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# Spatial Frictions

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September 2014

Abstract: The world is replete with spatial frictions. Shipping goods across cities entails trade frictions. Commuting within cities causes urban frictions. How important are these frictions in shaping the spatial economy? We develop and quantify a novel framework to address this question at three different levels: Do spatial frictions matter for the city-size distribution? Do they affect individual city sizes? Do they contribute to the productivity advantage of large cities and the toughness of competition in cities? The short answers are: no; yes; and it depends.

**Keywords:** trade frictions; urban frictions; city-size distribution; productivity; markups

**JEL Classification:** F12; R12

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## 1. Introduction

The world is replete with spatial frictions. Trade frictions for shipping goods across cities induce consumers and firms to spatially concentrate to take advantage of large local markets. Yet, such a concentration generates urban frictions within cities – people spend a lot of time on commuting and pay high land rents. Economists have studied this fundamental trade-off between agglomeration and dispersion forces for decades, analyzing how firms and workers choose their locations depending on the magnitudes of – and changes in – spatial frictions (Fujita *et al.*, 1999; Fujita and Thisse, 2002). However, little is known about the quantitative importance of urban and trade frictions in shaping the spatial economy. To what extent do spatial frictions matter for the city-size distribution? By how much do they affect individual city sizes? To what degree do they contribute to the productivity advantage of large cities and the toughness of competition in cities?

Answering these questions is difficult for at least two reasons. First, one needs a spatial model with costly trade and commuting, featuring endogenous location decisions. To investigate the productivity advantage of large cities and the toughness of competition in cities, productivity and markups also need to be endogenous and responsive to changes in spatial frictions. Second, to perform counterfactual analysis aimed at quantifying the importance of those frictions, one must keep track of all general equilibrium interactions when taking the model structurally to the data. To the best of our knowledge, there exist to date no spatial models dealing jointly with these difficulties.

We develop a novel multi-city general equilibrium model that can fill this gap. In our model, city sizes, their distribution, productivity, and markups are all endogenously determined and react to changes in urban and trade frictions. Given the population distribution, changes in spatial frictions affect productivity and markups, as well as wages, in cities. These changes, in turn, generate utility differences across cities, thereby affecting individual location decisions. In a nutshell, shocks to spatial frictions induce tougher competition and firm selection, as emphasized in the recent trade literature, and trigger population movements, as highlighted in urban economics and the 'new economic geography' (NEG). We quantify our framework with data for 356 US metropolitan statistical areas (MSAs) in 2007. The model performs well in replicating several empirical facts that are not used in the quantification stage, both at the MSA and firm levels.

We then conduct two counterfactual experiments. First, we consider a scenario where commuting within cities is costless. Second, we analyze a scenario where consumers face the same trade costs for local and non-local products. In both cases, we compare the actual and the counterfactual equilibria to assess the quantitative importance of spatial frictions for the city-size distribution, individual city sizes, as well as productivity and markups in cities. Those counterfactuals are meaningful as they provide bounds that suggest to what extent the US economic geography is affected by urban and trade costs.

What are our main quantitative findings? First, neither type of frictions significantly affects the US city-size distribution. Even in a world where urban or trade frictions are eliminated for all cities, that distribution would still follow the rank-size rule also known as Zipf's law. Second, eliminating spatial frictions would change individual city sizes within the stable distribution. Without urban frictions, large congested cities would gain, while small isolated cities would lose population. For example, the size of New York would increase by 8.5%, i.e., its size is limited by 8.5% by the presence of urban frictions. By contrast, in a world without trade frictions, large cities would shrink compared to small cities as local market access no longer matters. For example, the size of New York would decrease by 10.8%, i.e., its size is boosted by 10.8% by the presence of trade frictions. Turning to productivity and competition, eliminating trade frictions would lead to aggregate productivity gains of 68% and markup reductions of 40%, both of which are highly unevenly distributed across MSAs. Eliminating urban frictions generates smaller productivity gains up to 1.4%. Still it leads to a notable markup reduction of about 10% in the aggregate, but again with a lot of variation across MSAs. Summing up, our counterfactual analysis suggests that spatial frictions do not matter for the city-size distribution, they do matter for individual city sizes, and they matter differently for productivity and competition across cities.

To check the robustness of our results, we first extend the model to encompass external agglomeration economies that affect the productivity advantage of large cities in addition to firm selection.[1] We then implement an instrumental variable (IV) approach to deal with potential bias when estimating how individuals' location decisions are affected by changes in spatial frictions. In both cases, the key qualitative and quantitative results remain unchanged: the city-size distribution is fairly stable when spatial frictions are eliminated, and productivity and markup changes are very similar to those in our benchmark.

[1]The empirical findings by Combes *et al.* (2012) suggest that the productivity advantage of large cities is mainly due to such agglomeration externalities. Their results, however, rely on two identifying assumptions: a common productivity distribution for entrants in all cities; and no income effects, which allow for the separability of agglomeration and selection effects. In our model, there are both income effects and different productivity distributions for entrants across cities. Thus, our predictions are not comparable to theirs. In particular, it is a priori unclear whether agglomeration economies are more important than selection effects once income effects and city-specific productivity distributions are taken into account.

Our analysis contributes to both the recent empirical NEG and urban economics. It is fair to say that spatial models have so far been confronted with data mostly in a reduced-form manner. Two notable exceptions are Desmet and Rossi-Hansberg (2013) and Ahlfeldt *et al.* (2014). However, the latter authors focus on the internal structure of a single city, whereas the former assume that trade between cities is costless. Our framework allows for costly trade between cities and is, therefore, also related to structural trade models (see, among others, Eaton and Kortum, 2002; Combes and Lafourcade, 2011; Corcos *et al.*, 2012; Behrens *et al.*, 2014b; Holmes and Stevens, 2014). Yet, those models abstract from population movements across locations. Our contribution brings these various strands of literature closer together and provides, to our knowledge, the first structural estimation of an urban system model with costly trade across cities and costly commuting within cities.

