recent decades and particularly after World War II (Irwin, 2017), affect the *historical* distribution of cities within countries several hundred years ago. Using this strategy, the estimated effect of density on trade flows from our baseline results remains very similar. 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 underpinning the relationship between density affinity and trade. The goal of our density-affinity measure is to capture all possible effects of population density on industry-level productivity; therefore, the baseline measure does not take a stand on any particular mechanism. An important question, however, is which tangible industry-level characteristics drive our findings. Using data on the task content of production in each industry, we find that the relative importance of different tasks in more vs. less density-loving sectors is an important mechanism. Denser countries tend to have a comparative advantage in sectors that rely on more interactive and collaborative tasks, while less dense countries specialize in sectors that rely on interaction with machines. We also find evidence that the research and development (R&D) intensity and natural resource input share of each industry are additional intervening mechanisms, consistent with evidence that dense cities spur innovation (e.g. Duranton and Puga, 2001; Duranton and Puga, 2004; Moretti, 2012) and that only industries that do not rely on natural resources are free to locate in cities (Ades and Glaeser, 1995). Last, we rule out a range of additional potential mechanisms; for example, we find no evidence that the results are driven by industry-level skill or capital intensity, or reliance on service-sector inputs (e.g., Abdel-Rahman, 1994). Together, the mechanisms that we propose explain 65% of our baseline estimate, suggesting that additional and un-observed industry characteristics also contribute to industries' sorting and resulting international specialization.

Related Literature. This study is at the intersection of several areas of research. Our theoretical framework 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 aggregate factor abundance, but also from factor distribution within countries ("lumpiness"). The idea has been explored more recently by

Debaere (2004), Bernard, Robertson, and Schott (2010), and Brakman and Van Marrewijk (2013). We first provide a more general characterization of how within-country factor distributions can affect international comparative advantage. We then propose that the distribution of population density is one key source of "factor lumpiness" and document how, combined with variation in the casual effect of density on industry-level productivity, it affects patterns of trade.

This paper also builds on prior work studying the sorting of sectors across cities (e.g. Davis and Dingel, 2014; Gaubert, 2018) and the differential extent of agglomeration across sectors (Rosenthal and Strange, 2001; Holmes and Stevens, 2004; Ellison, Glaeser, and Kerr, 2010; Faggio, Silva, and Strange, 2017). We extend work in this area by developing a new strategy to estimate industry-specific sorting with respect to density and investigate the relationship between within-country sorting and cross-country trade.

We also extend a recent body of work studying the interplay between trade and within-country heterogeneity, often highlighting the effect of trade on within-country disparities (Autor, Dorn, and Hanson, 2013; Caliendo, Dvorkin, and Parro, 2015; Dix-Carneiro and Kovak, 2015). Some studies have highlighted the potential importance of within-country trade costs for international trade (Rauch, 1991; Coşar and Fajgelbaum, 2016; Ramondo, Rodríguez-Clare, and Saborío-Rodríguez, 2016; Sotelo, 2020; Fajgelbaum, 2022), and a large theoretical literature on international specialization arising from agglomeration, initiated by Krugman (1991), has given rise to studies of the interaction between domestic migration and traditional sources of comparative advantage (Van Marrewijk et al., 1997; Ricci, 1999; Pflüger and Tabuchi, 2016; Bakker, 2018; Pellegrina and Sotelo, 2021).

Finally, our empirical framework builds on existing analyses of non-traditional sources of comparative advantage; recent studies that rely on a similar framework include Nunn (2007), Costinot (2009), Chor (2010), Bombardini, Gallipoli, and Pupato (2012), and Cingano and Pinotti (2016).

Outline. 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. MODEL

We present a model that illustrates how within-country heterogeneity in density can affect a country's pattern of exports across industries. We show how two key ingredients — within-country heterogeneity in the cost of generating density ("housing productivity") and differential returns to agglomeration across industries — produce patterns of specialization both within and across countries. The model generates a closed form expression for country-by-sector exports and the exact regression equations that will guide our empirical analysis.

2.1 Environment

We study an economy in which countries exhibit domestic heterogeneity across inhabited locations, or "cities." A country i is composed of cities, indexed by $c \in C_i$, with equilibrium population L_c. The country's total population is $\bar{L}_i = \sum_c L_c$; workers are mobile across regions within a country, but not across borders. The economy consists of J tradable sectors indexed by $j = 1, ..., J$, as well as a non-tradable good specific to each city, "housing" (H_c). Tradable goods can be shipped from city c to city d, with iceberg trade costs $\tau_{c,d} \geq 1$.

2.1.1 Consumption

Workers in city c earn nominal wage w_c, and derive utility U_c from the consumption of housing and a Cobb-Douglas basket of tradable sectors:

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

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, with elasticity σ.

Assuming free within-country trade ($\tau_{c,c'} = 1$ if $c, c' \in C_i$), the price level in each tradable sector j is common across cities and equal to: $p_j = \big(\int_0^1 p_j(\omega)^{1-\sigma} dj\big)^{\frac{1}{1-\sigma}}$. The aggregate tradable price level in the country P is $P = \Pi_{j=1}^{J} p_j^{\alpha_j}$ and we define the price of housing in city c as p_{hc}. We assume that $\sigma > 1$, so that within each sector, varieties are substitutes. In a spatial equilibrium, utility for a worker with income Y_c is equalized across cities:

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

While locations are assumed to have equal land area, they differ in productivity in the housing sector so that the *effective* supply of land in location c is fixed at B_c, the key local congestion force in the model and source of heterogeneity across locations.[7] Equalizing housing supply and demand yields equilibrium housing prices in each city:

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

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, the disposable income Y_c of a worker in city c: $Y_c = w_c + T_c = \frac{w_c}{1-\beta\xi}$, where w_c is the wage in c. Combining this expression with

[7] As in Gaubert (2018), atomistic landowners in city produce housing using land and tradable goods. For simplicity, we assume that they divide spending on final goods used as inputs in housing production across the J industreis in the same manner as workers; alternatively, one could model the other, non-location-specific input into housing production as migrant labor living at zero cost on rural land and only consuming the final good. The details are given in Appendix B.

(2.1) yields an expression for city-level wages:

$$w_c = P(1-\beta\xi)\bar{U}^{\frac{1}{1-\beta\xi}}\beta^{\frac{\beta\xi}{1-\beta\xi}}\frac{L_c}{B_c}^{\frac{\beta\xi}{1-\beta\xi}} \tag{2.3}$$

2.1.2 Production

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

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

A producer draws a Ricardian productivity parameter in each variety of good j in location c, $\tilde{A}_{jc}$, from a Fréchet distribution, with cumulative distribution function:[8]

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

The unit cost of production for variety ω in sector j and location c is then $\frac{w_c}{\tilde{A}_{cj}}$.