The rest of the paper is organized as follows. In Section 2 we set up the basic model, and then analyze the equilibrium in Section 3. Section 4 describes our quantification procedure and discusses the model fit. We then turn to our counterfactual experiments in Section 5. Section 6 examines the robustness of our main results. Section 7 concludes. Several proofs and details about our model and quantification procedure are relegated to a supplementary online appendix.

## 2. The model

We consider an economy that consists of $K$ cities, with $L_r$ identical workers/consumers in city $r = 1,...,K$. Labor is the only factor of production.

### 2.1 Preferences and demands

There is a final consumption good, provided as a continuum of horizontally differentiated varieties. Consumers have identical preferences that display 'love of variety' and give rise to demands with variable elasticity. Let $p_{sr}(i)$ and $q_{sr}(i)$ denote the price and the per capita consumption of variety $i$ when it is produced in city $s$ and consumed in city $r$. Following Behrens and Murata (2007) the utility maximization problem of a representative consumer in city $r$ is given by:

$$\max_{q_{sr}(j),\, j\in\Omega_{sr}} \; U_r \equiv \sum_s \int_{\Omega_{sr}} \left[1 - \mathrm{e}^{-\alpha q_{sr}(j)}\right] \mathrm{d}j \qquad \text{s.t.} \quad \sum_s \int_{\Omega_{sr}} p_{sr}(j) q_{sr}(j) \mathrm{d}j = E_r, \tag{1}$$

where $\Omega_{sr}$ denotes the endogenously determined set of varieties produced in $s$ and consumed in $r$, and where $E_r$ denotes consumption expenditure. Solving (1) yields the following demand functions:

$$q_{sr}(i) = \frac{E_r}{N_r^c \overline{p}_r} - \frac{1}{\alpha}\left\{ \ln\left[\frac{p_{sr}(i)}{N_r^c \overline{p}_r}\right] + \eta_r \right\}, \quad \forall i \in \Omega_{sr}, \tag{2}$$

where $N_r^c$ is the mass of varieties consumed in city $r$, and

$$\overline{p}_r \equiv \frac{1}{N_r^c}\sum_s \int_{\Omega_{sr}} p_{sr}(j)\mathrm{d}j \quad \text{and} \quad \eta_r \equiv -\sum_s \int_{\Omega_{sr}} \ln\left[\frac{p_{sr}(j)}{N_r^c \overline{p}_r}\right]\frac{p_{sr}(j)}{N_r^c \overline{p}_r}\mathrm{d}j$$

denote the average price and the differential entropy of the price distribution, respectively.[2] Since marginal utility at zero consumption is bounded, the demand for a variety need not be positive. Indeed, as can be seen from (2), the demand for a local variety $i$ (respectively, a non-local variety $j$) is positive if and only if the price of variety $i$ (variety $j$) is lower than the reservation price $p_r^d$. Formally,

$$q_{rr}(i) > 0 \iff p_{rr}(i) < p_r^d \quad \text{and} \quad q_{sr}(j) > 0 \iff p_{sr}(j) < p_r^d,$$

where $p_r^d \equiv N_r^c \overline{p}_r \mathrm{e}^{\alpha E_r/(N_r^c \overline{p}_r) - \eta_r}$ depends on the price aggregates $\overline{p}_r$ and $\eta_r$. The definition of the reservation price allows us to express the demands for local and non-local varieties concisely as follows:

$$q_{rr}(i) = \frac{1}{\alpha}\ln\left[\frac{p_r^d}{p_{rr}(i)}\right] \quad \text{and} \quad q_{sr}(j) = \frac{1}{\alpha}\ln\left[\frac{p_r^d}{p_{sr}(j)}\right]. \tag{3}$$

Observe that the price elasticity of demand is given by $1/[\alpha q_{rr}(i)]$ for variety $i$, and respectively, by $1/[\alpha q_{sr}(j)]$ for variety $j$. Thus, if individuals consume more of those varieties, which is for instance the case when their expenditure increases, they become less price sensitive. Last, since $\mathrm{e}^{-\alpha q_{sr}(j)} = p_{sr}(j)/p_r^d$, the indirect utility in city $r$ is given by

$$U_r = N_r^c - \sum_s \int_{\Omega_{sr}} \frac{p_{sr}(j)}{p_r^d}\mathrm{d}j = N_r^c\left(1 - \frac{\overline{p}_r}{p_r^d}\right), \tag{4}$$

which we use to compute the equilibrium utility in the subsequent analysis.

## 2.2 *Technology and market structure*

Prior to production, firms decide in which city they enter and engage in research and development. The labor market in each city is perfectly competitive, so that all firms take

[2] As shown in Reza (1994, pp.278-279), the differential entropy takes its maximum value when there is no dispersion, i.e., $p_{sr}(i) = \overline{p}_r$ for all $i \in \Omega_{sr}$ for all $s$. In that case, we would observe $\eta_r = -\ln(1/N_r^c)$ and thus $q_{sr}(i) = E_r/(N_r^c \overline{p}_r)$ by (2). Behrens and Murata (2007, 2012a,b) focus on such a symmetric case. In contrast, this paper considers firm heterogeneity, so that not only the average price $\overline{p}_r$ but the entire price distribution matter for the demand $q_{sr}(i)$. The differential entropy $\eta_r$ captures the latter price dispersion.

the wage rate $w_r$ as given. Entry in city $r$ requires a fixed amount $F$ of labor paid at the market wage. Each firm $i$ that enters in city $r$ discovers its marginal labor requirement $m_r(i) \geq 0$ only after making this irreversible entry decision. We assume that $m_r(i)$ is drawn from a known, continuously differentiable distribution $G_r$.[3] We introduce *trade frictions* into our model by assuming that shipments from city $r$ to city $s$ are subject to trade costs $\tau_{rs} \geq 1$ for all $r$ and $s$, which firms incur in terms of labor. Since entry costs are sunk, firms will survive (i.e., operate) provided they can charge prices $p_{rs}(i)$ above marginal costs $\tau_{rs} m_r(i) w_r$ in at least one city. The surviving firms operate in the same city where they enter.

We assume that product markets are segmented, i.e., resale or third-party arbitrage is sufficiently costly, so that firms are free to price discriminate between cities. The operating profit of a firm $i$ located in city $r$ is then as follows:

$$\pi_r(i) = \sum_s \pi_{rs}(i) = \sum_s L_s q_{rs}(i) \left[ p_{rs}(i) - \tau_{rs} m_r(i) w_r \right], \tag{5}$$

where $q_{rs}(i)$ is given by (3). Each surviving firm maximizes (5) with respect to its prices $p_{rs}(i)$ separately. Since there is a continuum of firms, no individual firm has any impact on $p_r^d$, so that the first-order conditions for (operating) profit maximization are given by:

$$\ln \left[ \frac{p_s^d}{p_{rs}(i)} \right] = \frac{p_{rs}(i) - \tau_{rs} m_r(i) w_r}{p_{rs}(i)}, \quad \forall i \in \Omega_{rs}. \tag{6}$$

A price distribution satisfying (6) is called a *price equilibrium*. Equations (3) and (6) imply that $q_{rs}(i) = (1/\alpha)[1 - \tau_{rs} m_r(i) w_r / p_{rs}(i)]$. Thus, the minimum output that a firm in market $r$ may sell in market $s$ is given by $q_{rs}(i) = 0$ at $p_{rs}(i) = \tau_{rs} m_r(i) w_r$. This, by (6), implies that $p_{rs}(i) = p_s^d$. Hence, a firm located in $r$ with draw $m_{rs}^x \equiv p_s^d / (\tau_{rs} w_r)$ is just indifferent between selling and not selling to $s$, whereas all firms in $r$ with draws below $m_{rs}^x$ are productive enough to sell to $s$. In what follows, we refer to $m_{ss}^x \equiv m_s^d$ as the *internal cutoff* in city $s$, whereas $m_{rs}^x$ with $r \neq s$ is the *external cutoff*. External and internal cutoffs are linked as follows:[4]

$$m_{rs}^x = \frac{\tau_{ss}}{\tau_{rs}} \frac{w_s}{w_r} m_s^d. \tag{7}$$

[3]Differences in $G_r$ across cities thus reflect production amenities such as local knowledge that are not transferable across space. Firms take those differences into account when making their entry decisions.

[4]Expression (7) reveals an interesting relationship of how trade costs and wage differences affect firms' abilities to break into different markets. In particular, when wages are equalized across cities ($w_r = w_s$) and internal trade is costless ($\tau_{ss} = 1$), all external cutoffs must fall short of the internal cutoffs since $\tau_{rs} > 1$. Breaking into market $s$ is then always harder for firms in $r \neq s$ than for local firms in $s$, which is the standard case in the firm heterogeneity literature (e.g., Melitz, 2003; Melitz and Ottaviano, 2008). However, in the presence of wage differences and internal trade costs, the internal cutoff need not be larger than the external cutoff in equilibrium. The usual ranking $m_s^d > m_{rs}^x$ prevails only when $\tau_{ss} w_s < \tau_{rs} w_r$.

Given those cutoffs and a mass of entrants $N_r^E$ in city $r$, only $N_r^p = N_r^E\, G_r\left(\max_s\left\{m_{rs}^x\right\}\right)$ firms survive, namely those which are productive enough to sell at least in one market (which need not be their local market). The mass of varieties consumed in city $r$ is then

$$N_r^c = \sum_s N_s^E G_s(m_{sr}^x), \tag{8}$$

which is the sum of all firms that are productive enough to sell to market $r$.

Since all firms in each city differ only by their marginal labor requirements, we can express all firm-level variables in terms of $m$. Specifically, solving (6) by using the Lambert $W$ function, defined as $\varphi = W(\varphi)\mathrm{e}^{W(\varphi)}$, the profit-maximizing prices and quantities, as well as operating profits, are given by:[5]

$$p_{rs}(m) = \frac{\tau_{rs} m w_r}{W}, \quad q_{rs}(m) = \frac{1}{\alpha}\left(1 - W\right), \quad \pi_{rs}(m) = \frac{L_s \tau_{rs} m w_r}{\alpha}(W^{-1} + W - 2), \tag{9}$$