Here we introduce the key assumption of the model: the relationship between population density and industry-level productivity in a location. We assume that the scale of a sector's productivity in city c depends on (i) the city's equilibrium population density D_c, and (ii) the extent to which each sector benefits from local density, $\tilde{\eta}_j$. In particular, we let: $A_{jc} = D_c^{\tilde{\eta}_j}$.

The sector-specific "density elasticity," $\tilde{\eta}_j$, mediates the relationship between density and sector-specific productivity. Variation in $\tilde{\eta}_j$ across sectors—the extent to which industry productivity benefits from local agglomeration—will be central to our empirical analysis, and is the key modeling assumption. The idea that industries could benefit differentially from urban density has been argued in prior work (e.g. Rosenthal and Strange, 2004; Faggio, Silva, and Strange, 2017) and is corroborated by our empirical estimates in Section 3.[9]

2.1.3 Trade across cities

Under the maintained assumption of zero trade costs within a country, cost minimization by consumers in any location d 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:

$$\pi_{dcj} = \pi_{cj} = \frac{p_{cj}X_{dcj}}{X_{dj}} = \frac{(D_c^{\tilde{\eta}_j})^{\theta}w_c^{-\theta}}{\sum_{c'}(D_{c'}^{\tilde{\eta}_j})^{\theta}w_{c'}^{-\theta}} \tag{2.4}$$

[8] We assume the distribution has shape parameter $\theta > \sigma - 1$. θ, 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.

[9] We remain agnostic here about the specific source of sector-specific density affinity; in section 4.5, we explore potential determinants of $\tilde{\eta}_j$.

where π_{dcj} denotes spending in city d on goods in sector j produced in city c.[10]

2.1.4 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.[11] This generates the tradable goods market clearing condition:

$$w_c L_{jc} = \alpha_j \frac{(A_c D_c^{\tilde{\eta}_j})^\theta w_c^{-\theta}}{\sum_{c'} (A_{c'} D_{c'}^{\tilde{\eta}_j})^\theta w_{c'}^{-\theta}} \sum_d w_d L_d \tag{2.5}$$

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:[12]

$$p_j \propto \big[\sum_{c'} (A_{c'} D_{c'}^{\tilde{\eta}_j})^\theta w_{c'}^{-\theta}\big]^{-\frac{1}{\theta}} \propto \big[\sum_{c'} (A_{c'} D_{c'}^{\tilde{\eta}_j - \frac{\beta\xi}{1-\beta\xi}})^\theta\big]^{-\frac{1}{\theta}} \tag{2.6}$$

Trade balance requires that tradable spending from all locations on all goods produced in location c is equivalent to the total wage bill in location c:

$$w_c L_c = \sum_j \sum_d \pi_{dcj} \alpha_j (1-\beta\xi) Y_d L_d = \sum_j \alpha_j \pi_{cj} \sum_d w_d L_d = \sum_d w_d L_d \sum_j \alpha_j \pi_{cj} \tag{2.7}$$

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:

$$\frac{L_{jc}}{L_{j'c}} = \frac{\alpha_j}{\alpha_{j'}} (\frac{p_j}{p_{j'}})^\theta D_c^{\theta(\tilde{\eta}_j - \tilde{\eta}_{j'})} \tag{2.8}$$

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

$$\sum_j L_{jc} = L_c \tag{2.9}$$

The labor market clears for the country as a whole:

$$\sum_c L_c = \sum_c \sum_j L_{jc} = \bar{L} \tag{2.10}$$

[10] This expression is derived in Appendix B and 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.

[11] 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 $\alpha_j(1-\beta\xi)Y_d L_d \pi_{jc} = \alpha_j w_d L_d \pi_{jc}$.

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

We 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; housing prices satisfy (2.2); trade shares satisfy (2.4); wages satisfy (2.5) and (2.7); tradable prices satisfy (2.6); and labor allocations satisfy (2.8), (2.9) and (2.10).*

2.2 Implications

2.2.1 Within-Country Specialization

We now investigate the domestic sorting of production generated by the model. Double-differencing spending shares (2.4) from any location d across two goods j and j' and locations c and c' yields:

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

The absolute unit cost of production is increasing in density D_c; however, due to the need to compensate workers with higher nominal wages, as D_c increases costs increase relatively faster in sectors with lower $\tilde{\eta}_j$. Denser cities thus have a comparative advantage in sectors that benefit more from agglomeration. Immediately, this implies:

Lemma 1. *The share of the labor force employed in higher $\tilde{\eta}_j$ sectors is relatively larger in denser cities:*

$$\left(\frac{L_{jc}}{L_{j'c}}\right)/\left(\frac{L_{jc'}}{L_{j'c'}}\right) = \left(\frac{w_c L_{jc}}{w_c L_{j'c}}\right)/\left(\frac{w_{c'} L_{jc'}}{w_{c'} L_{j'c'}}\right) = \left(\frac{\pi_{jc}}{\pi_{j'c}}\right)/\left(\frac{\pi_{jc'}}{\pi_{j'c'}}\right) = \frac{D_c}{D_{c'}}^{\theta(\tilde{\eta}_j - \tilde{\eta}_{j'})} \tag{2.12}$$

A log-linear expression for L_{jc} then takes the form:

$$\log(L_{jc}) = \kappa_c + \lambda_j + \tilde{\eta}_j \theta \times \log(D_C) \tag{2.13}$$

Thus, within countries, employment in more density-loving sectors (high-$\tilde{\eta}_j$) disproportionately takes place in denser locations.[13] In our empirical analysis, we use Equation 2.13 to estimate a value for $\eta_j = \tilde{\eta}_j \theta$ for each sector j (see Section 3.3). Moreover, motivated by the model mechanism in which exogenous variation in housing productivity, B_c is the main supply-side shifter of local density, we use geological instruments for $\log(D_C)$ that shift construction costs independently from local demand conditions when we estimate (2.13). Equation 2.3 serves as our first-stage identifying variation in local population density. Our estimates of the η_j of each sector is the key industry-level variation in our main empirical analysis.

[13]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.

2.2.2 Cross-Country Specialization

Next, we turn to the model's implications for international trade. Conditional on a fixed distribution of location-level population, the closed economy price index in sector j relative to j' is lower when $\tilde{\eta}_j > \tilde{\eta}_{j'}$. Stronger agglomeration forces in a sector increase productivity in all cities, and lower equilibrium prices for any distribution of density. A more dispersed population implies relatively more variation in sourcing prices across producing locations for higher $\tilde{\eta}_j$ sectors. Substitution across sourcing cities 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 $\tilde{\eta}_j$ 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 J 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.