where $W$ denotes the Lambert $W$ function with argument $\mathrm{e}m/m_{rs}^x$, which we suppress to alleviate notation. Since $W(0) = 0$, $W(\mathrm{e}) = 1$ and $W' > 0$ for all non-negative arguments, we have $0 \leq W \leq 1$ for $0 \leq m \leq m_{rs}^x$. The expressions in (9) show that a firm in $r$ with a draw $m_{rs}^x$ charges a price equal to marginal cost, faces zero demand, and earns zero operating profits in market $s$. Furthermore, using the properties of $W'$, we readily obtain $\partial p_{rs}(m)/\partial m > 0$, $\partial q_{rs}(m)/\partial m < 0$, and $\partial \pi_{rs}(m)/\partial m < 0$. In words, firms with higher productivity (lower $m$) charge lower prices, sell larger quantities, and earn higher operating profits. These properties are similar to those of the Melitz (2003) model with constant elasticity of subtitution (CES) preferences. Yet, our specification with variable demand elasticity also features higher markups for more productive firms. Indeed, the markup for a firm located in city $r$ and a consumer located in city $s$,

$$\Lambda_{rs}(m) \equiv \frac{p_{rs}(m)}{\tau_{rs} m w_r} = \frac{1}{W}, \tag{10}$$

implies that $\partial \Lambda_{rs}(m)/\partial m < 0$. Unlike Melitz and Ottaviano (2008), who use quasi-linear preferences, we incorporate this feature into a full-fledged general equilibrium model with income effects for varieties.

### 2.3 *Urban structure*

Each city consists of a large amount of land that stretches out on a two-dimensional featureless plane. Land is used for housing only. Each agent consumes inelastically one

[5]Further details about the Lambert $W$ function, the technical properties of which are key to making our model tractable, can be found in the supplementary online appendix.

unit of land, and the amount of land available at each location is set to one. All firms in city $r$ are located at a dimensionless Central Business District (CBD). A monocentric city of size $L_r$ then covers the surface of a disk with radius $\overline{x}_r \equiv \sqrt{L_r/\pi}$, with the CBD located in the middle of that disk and the workers evenly distributed within it.

We introduce *urban frictions* in a standard way into our model by assuming that agents commute to the CBD for work. In particular, we assume that each individual in city $r$ is endowed with $\overline{h}_r$ hours of time, which is the gross labor supply per capita in hours, including commuting time. Commuting costs are of the 'iceberg' type: the *effective* labor supply of a worker living at a distance $x_r \leq \overline{x}_r$ from the CBD is given by

$$s_r(x_r) = \overline{h}_r \mathrm{e}^{-\theta_r x_r}, \tag{11}$$

where $\theta_r \geq 0$ captures the time loss due to commuting and thus measures the commuting technology of city $r$.[6] The *total effective labor supply* at the CBD is then given by

$$S_r = \int_0^{\overline{x}_r} 2\pi x_r s_r(x_r) \mathrm{d}x_r = \frac{2\pi \overline{h}_r}{\theta_r^2} \left[1 - \left(1 + \theta_r \sqrt{L_r/\pi}\right) \mathrm{e}^{-\theta_r \sqrt{L_r/\pi}}\right]. \tag{12}$$

Define the *effective labor supply per capita* as $h_r \equiv S_r/L_r$, which is the average number of hours worked in city $r$. It directly follows from (12) that $S_r$ is positive and increasing in $L_r$, while $h_r$ is decreasing in $L_r$: given gross labor supply per capita $\overline{h}_r$ and commuting technology $\theta_r > 0$, the effective labor supply per capita is lower in a larger city.[7] We can further show that $\partial h_r/\partial \theta_r < 0$. The effective labor supply per capita is lower, ceteris paribus, the more severe the urban frictions are in city $r$, that is, the worse the commuting technology is. Notice that with $\theta_r = 0$ we would have $h_r = \overline{h}_r$ for all $L_r$ workers.

Since firms locate at the CBD, the wage income net of commuting costs earned by a worker residing at the city edge is $w_r s_r(\overline{x}_r) = w_r \overline{h}_r \mathrm{e}^{-\theta_r \overline{x}_r}$. Because workers are identical, the wages net of commuting costs and land rents are equalized across all locations in the city: $w_r s_r(x_r) - R_r(x_r) = w_r s_r(\overline{x}_r) - R_r(\overline{x}_r)$, where $R_r(x_r)$ is the land rent at a distance $x_r$ from the CBD. The equilibrium land rent schedule is then given by $R_r^*(x_r) = w_r(\mathrm{e}^{-\theta_r x_r} - \mathrm{e}^{-\theta_r \overline{x}_r})\overline{h}_r + R_r(\overline{x}_r)$, which yields the following aggregate land rents:

$$\mathrm{ALR}_r = \int_0^{\overline{x}_r} 2\pi x_r R_r^*(x_r) \mathrm{d}x_r = \frac{2\pi w_r \overline{h}_r}{\theta_r^2} \left[1 - \left(1 + \theta_r \overline{x}_r + \frac{\theta_r^2 \overline{x}_r^2}{2}\right) \mathrm{e}^{-\theta_r \overline{x}_r}\right] + L_r R_r(\overline{x}_r). \tag{13}$$

[6] We use an exponential commuting cost since a linear specification, as in, e.g., Murata and Thisse (2005), is subject to a boundary condition to ensure positive effective labor supply at each location in the city. Keeping track of this condition becomes tedious with multiple cities and intercity movements of people. The exponential specification has been used extensively in the literature (e.g., Lucas and Rossi-Hansberg, 2002), and the convexity of the time loss with respect to distance from the CBD can also be justified in a modal choice framework of intra-city transportation (e.g., Glaeser, 2008, pp.24–25).

[7] Here we abstract from an "urban rat race" in larger cities. However, when quantifying the model in Section 4, we use data on $\overline{h}_r$ across MSAs, which shows that $\overline{h}_r$ is higher in big cities like New York.