To make the results as stark as possible, we assume all countries have the same total population $\bar{L} = L_i$. We let land area 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, $\tilde{w}_{ij}$as the average wage in sector j in country i, and M_i as country i's aggregate wage bill. We can then state the following aggregation result:

Proposition 1. *Exports of sector j from country i to country n are given by*

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

where the country level productivity parameter is:

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

Moreover, the aggregate wage bill can be expressed as:

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

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

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

Proof. See Appendix B. □

The country-by-sector composite productivity shifter T_{ij} is relatively higher for density-loving (high $\tilde{\eta}_j$) goods in countries with a more spatially concentrated population (which are, all else equal, countries with more variance in sector-neutral housing productivity B_c). Even though all countries have the same total population, the within-country population distribution drives patterns of cross-country trade. This is made clear by the following corollary:

Corollary 1. *A second-order approximation to the T_{ij} country-by-sector productivity shifter yields that it is increasing in the product of the within-country variance of density and a function of the density affinity:*

$$T_{ij} \simeq \eta_j(\eta_j - 1) \sum_{c \in C_i} (\tilde{d}_c)^2$$

For $\eta_j \geq \bar{\eta}$, this country-by-sector productivity shifter is increasing in an interaction term between sectoral density affinity η_j and within-country density population-weighted density $D_i = \sum_{c \in C_i} (\tilde{d}_c)^2$, so that a log-linear approximation to country-level exports can be expressed as:

$$\log(X)_{ij} = \log(\sum_n X_{inj}) \simeq \xi_i + \nu_j + \beta D_i \times \eta_j + o(X) \tag{2.14}$$

Proof. See Appendix B. □

Conditional on fixed effects at the country and industry-level, exports from country i in industry j are increasing in the interaction between country-level population weighted density and industry-level density affinity. As our main test of the theory and hypothesis, in our empirical analysis we will use Equation 2.14 to estimate β. We will estimate η_j using the empirical analog to Equation 2.13 and we will measure population-weighted density D_i for each country using global grid cell level population estimates.

2.2.3 From Theory to Measurement: Population-Weighted Density

From the equilibrium definition in Section 2.1, the population distribution can be expressed as the labor market clearing (2.10), along with a system of C equations that depend on city-level population-weighted density, city-level population weighted amenities, and a constant term:

$$L_c D_c^{\frac{\beta\xi}{1-\beta\xi}} = \sum_j \alpha_j \frac{(A_c D_c^{\tilde{\eta}_j - \frac{\beta\xi}{1-\beta\xi}})^\theta}{\sum_{c'} (A_{c'} D_{c'}^{\tilde{\eta}_j - \frac{\beta\xi}{1-\beta\xi}})^\theta} \sum_d L_d D_d^{\frac{\beta\xi}{1-\beta\xi}} \tag{2.15}$$

There is a unique equilibrium when the maximum sector-level density elasticity ($\tilde{\eta}_{max} = \max_j \tilde{\eta}_j > 0$) is "not too large" relative to the share of land in housing production (ξ); this makes congestion forces strong enough to offset multiple equilibria.[14]

[14] The proof is analogous to Redding (2016). For a sufficiently small $\tilde{\eta}_{max}$, 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 $\tilde{\eta}_j$'s, reinforce this phenomenon, but do not offset it if they are small enough.

At the country level a greater dispersion of B_c leads to greater equilibrium D_c dispersion. In particular, the population density distribution in an economy with more dispersed B_c is second-order stochastically dominated by the population density distribution in an economy with less dispersed A_c^* (see Appendix B), and we will observe the footprint of productivity dispersion across cities in the dispersion (or concentration) of population. In the special case where total population is held constant, which we ensure in our empirical analysis by controlling for total population and land area, greater dispersion in the exogenous B_c's can be mapped directly to greater country-level "population-weighted density" (directly given by the variance of population across equally-sized locations):

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

which captures the local population density experienced by the average worker in the economy. While, as discussed below, there are several intuitively appealing features of using this as our county-level parameterization of population concentration, the model also indicates that it is the observable consequence of dispersion (or lack thereof) of the primitive productivity distribution. This is the measure we estimate next in Section 3, and use as our main measure of population concentration ("density") in Section 4.1.

3. Measurement

In this section, we first describe the main data sources used in the empirical analysis. We then describe how we measure both country-level population-weighted density (D_i) and industry-level density affinity (η_j).

3.1 Data Sources

Economic Geography. 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 suppression.[15] We use these data as part of our strategy to estimate industry-level density affinity.

To construct instruments for local density, we compile data on distance to subterranean bedrock for all US CBSAs. Raster data displaying the distance to bedrock of each 250m grid cell in the US, which we use to construct the instruments, are from the International Soil Reference and Information Centre (ISRIC) *SoilGrid* project.[16]

We also compile data on a range of industry-level characteristics to use as control variables in our main analysis. From the latest available year in the NBER-CES Manufacturing Industry Database, we collect industry-level information on capital intensity, the labor share, and average wages. We also

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

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

compile data from the American Community Survey to control for the age and gender breakdown, as well as detailed measures of the educational attainment of the workforce in each industry.

Density. Spatial data on global population density are obtained from the *LandScan* Database.[17] 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.[18] The resulting population count is an ambient or average day/night population count. We use the the *LandScan* data to compute state and country-level estimates of population-weighted density. We also replicate our results using several alternative sources of gridded poulation data, including the Global Human Settlement Layer, the Gridded Population of the World, and the WorldPop Project. For our instrumental variables analysis, we also rely on new measures of historical population and city size distributions constructed from data sets recently introduced by Reba, Reitsma, and Seto (2016) and Fang and Jawitz (2018).

Trade. US State-level international exports from 2016 are collected from the US Census Bureau's USATradeonline database.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. We map HS4 industries to NAICS-4 industries using the crosswalk developed by Pierce and Schott (2012).

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 information 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.

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

[18] 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*

3.2 Estimating State and Country Level Density

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. 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.[19]

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 and rural areas, D_i will be small. Figure 1 in the Introduction displays the variation in our measure of country-level density across countries.

Figure 2 plots the distribution of D_i across US states. While, intuitively, populous and urban states like New York and California have high measures of D_i, so do Massachusetts and Washington; large states like Texas and Florida, with their large but more sprawling cities, are in the middle of the distribution. As with the country-level figure, one lesson from this map is that traditional measures of urbanization or average density fail to capture variation in experienced density, the key mechanism behind urban spillovers. For example, while the experienced density of individuals in New York State is substantially higher than Texas or Florida, the urbanization rate in the 2010 census was comparable in all three states (87.9, 84.7, and 91.2 respectively).

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. 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. Thus, none of our results are driven by differences between agriculture and non-agriculture, or any other broader sectors of the economy.

We compute a "density-elasticity" for each industry by estimating the following empirical analog of the the model's Equation (2.13):

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

where c indexes cities and j indexes sectors. $\log(L_{cj})$ is the (log of the) number of employees in industry j and location (city) c. α_c and γ_j are city and sector fixed-effects, respectively. D_c is population

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

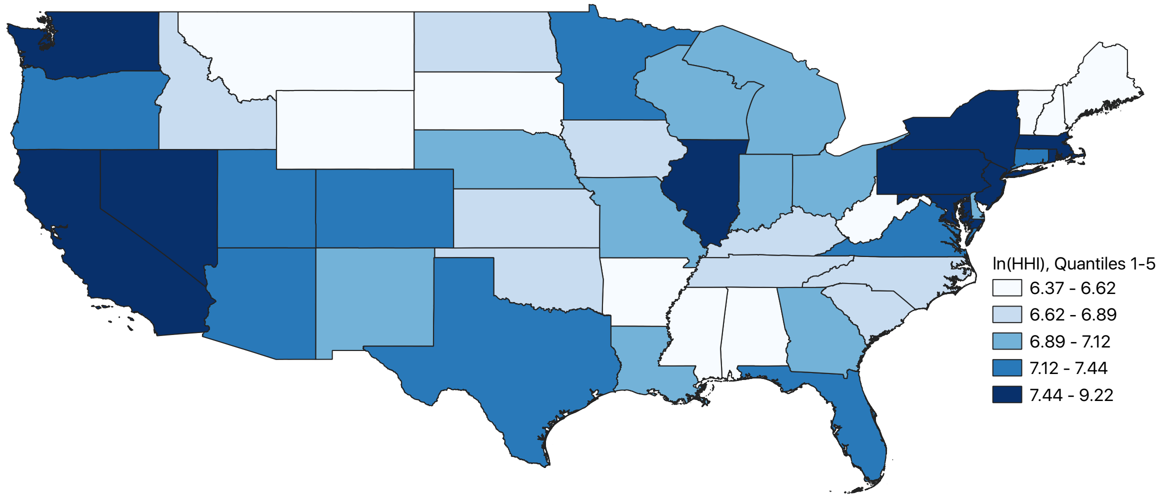


Figure 2: **Population weighted population density across US states.** The figure is a map in which US states are color-coded based on their population-weighted density quintile. Darker shaded states have higher population-weighted density.

density at the level of the Core Based Statistical Area (CBSA), our empirical analog of the "cities" in the model, and $\mathbb{I}_j$ 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. These elasticities capture the extent to which each industry tends to be more or less represented in denser locations.

We first estimate Equation (3.1) using OLS and report the ten sectors with the highest and lowest density elasticities in Panel A of Table 1. 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 purely correlational estimates. 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. Subterranean geology affects ease of vertical construction, and hence potential population density, but is unlikely to independently affect other city-level characteristics. Our instrument is the (log of the) average distance of each CBSA to subterranean bedrock. 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 (e.g. Schuberth, 1968; Landau and Condit, 1999).[20] By exogenously shifting density, we estimate the response of industry specialization to density alone, capturing the causal effect of a marginal change in city-level density on industry-level production.

The correlation between CBSA-level density and the log of the distance to bedrock is shown in Figure 3. 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 subterranean bedrock systematically shifts equilibrium population density. The necessary identi-

[20]Past research has made 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; Combes et al., 2010; Duranton and Turner, 2018).

Table 1: The Ten Most and Least Density Elastic Industries: OLS and IV Estimates

(1)	(2)	(3)	(4)
	Top Ten Industries by Density Elasticity		*Bottom Ten Industries by Density Elasticity*
NAICS Code	Industry Name	NAICS Code	Industry Name
	Panel A: OLS Estimates		
3222	Converted Paper Product Manufacturing	3117	Seafood Product Preparation and Packaging
3345	Navigational, Measuring, Electromed., and Cntrl Instruments	3131	Fiber, Yarn, and Thread Mills
3261	Plastics Product Manufacturing	3112	Grain and Oilseed Milling
3344	Semiconductor and Other Elec. Comp. Manufacturing	3365	Railroad Rolling Stock Manufacturing
3363	Motor Vehicle Parts Manufacturing	3162	Footwear Manufacturing
3339	Other General Purpose Machinery Manufacturing	3361	Motor Vehicle Manufacturing
3342	Communications Equipment Manufacturing	3221	Pulp, Paper, and Paperboard Mills
3321	Forging and Stamping	3161	Leather and Hide Tanning and Finishing
3255	Paint, Coating, and Adhesive Manufacturing	3211	Sawmills and Wood Preservation
3353	Electrical Equipment Manufacturing	3122	Tobacco Manufacturing
	Panel B: IV Estimates (Bedrock Instrument)		
3117	Seafood Product Preparation and Packaging	3361	Motor Vehicle Manufacturing
3151	Apparel Knitting Mills	3331	Ag., Construction, and Mining Machinery Manufacturing
3342	Communications Equipment Manufacturing	3112	Grain and Oilseed Milling
3121	Beverage Manufacturing	3325	Hardware Manufacturing
3219	Other Wood Product Manufacturing	3221	Pulp, Paper, and Paperboard Mills
3132	Fabric Mills	3339	Other General Purpose Machinery Manufacturing
3371	Household and Institutional Furniture and Cabinet Manuf.	3111	Animal Food Manufacturing
3344	Semiconductor and Other Elec. Comp. Manufacturing	3274	Lime and Gypsum Product Manufacturing
3113	Sugar and Confectionery Product Manufacturing	3114	Fruit and Veg. Preserving and Specialty Food Manuf.
3211	Sawmills and Wood Preservation	3346	Manuf. and Reproducing Magnetic and Optical Media

fication assumption is that distance to subterranean bedrock only affects industry sorting through its impact on ease of construction and hence population density.[21]

We then generate IV-2SLS estimates η_j using the interaction between industry-level indicators ($\mathbb{I}_j$) and (log of) distance to bedrock as the instruments. Industries with the highest and lowest IV estimates of η_j are listed Panel B of Table 1. As a robustness check, since some of the CBP employment data are imputed, we also estimate versions of η_j for each sector using city-by-sector level data on the number of establishments; below, we show all results are very similar using this alternative measure.[22]

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 industries that are skill-intensive (e.g. Semi-conductor and Other Electronic Component Manufacturing) and industries that are not skill-intensive (e.g. Beverege Manufactur-

[21] 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.). These estimates and their possible parameterizations are available upon request.

[22] Equation 2.13 of the model, the estimating equation in this section, also holds when the dependent variable is log of city-by-industry establishments, so long as there are decreasing returns to scale at the establishment level.