We assume that each worker in city $r$ owns an equal share of the land in that city, and thus receives an equal share of aggregate land rents. Furthermore, each worker has an equal claim to aggregate profits $\Pi_r$ in the respective city. Accordingly, the per capita expenditure which consists of the wage net of commuting costs and land rents, plus a share of aggregate land rents and profits, is then given by $E_r = w_r \overline{h}_r \mathrm{e}^{-\theta_r \sqrt{L_r/\pi}} - R_r(\overline{x}_r) + \mathrm{ALR}_r/L_r + \Pi_r/L_r = w_r h_r + \Pi_r/L_r$.

# 3. Equilibrium

## 3.1 Single city case

To illustrate how our model works, we first consider the case of a single city. There are two equilibrium conditions in that case: zero expected profits; and labor market clearing. These two conditions can be solved for the internal cutoff $m^d$ and the mass of entrants $N^E$, which completely characterize the market equilibrium. For notational convenience, we drop the subscript $r$ and normalize the internal trade costs to one.

Using (5) and (9), the zero expected profit (ZEP) condition $\int_0^{m^d} \pi(m)\mathrm{d}G(m) = Fw$ can be rewritten as:

$$\frac{L}{\alpha}\int_0^{m^d} m(W^{-1} + W - 2)\mathrm{d}G(m) = F, \tag{14}$$

which is a function of $m^d$ only and yields a unique equilibrium cutoff because the left-hand side of (14) is shown to be strictly increasing in $m^d$ from 0 to ∞. Furthermore, using (9), the labor market clearing (LMC) condition, $N^E[L\int_0^{m^d} mq(m)\mathrm{d}G(m) + F] = S$, can be expressed as follows:

$$N^E\left[\frac{L}{\alpha}\int_0^{m^d} m\,(1-W)\,\mathrm{d}G(m) + F\right] = S, \tag{15}$$

which can be uniquely solved for $N^E$ given the cutoff $m^d$ obtained from (14).[8]

As in Melitz and Ottaviano (2008) and many other existing studies, we choose a particular distribution function for firms' productivity draws, $1/m$, namely a Pareto distribution: $G(m) = (m/m^{\max})^k$, where $m^{\max} > 0$ and $k \geq 1$ are the upper bound and the shape parameter, respectively. This distribution is useful for deriving analytical results and taking the model to data. In particular, we obtain the following closed-form

[8]From the ZEP condition $L\int_0^{m^d}[p(m) - mw]\,q(m)\mathrm{d}G(m) = Fw$, and from the budget constraint $N^E\int_0^{m^d} p(m)q(m)\mathrm{d}G(m) = E$, we get $EL/(wN^E) = L\int_0^{m^d} mq(m)\mathrm{d}G(m) + F$ which, together with LMC, yields $E = (S/L)w = hw$. The per capita expenditure thus depends only on effective labor supply per capita and the wage in equilibrium, whereas profits per capita, $\Pi/L$, are zero.

solutions for the equilibrium cutoff and the mass of entrants in the single city case:

$$m^d = \left(\frac{\mu^{\max}}{L}\right)^{\frac{1}{k+1}} \quad \text{and} \quad N^E = \frac{\kappa_2}{\kappa_1 + \kappa_2}\frac{S}{F}, \tag{16}$$

where $\mu^{\max} \equiv \left[\alpha F (m^{\max})^k\right] / \kappa_2$ and $\kappa_1$ and $\kappa_2$ are positive constants that solely depend on $k$. The term $\mu^{\max}$ can be interpreted as an inverse measure of *technological possibilities*: the lower is the fixed labor requirement for entry, $F$, or the lower is the upper bound, $m^{\max}$, the lower is $\mu^{\max}$ and, hence, the better are the city's technological possibilities.

How do population size and technological possibilities affect entry and selection? Recall from (12) that $S$ is increasing in $L$. The second expression in (16) then shows that there are more entrants $N^E$ in a larger city. The first expression in (16), in turn, shows that a larger $L$ or a smaller $\mu^{\max}$ entail a smaller cutoff $m^d$ and, thus, a lower survival probability $G(m^d)$ of entrants. This tougher selection maps into higher average productivity, $\overline{M} \equiv \overline{1/m} = [1/G(m^d)] \int_0^{m^d} (1/m) \mathrm{d}G(m) = [k/(k-1)](1/m^d)$ under a Pareto distribution. The mass of surviving firms $N^p = N^E G(m^d)$, which is equivalent to consumption diversity $N^c$ in the single city case, is then equal to

$$N = \frac{\alpha}{\kappa_1 + \kappa_2}\frac{h}{m^d} = \frac{\alpha h}{\kappa_1 + \kappa_2}\left(\frac{L}{\mu^{\max}}\right)^{\frac{1}{k+1}}. \tag{17}$$

Since firms are heterogeneous and have different markups and market shares, the simple (unweighted) average of markups is not an adequate measure of consumers' exposure to market power. Using (9) and (10), we hence define the (expenditure share) weighted average of firm-level markups as follows:

$$\overline{\Lambda} \equiv \frac{1}{G(m^d)} \int_0^{m^d} \frac{p(m)q(m)}{E} \Lambda(m) \mathrm{d}G(m) = \frac{\kappa_3}{\alpha}\frac{m^d}{h}, \tag{18}$$

where $\kappa_3$ is a positive constant that solely depends on $k$.[9] Note that the average markup is proportional to the cutoff. It thus follows from (17) and (18) that our model displays pro-competitive effects, since $\overline{\Lambda} = [\kappa_3/(\kappa_1 + \kappa_2)]\,(1/N)$ decreases with the mass of competing firms. Finally, the indirect utility in the single city case can be expressed as

$$U = \alpha \left[\frac{1}{(k+1)(\kappa_1 + \kappa_2)} - 1\right] \frac{h}{m^d} = \left[\frac{1}{(k+1)(\kappa_1 + \kappa_2)} - 1\right] \frac{\kappa_3}{\overline{\Lambda}}, \tag{19}$$

where the term in square brackets is, by construction, positive for all $k \geq 1$. Alternatively, the indirect utility can be written as $U = [1/(k+1) - (\kappa_1 + \kappa_2)]N$. Hence, as can be

[9] Recent empirical work by Feenstra and Weinstein (2010) uses a similar (expenditure share) weighted average of markups in a translog framework.

seen from expressions (16)–(19), a city with better technological possibilities allows for higher utility because of tougher selection, tougher competition, and greater consumption diversity.