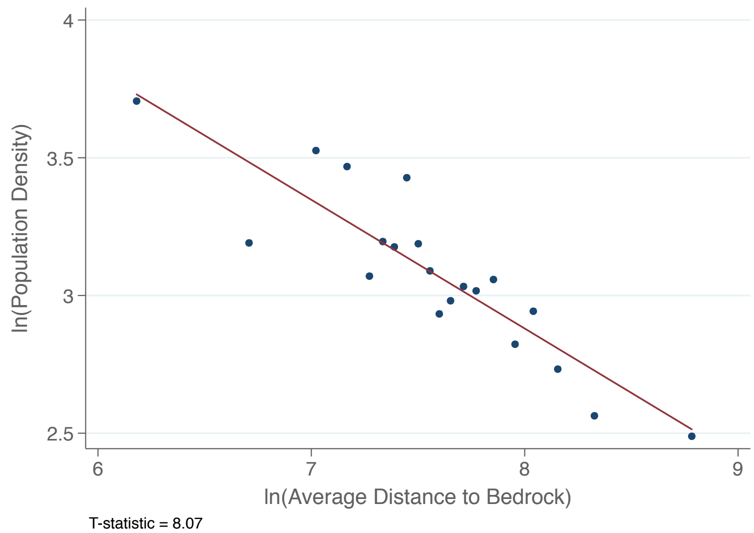


Figure 3: **Distance to Bedrock and Population Density.** The figure is a binned scatter plot. It reports the correlation between log of distance to bedrock and log of population density at the CBSA level. The t-statistic is 8.07.

ing). The same is true for capital intensity.[23]

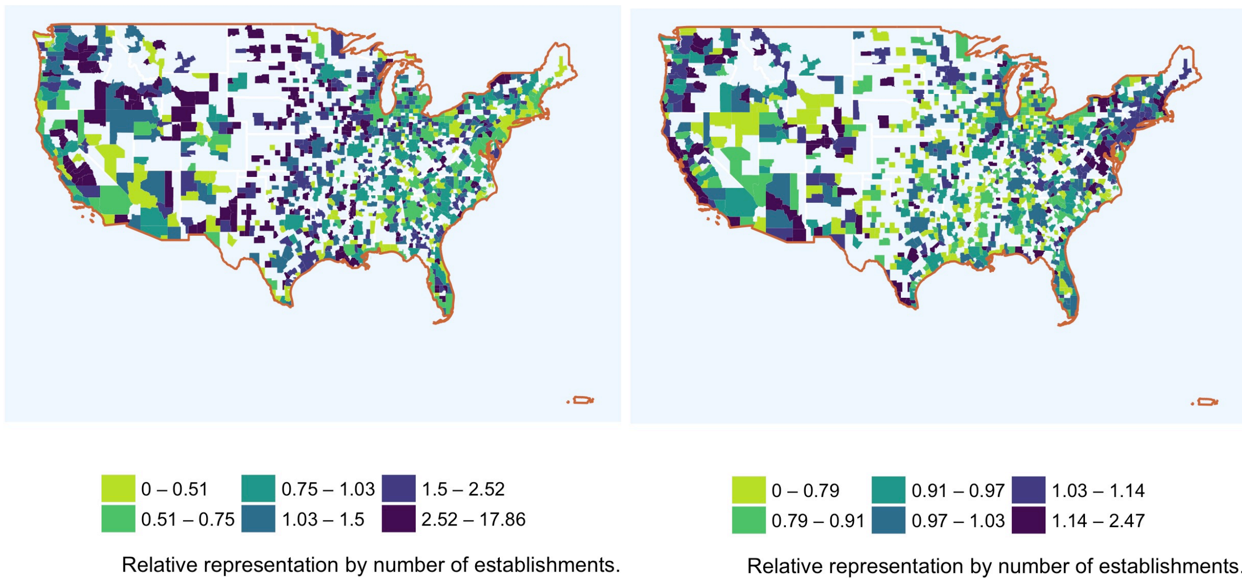
Figure 4 shows the distribution of establishments in the top and bottom ten sectors listed in Panel B of Table 1 across the US. For each CBSA c and sector j, we compute:

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

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.

Figure 4a shows the distribution of low-η_j sectors; they are disproportionately located in Upper Midwest and Central and Northern Plains regions (purple-shaded regions). Figure 4b shows the distribution of high-η_j sectors; they 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 states as well–almost all states have locations in which both high and low η_j sectors are disproportionately produced.

[23]Moreover, motor vehicle manufacturing, for example, the top of Nunn (2007)'s list of contract intensive industries, but are at opposite ends of our list. The same is true of Manufacturing and Reproducing Magnetic and Optical Media.



(a) Low η_j Sectors

(b) High η_j Sectors

Figure 4: **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

4. Results: Density and the Pattern of Trade

This section presents our main findings that denser states and countries have a comparative advantage in density-loving sectors. We first introduce our main estimating framework, and then present our baseline state-by-sector and country-by-sector results. Next, we present instrumental variables estimates that corroborate the baseline findings, and investigate the potential mechanisms that underpin the main result.

4.1 Estimation Framework

To investigate whether population-weighted density, D_i, is a systematic source of comparative advantage, our main empirical estimating equation is:

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

where i indexes states or countries and j indexes sectors. This is the empirical analog of Equation 2.14 from the model. The unit of observation is a country (or state)-by-sector pair, and 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 industry-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. 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 and a log-transformed dependent variable.[24]

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.[25] Since all specifications include country (or state) and industry fixed effects, any characteristics that vary only across countries or industries are fully absorbed. In order to probe the robustness of our estimates of β and make sure they are not biased by some omitted characteristic, we report estimates that include a range of controls that vary at the state-by-sector or country-by-sector level (X'_{ij}), described in detail below. In Section 4.4 we propose an instrumental variables strategy that exploits variation in historical population and city size distributions as shifters of modern population density.

4.2 US State-Level Results

We first present estimates of Equation 4.1 across US states. 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. Moreover, while many models of international trade consider the entire US as a single "point," different parts of the US specialize in vastly different industries (see e.g. Irwin (2017) for a long-term perspective). Thus, as a preliminary test of our hypothesis that regions with greater population-weighted density specialize in the export of density-loving industries, we present results at the US state-by-industry level.[26]

Panel A of Table 2 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 β 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 hand side (along with state and industry fixed effects).

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 increases the dependent variable by 0.139 standard deviations. Next, we probe the sensitivity of this

[24] 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.

[25] 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).

[26] 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.

Table 2: State-Level Results: Density and Comparative Advantage

	(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

baseline finding.

Sensitivity: Additional Controls. The remaining specifications in Table 2 investigate the robustness of this baseline result to the inclusion of additional controls. In order to rule out the possibility that the results are driven by state-level differences in education and comparative advantage in high-skill industries (Davis and Dingel, 2014), 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 that may be correlated with D_i. 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 baseline estimate. However, the coefficient of interest remains very similar after including these 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.

Sensitivity: Measurement. The results are also not sensitive slight variations in our strategy to estimate the η_j of each sector or trade values. In columns 6-7 of Table 2 we repeat the specifications from columns 1 and 5—the specifications without any controls and the specification with all controls—and construct the η_j using industry-level establishment data rather than employment data. Reassuringly, in both columns 6 and 7 and in both Panels A and B, our coefficient of interest is positive and highly significant. More generally, Table A1 reports estimates from a series of additional specifications; each reported coefficient in Table A1 is estimated from a separate regression. The results are very similar if we use the versions of η_j estimated using OLS (instead of IV) and using city-level data on payroll, rather than employment or establishments. All findings are also similar if we exclude state-industry pairs with zero exports (Table A2).

4.3 Country-Level Estimates

We now turn to the main result 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 pseudo-maximum likelihood estimates while Panel B reports OLS estimates. 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 have a revealed comparative advantage in density-loving sectors.

In column 2, we control directly for traditional determinants of comparative advantage, including capital and skill intensity (Romalis, 2004).[27] 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.

These estimates indicate that the distribution of population within countries is a potentially important determinant of comparative advantage and patterns of trade. Our point estimate from column 2, when factor endowment controls are included, implies that a one standard deviation increase in the density interaction increases the outcome variable by 0.113 standard deviations. This is slightly

[27] 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.

Table 3: Country-Level Results: Density and Comparative Advantage

	(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.

larger in magnitude than the coefficient on the capital interaction, which implies a standardized beta coefficient of 0.109.[28] As we include additional controls (below), the magnitude of the coefficient of interest rises and implies a beta coefficient on the density interaction of 0.276.

Sensitivity: Additional Controls. The remaining columns of Table 3 probe the sensitivity of the estimates to the inclusion of additional controls. 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. In Table A3 we reproduce our findings after including continent-by-industry fixed effects; this specification flexibly controls for differences in *industry-specific* productivity and trade in

[28]Reassuringly, 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.

different parts of the world, and again the results are very similar.

Next, we investigate the robustness of the result to the inclusion of industry-level controls. 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, suggesting that our findings are not driven by standard determinants of comparative advantage or other measurable country or industry level characteristics.

Sensitivity: Measurement. We next investigate whether the results are sensitive to our measurement strategies. Table A5 documents that the results are not sensitive to the use of our alternative estimates of η_j, estimated using establishment or payroll data. The estimates are also very similar after excluding countries in the bottom 10% of the income and population distributions. 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. As in the case of our state-level estimates, the findings are also very similar if we include country-industry pairs with zero exports (Table A2).

Finally, we show that the results are robust to using alternative sources of of population data. While our baseline results rely on the Landscan database, other organizations, using slightly different methodologies to account for sparse data in parts of the world, also produce gridded global population estimates. Alternative population databases include the Global Human Settlement Layer, the Gridded Population of the World, and the WorldPop Project. We measure country-level population density using each of these data sets and re-estimate our baseline results after computing the independent variable of interest from each data source. These results are presented in Table A4 and our findings are very similar across population data sources.[29]

4.4 Endogeneity: Instrumental Variables Estimates

This section proposes an instrument for 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 state or 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 that density is 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 a state or country's *historical* population distribution to construct instruments for the population distribution 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

[29]We thank Richard Delome for pointing this out to us, and rely on his version of the data sets which can be found here: https://github.com/richarddelome/density_metrics/blob/master/README.md?fbclid=IwAR1KQ1KJB5FeLW45R0HXA63gfET9XT8jS7ecmaQ9h-B7LmPYuJW1ODAdK98.

World War II (e.g. Irwin, 2017), have a direct effect on the population distribution in in 1900.

The ideal instrument for our purposes would be a historical measure of population weighted density, analogous to our contemporary measure. For each US state, we construct exactly such a measure using grid cell level estimates of the historical US population distribution presented in Fang and Jawitz (2018).[30] Using this gridded data set, we compute the population weighted density of each US state in 1900 (D_i^{1900}).[31] The first stage estimating equation is thus:

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

where we hypothesize that $\xi >> 0$. This would indicate that historical population-weighted density is a strong predictor of state-level population-weighted density today.

Our state-level IV-2SLS estimate of Equation 4.1, in which the first stage estimating equation is (4.2), is presented in column 1 of Table 4. In column 4, we report the version of the estimate when η_j is estimated from data on establishments. The IV-2SLS coefficient estimates are positive, statistically significant, and similar in magnitude to the OLS estimates, suggesting that our state-level findings are not driven by reverse causality. Moreover, the first stage relationship is also strong; the Kleibergen-Paap first stage F-statistic is 25.159.

While it is possible to directly estimate the historical population weighted density of each US state, to our knowledge this is not possible at the country level. Therefore, we need an alternative strategy to construct the country-level instruments. In order to adapt the logic of our identification strategy to the country-level analysis, we determine 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).[32] Intuitively, high D_i corresponds to having a high city population concentrated in a relatively small number of cities. For each state and country, we therefore compute the total population across all cities (p_i^{1900}), as well as the inverse number of cities (c_i^{1900}). We include both, as well as their interaction ($p_i^{1900} \cdot c_i^{1900}$), all 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 state had high overall city population concentrated in a small number of cities.

The first stage estimating equation using the city-level data is:

$$\eta_j^{IV} \ln(D_i) = \zeta \cdot c_i^{1900} \cdot \eta_j^{IV} + \xi \cdot p_i^{1900} \cdot \eta_j^{IV} + \phi \cdot p_i^{1900} \cdot c_i^{1900} \cdot \eta_j^{IV} + \alpha_i + \gamma_j + +X_{ij}'\Gamma + e_{ij} \tag{4.3}$$

and we hypothesize that $\phi > 0$. States (and below, 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.

[30] Fang and Jawitz (2018) combine historical census data with population modeling techniques to construct a spatially explicit distribution of the US population for each decade since 1790. While the most advanced version of their model also uses socioeconomic characteristics of each region to predict population, we use the "Level 4" version of the model that does not take socioeconomic characteristics into account.

[31] We select the year 1900 for comparability with our country-level IV estimates, which have additional data constraints and are reported below.

[32] 1900 was chosen because it is the oldest year with broad and global coverage.

Table 4: State-Level Results: IV Estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	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		
D_c x η_j	0.231**	0.149**	0.288***	1.098***	0.657*	0.951***
	(0.0878)	(0.0692)	(0.0865)	(0.408)	(0.381)	(0.349)
ln(population) x η_j			-0.106			-0.0921
			(0.0816)			(0.0738)
K-P F-Statistic	25.159	45.755	25.411	25.251	45.127	37.259
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
States	48	39	39	48	39	39
Observations	4,182	4,132	4,182	4,132	4,132	4,182

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 1-3 and estalishments in columns 4-6. All estimates report IV-2SLS estimates. In columns 1 and 3, the excluded instrument is an interaction between sector-level density affinity and state-level population weighted density computed from the US 1900 poplulation distribution. In columns 2-3 and 5-6, the excluded instruments are the total urban population in the state in 1900, the inverse number of cities, and the interaction between the two. The Kleibergen-Paap F-statistic for each first stage regression is reported 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.