The impact of city size on consumption diversity, the average markup, and the indirect utility can be established as follows. Using (12) and (16), we can rewrite the indirect utility as

$$U = \alpha \left[ \frac{1}{(k+1)(\kappa_1+\kappa_2)} - 1 \right] \left\{ \frac{2\pi \overline{h}}{\theta^2 L} \left[ 1 - \left(1 + \theta\sqrt{L/\pi}\right) \mathrm{e}^{-\theta\sqrt{L/\pi}} \right] \right\} \left( \frac{L}{\mu^{\max}} \right)^{\frac{1}{k+1}}. \quad (20)$$

The term in braces in (20) equals the effective labor supply per capita, $h$, which decreases with $L$. The last term in expression (20) captures the cutoff productivity level, $1/m^d$, which increases with $L$. The net effect of an increase in $L$ on the indirect utility $U$ is thus ambiguous, highlighting the trade-off between a dispersion force (urban frictions) and an agglomeration force (tougher firm selection) inherent in our model. Yet, it can be shown that $U$ is single-peaked with respect to $L$ as in Henderson (1974). Since the indirect utility is proportional to $N$, it immediately follows that consumption diversity also exhibits a $\cap$-shaped pattern, while the average markup $\overline{\Lambda}$ is $\cup$-shaped with respect to population size $L$.

Observe that for now in our model, larger cities are more productive because of tougher selection, but not because of technological externalities associated with agglomeration. In line with an abundant empirical literature (e.g., Rosenthal and Strange, 2004), we extend our framework to allow for such agglomeration economies in Section 6.

### 3.2 *Urban system: Multiple cities*

We now turn to the urban system with multiple cities. The timing of events is as follows. First, workers/consumers choose their locations. Second, given the population distribution across cities, firm entry, selection and production take place.[10] We start the analysis by deriving the market equilibrium conditions for given city sizes, and then define the spatial equilibrium where individuals endogenously choose their locations.

#### 3.2.1 *Market equilibrium*

There are three sets of market equilibrium conditions in the urban system. For each city, LMC and ZEP can be written analogously as in the single city setup. In addition, trade

[10]This timing simplifies our model because we need not specify which types of firms relocate as workers move across cities. The spatial sorting of firms or workers is not the topic of the present paper.

must be balanced for each city, which is equivalent to saying that each consumer's budget constraint is satisfied with equality in our static economy.

As in the single city case, we assume Pareto distributions for productivity draws. The shape parameter $k \geq 1$ is assumed to be identical, but the upper bounds are allowed to vary across cities, i.e., $G_r(m) = (m/m_r^{\max})^k$. Under this assumption, the market equilibrium conditions – LMC, ZEP, and the trade balance – can be written as follows:

$$N_r^E \left[ \frac{\kappa_1}{\alpha \left(m_r^{\max}\right)^k} \sum_s L_s \tau_{rs} \left( \frac{\tau_{ss}}{\tau_{rs}} \frac{w_s}{w_r} m_s^d \right)^{k+1} + F \right] = S_r. \tag{21}$$

$$\mu_r^{\max} = \sum_s L_s \tau_{rs} \left( \frac{\tau_{ss}}{\tau_{rs}} \frac{w_s}{w_r} m_s^d \right)^{k+1}, \tag{22}$$

$$\frac{N_r^E w_r}{\left(m_r^{\max}\right)^k} \sum_{s \neq r} L_s \tau_{rs} \left( \frac{\tau_{ss}}{\tau_{rs}} \frac{w_s}{w_r} m_s^d \right)^{k+1} = L_r \sum_{s \neq r} \tau_{sr} \frac{N_s^E w_s}{\left(m_s^{\max}\right)^k} \left( \frac{\tau_{rr}}{\tau_{sr}} \frac{w_r}{w_s} m_r^d \right)^{k+1}. \tag{23}$$

where $\mu_r^{\max} \equiv \left[\alpha F \left(m_r^{\max}\right)^k\right] / \kappa_2$ denotes technological possibilities. Note that $\mu_r^{\max}$ is city-specific, and captures the local production amenities that are not transferable across space.