First, in order to validate this strategy, we reproduce our state-by-sector IV estimates using the instruments constructed from the historical city-level data. These estimates are reported in columns 2-3 of Table 4. The sample is reduced to 39 states because 11 states have no cities in the Chandler (1987) data in 1900. Nevertheless, the estimates remain positive and highly significant albeit somewhat smaller in magnitude. Since p_i^{1900} (total urban population in 1900), one of the excluded instruments, will likely be mechanically correlated with modern population, we control for modern (log of) country population interacted with η_j in column 3; the coefficient of interest remains positive and significant and increases in magnitude. Analogous estimates in which η_j is computed from data on establishments are reported in columns 5-6, and the results are very similar. Next, we turn to IV-2SLS estimates of our country-level results. Across countries, we rely exclusively on the instruments constructed from the Chandler (1987) city-level data. Although this is a limitation, it is worth noting that across US states, our instrument constructed from the Chandler (1987) data and our direct estimate of historical population weighted density are highly positively correlated; the binned partial correlation plot is reported in Figure 5.

Next, we turn to IV estimates of our main country-level results. Country-by-industry estimates of Equation 4.1 are presented in Panel A of Table 5; the first stage estimating equation is Equation 4.3

Table 5: Country-Level Results: 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.

and first stage estimates are reported in Panel B. For comparison, Panel C reports OLS estimates. Our baseline country-level IV-2SLS estimate is reported in column 1 of Table 5. The coefficient estimate 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. Reassuringly, and following the state-level analysis, in the first stage specification we find that $\phi > 0$ while the direct effects of p_i^{1900} and c_i^{1900} are both negative. 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.

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, 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.

One potential concern with using the Chandler (1987) 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).

Taken together, 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 important and causal determinant of patterns of trade.

4.5 Mechanisms: What drives density affinity?

We next investigate the 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 might drive the baseline estimates. Our approach is to estimate versions of our baseline estimating equation:

$$y_{ij} = \alpha_i + \gamma_j + \xi \cdot \ln(D_i) \cdot Z_j + X_{ij}'\Gamma + e_{ij} \tag{4.4}$$

where Z_j is a vector of sector-level characteristics that potentially determine density affinitty (η_j). We investigate a variety of potential characteristics Z_j. If $\xi = 0$, we interpret that as evidence that Z_j does not drive our main results, whereas if $Z_j > 0$ we interpret that as evidence that Z_j is a potential intervening mechanism. Finally, in order to determine whether our candidate mechanisms can explain our main findings, we add $\eta_j \cdot \ln(D_i)$ to Equation 4.4 and document the extent to which its effect is attenuated by the inclusion of the $Z_j \cdot \ln(D_i)$

First, some recent work has highlighted the greater skill and level of human capital in cities (Davis and Dingel, 2014). In the baseline specification, we control flexibly for the potential role of variation in skill or education, both across sectors and across countries. In column 1 of Table 6, 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 positive but statistically insignificant; we also do not find evidence that education is driving the result if we break the industry-level education measure into a larger number of discrete bins (not reported). 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 sectors that rely more on local services may therefore benefit disproportionately from density (Abdel-Rahman and Fujita, 1990; Abdel-Rahman and Fujita, 1993). However, we do not find evidence that service reliance explains 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. Indeed, 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 6), suggesting that indeed denser countries export less in sectors that rely on natural resources. This is consistent with the idea that resource-reliant sectors locate away from urban centers and that dense countries are disproportionately productive in industries that do not rely on natural resources.

Yet another 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. Our baseline 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. 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 6. 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.

Finally, we take a more hands-off approach and investigate whether the task content of production in each sector drives the relationship between density affinity and comparative advantage. To measure the task content of each industry, we follow Lanz, Miroudot, and Nordås (2013) and combine data from O*NET on the task content of each occupation with data on occupations by industry from the Occupational Employment Statistics (for the US) and the Labour Force Survey (for the European Union).[33] We aggregate the task content of each occupation to the industry level by weighting each occupation by its share of total employment in the industry (see Section 4 of Lanz, Miroudot, and Nordås, 2013). This yields an industry-level measure of the importance of each of the forty-one

[33] A potential shortcoming of this approach is the fact that we only have data on the task content of production for the US. Taylor et al. (2008), however, document that the task content of different occupations is very similar across countries.

Table 6: Exploring Potential Mechanisms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Dependent Variable is Total Exports from the Country-Sector						
D_i x η_j					0.780***	0.281*	0.269*
					(0.183)	(0.143)	(0.163)
D_i x (Share Employment College Educated)$_j$	0.996						
	(1.944)						
D_i x (Services Input Share)$_j$		-0.646					
		(0.620)					
D_i x (Nat. Resource Input Share)$_j$			-1.575**			0.595	
			(0.652)			(0.679)	
D_i x (R&D per Worker)$_j$				0.0844**		0.0242	
				(0.0378)		(0.0276)	
D_i x (Share STEM Workers)$_j$				1.124**		3.938***	
				(0.525)		(0.948)	
Task Controls	No	No	No	No	No	Yes	Yes
Country Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,437	8,437	8,437	8,333	8,437	8,333	8,437

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. 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.

O*NET tasks, each of which we interact with country-level density and include on the right hand side of our baseline estimating equation.

While this analysis is necessarily speculative, our main conclusion is that sectors that rely on more interactive and collaborative tasks are disproportionately exported from denser places. The tasks that are important in sectors that disproportionately export from denser countries include "Guiding, Directing, and Motivating Subordinates," "Coaching and Developing Others," "Communicating with Persons Outside Organization" and "Provide Consultation and Advice to Others," and "Selling or Influencing Others." Also in this set are tasks involving technical skill, including "Estimating the Quantifiable Characteristics of Products, Events, or Information" and "Documenting/Recording Information." These findings dovetail with recent work by Michaels, Rauch, and Redding (2019) documenting that since 1880, in the US there has been a dramatic increase in the employment share of "interactive" occupations in metro areas.

Meanwhile, the set of tasks that are significantly less likely to be important in sectors exported by denser countries tend to involve interaction with machines, including "Controlling Machines and Processes," "Operating Vehicles, Mechanized Devices, or Equipment," "Repairing and Maintaining Mechanical Equipment." The tasks "Handling and Moving Objects" and "Inspecting Equipment, Structures, or Material" also enter with negative coefficients of similar magnitude; however, they are not statistically significant. The full set of tasks that enter the regression, positively or negatively, with a significant coefficient ($p < 0.1$) are listed in Table A6.