The $3 \times K$ conditions (21)–(23) depend on $3 \times K$ unknowns: the wages $w_r$, the masses of entrants $N_r^E$, and the internal cutoffs $m_r^d$. The external cutoffs $m_{rs}^x$ can be obtained from (7). Combining (21) and (22), we can immediately show that

$$N_r^E = \frac{\kappa_2}{\kappa_1 + \kappa_2} \frac{S_r}{F}, \tag{24}$$

which implies that more firms choose to enter in larger cities in equilibrium. Adding the term in $r$ that is missing on both sides of (23), and using (22) and (24), we obtain the following equilibrium relationship:

$$\frac{h_r}{\left(m_r^d\right)^{k+1}} = \sum_s S_s \tau_{rr} \left( \frac{\tau_{rr}}{\tau_{sr}} \frac{w_r}{w_s} \right)^k \frac{1}{\mu_s^{\max}}. \tag{25}$$

The $2 \times K$ conditions (22) and (25) summarize how wages, cutoffs, technological possibilites, trade costs, population sizes, and effective labor supplies are related in the market equilibrium. Using those expressions, it can be shown that the mass of varieties consumed in city $r$ is inversely proportional to the internal cutoff, and proportional to the effective labor supply per capita in that city:

$$N_r^c = \frac{\alpha}{(\kappa_1 + \kappa_2)\tau_{rr}} \frac{h_r}{m_r^d}. \tag{26}$$

Furthermore, the (expenditure share) weighted average of markups that consumers face in city $r$ can be expressed as follows:

$$\overline{\Lambda}_r \equiv \frac{\sum_s N_s^E \int_0^{m_{sr}^x} \frac{p_{sr}(m) q_{sr}(m)}{E_r} \Lambda_{sr}(m) \mathrm{d}G_s(m)}{\sum_s N_s^E G_s(m_{sr}^x)} = \frac{\kappa_3 \tau_{rr}}{\alpha} \frac{m_r^d}{h_r}. \tag{27}$$

It follows from (26) and (27) that there are pro-competitive effects, since $\overline{\Lambda}_r$ decreases with the mass $N_r^c$ of competing firms in city $r$ as $\overline{\Lambda}_r = [\kappa_3/(\kappa_1+\kappa_2)](1/N_r^c)$. Last, the indirect utility is given by

$$U_r = \frac{\alpha}{\tau_{rr}} \left[ \frac{1}{(k+1)(\kappa_1+\kappa_2)} - 1 \right] \frac{h_r}{m_r^d} = \left[ \frac{1}{(k+1)(\kappa_1+\kappa_2)} - 1 \right] \frac{\kappa_3}{\overline{\Lambda}_r}, \tag{28}$$

which implies that greater effective labor supply per capita, $h_r = S_r/L_r$, tougher selection, and a lower average markup in city $r$ translate into higher indirect utility. Alternatively, the indirect utility can be rewritten as $U_r = [1/(k+1) - (\kappa_1+\kappa_2)]N_r^c$, i.e., it is proportional to the mass of varieties consumed in city $r$.

### 3.2.2 *Spatial equilibrium*

We now move to the spatial equilibrium where individuals endogenously choose their locations. We introduce city-specific amenities and taste heterogeneity in residential location into our model. This is done for two reasons. First, individuals in reality choose their location not only based on wages, prices, and consumption diversity that result from market interactions, but also based on non-market features such as amenities (e.g., climate or landscape). Second, individuals do not necessarily react in the same way to regional gaps in wages and cost-of-living (Tabuchi and Thisse, 2002; Murata, 2003). Such taste heterogeneity tends to offset the extreme outcome that often arises in typical NEG models, namely that *all* mobile economic activity concentrates in a single city. When we take our model to data, taste heterogeneity is thus useful for capturing an observed non-degenerate equilibrium distribution of city sizes.

We assume that the location choice of an individual $\ell$ is based on linear random utility $V_r^\ell = U_r + A_r + \xi_r^\ell$, where $U_r$ is given by (28) and $A_r$ subsumes city-specific amenities that are equally valued by all individuals. For the empirical implementation, we assume that $A_r \equiv A(A_r^o, A_r^u)$, where $A_r^o$ refers to observed amenities such as coastal location and $A_r^u$ to the unobserved part. The random variable $\xi_r^\ell$ then captures idiosyncratic taste differences in residential location. Following McFadden (1974), we assume that the $\xi_r^\ell$ are i.i.d. across individuals and cities according to a double exponential distribution with zero mean and variance equal to $\pi^2\beta^2/6$, where $\beta$ is a positive constant. Since $\beta$ has a positive relationship with variance, the larger the value of $\beta$, the more heterogeneous are the consumers' attachments to each city. Given the population distribution, an individual's probability of choosing city $r$ can then be expressed as a logit form:

$$\mathbb{P}_r = \Pr\left(V_r^\ell > \max_{s\neq r} V_s^\ell\right) = \frac{\exp((U_r + A_r)/\beta)}{\sum_{s=1}^K \exp((U_s + A_s)/\beta)}. \tag{29}$$

If $\beta \to 0$, which corresponds to the case without taste heterogeneity, people choose their location based only on $U_r + A_r$, i.e., they choose a city with the highest $U_r + A_r$ with probability one. By contrast, if $\beta \to \infty$, individuals choose their location with equal probability $1/K$. In that case, taste for residential location is extremely heterogeneous, so that $U_r + A_r$ does not affect location decisions at all.

A *spatial equilibrium* is defined as a city-size distribution satisfying

$$\mathbb{P}_r = \frac{L_r}{\sum_{s=1}^K L_s}, \quad \forall r. \tag{30}$$

In words, a spatial equilibrium is a fixed point where the choice probability of each city is equal to that city's share of the economy's total population. In theory, there can be multiple city-size distributions satisfying (30). However, this is not an issue given the aim of our paper. Indeed, in Section 4, where we take our model to data, we plug the observed US city sizes into the right-hand side of (30) and uniquely back out $(U_r + A_r)/\beta$ such that this population distribution is a spatial equilibrium.

### 3.3 *The impact of spatial frictions: An example with two cities*

In the counterfactual analysis in Section 5, we simulate how city sizes, their distribution, productivity, and markups would look like when either urban or trade frictions change. To build intuition for these counterfactual experiments, we now consider an example with two cities, as is standard in the literature. The formal analysis is in the supplementary online appendix, whereas the main text focuses on the intuition of how spatial frictions affect the fundamental trade-off between agglomeration and dispersion forces.