We next investigate whether these sector-level characteristics drive the effect of density-affinity in our main results. In column 5 of Table 6 we reproduce the baseline estimate for reference. In column 6, we include controls for all potentially relevant mechanisms described in this section. While the coefficient on the density affinity variable remains positive and (Weakly) significant, its magnitude is reduced by over half, suggesting that the mechanisms described in this section do explain part of the sector-level variation that drives the comparative advantage of denser countries. In column 7, we include only the task content interactions, and the coefficient on the density affinity variable remains similar, suggesting that the task content of more vs. less density-loving sectors form an important underlying mechanism. Nonetheless, it does not fully explain our baseline results, suggesting that additional and unobserved 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, and we leave a deeper exploration of the determinants of density affinity to future work.

5. Conclusion

This paper argues that some countries specialize in density: countries with an abundance of dense cities export relatively more in density-loving 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 have identical factor endowments in the aggregate, they may specialize in vastly different industries because the domestic distribution of factors of production shapes comparative advantage. In particular, a key determinant of patterns of trade across countries might lie in the spatial distribution of people within them.

We first uncover substantial heterogeneity in the density-affinity of tradable sectors, using a strategy that exploits subterranean geology as a shifter of location-specific population density; while some sectors are disproportionately located in large cities, others are more disproportionately found in smaller cities or suburban areas. Next, we show 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. Population density and distribution affect not only domestic productivity and inequality, but also comparative advantage and international trade.

The implications of these findings extend into the realms of policy, and we believe that the interaction between spatial heterogeneity, trade, and politics is an important area for future work. First, this paper's results suggest that place-based policies might have systematically heterogeneous effects across industries, even to the point of affecting international specialization. By disproportionately benefiting certain places, and perhaps even altering the population distribution, policy could affect sector-level comparative advantage. Second, it is a common feature of politics in most countries that more or less dense places achieve different levels of political representation. In the US, for example, institutions like the Senate, the Electoral College, and even the lags in House re-districting, lead to the systematic over-representation of less dense areas. Our analysis suggests that this inherently leads to an uneven level of political representation across *sectors*; the resulting political inequality could have major implications for trade policy and the approach to politics that each industry pursues.

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APPENDICES

A Appendix Figures and Tables

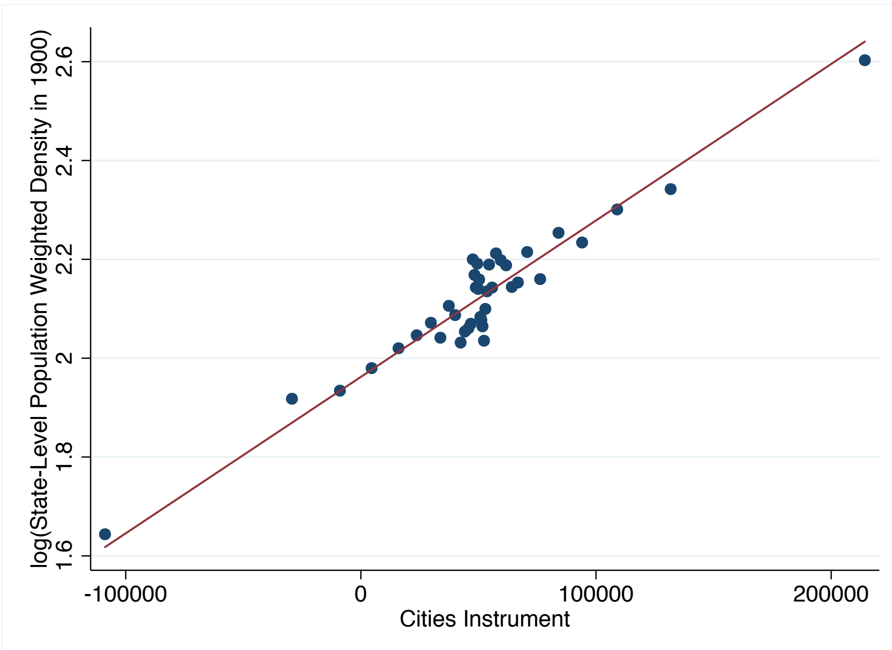

Figure 5: **Correlation Between Both US State-Level Instruments.** This figure presents the partial correlation, conditional on state and industry fixed effects, between (i) log of US state-level population weighted density in 1900, estimated from the Fang and Jawitz (2018) data set, and (ii) the interaction between total 1900 city population and the inverse number of cities, estimated from the Chandler (1987) data set.

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: Main 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 x η_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 × 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: Main Results: Robustness to Alternative Sources of Population Data

	(1)	(2)	(3)	(4)
Gridded Population Data Set:	LandScan (Baseline)	Global Human Settlement Layer	Gridded Population of the World	Worldpop Project
D_i x η_j	0.456***	0.468***	0.443***	0.497***
	(0.111)	(0.125)	(0.0956)	(0.102)
Country FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Countries	134	134	134	134
Observations	10,547	10,547	10,547	10,547

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. Population weighted density is computed from a different data set in each column, and the data source is listed at the top 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 A5: Main Results: 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.

Table A6: Tasks Associated with Sectors that are the Comparative Advantage of More vs. Less Dense Countries

Panel A: Tasks Associated with CA Sectors in More Dense Countries
Guiding, Directing, and Motivating Subordinates
Coaching and Developing Others
Estimating the Quantifiable Characteristics of Products, Events, or Information
Identifying Objects, Actions, and Events
Selling or Influencing Others
Documenting/Recording Information
Communicating with Persons Outside Organization
Making Decisions and Solving Problems
Provide Consultation and Advice to Others
Panel B: Tasks Associated witrh CA Sectors in Less-Dense Countries
Controlling Machines and Processes
Operating Vehicles, Mechanized Devices, or Equipment
Performing for or Working Directly with the Public
Repairing and Maintaining Mechanical Equipment
Resolving Conflicts and Negotiating with Others
Assisting and Caring for Others
Scheduling Work and Activities
Analyzing Data or Information

Notes: This table lists the set of tasks whose interaction with population weighted density yielded a positive and significant coefficient estimate in Equation 4.4 (Panel A) and the set of tasks whose interaction with population weighted density yielded a negative and significant coefficient estimate in Equation 4.4.

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 owns an amount γ of local land, and produces housing according to the production function: $H_c(\gamma) = \gamma^{\xi}(\frac{X_{hc}(\gamma)}{1-\xi})^{1-\xi}$. They face 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:[34]

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

where π_{dcj} denotes spending in city d on goods in sector j produced in city c, equation 2.4 in the model.

B.3 Proposition 1

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 2.5 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:

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

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:

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

[34]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

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

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

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

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:

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

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

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 1.