We assume that trade costs are symmetric ($\tau_{12} = \tau_{21} = \tau$ and $\tau_{11} = \tau_{22} = t$), and that intra-city trade is less costly than inter-city trade ($t \leq \tau$).[11] The market equilibrium for any given city sizes $L_1$ and $L_2$ is then uniquely determined, and yields the relative wage $\omega \equiv w_1/w_2$ and the two internal cutoffs $m_1^d$ and $m_2^d$.

[11] Imposing the assumption $t \leq \tau$ is not very restrictive. Indeed, the inequality $\tau_{rr} < \min_s \tau_{rs} = \min_s \tau_{sr}$ holds in 352/356 $\approx$ 99% of the cases in our subsequent application using US data.

Now suppose that city 1 is larger than city 2 ($L_1 > L_2$) while the two cities are identical with respect to their gross labor supplies per capita ($\overline{h}_1 = \overline{h}_2 = \overline{h}$), commuting technologies ($\theta_1 = \theta_2 = \theta$), and technological possibilities ($\mu_1^{\max} = \mu_2^{\max} = \mu^{\max}$). Then, the market equilibrium is such that *the larger city has the higher wage ($\omega > 1$) and the lower cutoff ($m_1^d < m_2^d$)*. The intuition is that – due to trade frictions – firms in the larger city have an advantage in terms of local market size, and this advantage must be offset by higher production costs and tougher selection in equilibrium.

Turning to choice probabilities, for any given city sizes $L_1$ and $L_2$, (29) can be written as

$$\mathbb{P}_1 = \frac{\exp(\Upsilon/\beta)}{\exp(\Upsilon/\beta) + 1} \quad \text{and} \quad \mathbb{P}_2 = \frac{1}{\exp(\Upsilon/\beta) + 1},$$

where $\Upsilon \equiv (U_1 - U_2) + (A_1 - A_2)$. Hence, $\mathbb{P}_1$ is increasing and $\mathbb{P}_2$ is decreasing in $\Upsilon$. Plugging (28) into the definition of $\Upsilon$, we readily obtain

$$\Upsilon = \left(\frac{\alpha}{t}\right) \left[\frac{1}{(k+1)(\kappa_1 + \kappa_2)} - 1\right] \left(\frac{h_1}{m_1^d} - \frac{h_2}{m_2^d}\right), \tag{31}$$

where we set $A_1 = A_2$ for simplicity. Recalling that $L_1 > L_2$, the lower cutoff in city 1 ($m_1^d < m_2^d$) constitutes an agglomeration force as it raises the indirect utility difference $\Upsilon$. Yet, due to urban frictions, the larger city also has lower effective labor supply per capita ($h_1 < h_2$), which negatively affects $\Upsilon$, thus representing a dispersion force.

For the population distribution $L_1 > L_2$ to be a spatial equilibrium, condition (30) requires that $\mathbb{P}_1 > \mathbb{P}_2$, which in turn implies $\Upsilon > 0$ and $h_1/m_1^d > h_2/m_2^d$ by (31). The larger city then has greater consumption diversity ($N_1^c > N_2^c$) according to (26) and a lower average markup ($\overline{\Lambda}_1 < \overline{\Lambda}_2$) according to (27) than the smaller city. Taking such a spatial equilibrium as the starting point, we now consider what happens if either urban frictions or trade frictions are eliminated.

*No urban frictions.* Our first counterfactual experiment will be to eliminate urban frictions while leaving trade frictions unchanged. This is equivalent to setting $\theta = 0$, holding $\tau$ and $t$ constant. In what follows, we consider how $\Upsilon$ is affected by such a change. This allows us to study if eliminating urban frictions involves more agglomeration (larger $\mathbb{P}_1$) or more dispersion (smaller $\mathbb{P}_1$). Let $\widetilde{\Upsilon}$ be the value of $\Upsilon$ in the counterfactual scenario, keeping city sizes fixed at their initial levels. Other counterfactual values are also denoted with a tilde. Observing that $\widetilde{h}_1 = \widetilde{h}_2 = \overline{h}$ when $\theta = 0$, we have

$$\text{sign}\left\{\widetilde{\Upsilon} - \Upsilon\right\} = \text{sign}\left\{\frac{\overline{h} - h_1}{\widetilde{m}_1^d} - \frac{\overline{h} - h_2}{\widetilde{m}_2^d} + h_1\left(\frac{1}{\widetilde{m}_1^d} - \frac{1}{m_1^d}\right) - h_2\left(\frac{1}{\widetilde{m}_2^d} - \frac{1}{m_2^d}\right)\right\}. \tag{32}$$

The first two terms in (32) stand for the direct effects of eliminating urban frictions. In the initial situation where $\theta > 0$, we know that $h_1 < h_2 < \overline{h}$ as urban frictions are greater in the larger city. We also know that $m_1^d < m_2^d$ holds even without urban frictions as $L_1 > L_2$, so that $\widetilde{m}_1^d < \widetilde{m}_2^d$. Hence, the first positive term always dominates the second negative term, thus showing that the direct effects favor the large city by increasing the probability $\mathbb{P}_1$ of choosing city 1. However, eliminating urban frictions also induces indirect effects through the cutoffs, which are captured by the second two terms in (32). Both of these terms are negative and thus work in the opposite direction than the direct effects. Specifically, it can be shown that setting $\theta = 0$ implies $m_1^d < \widetilde{m}_1^d < \widetilde{m}_2^d < m_2^d$. That is, average productivity goes down in the larger city when the population distribution is held fixed, while it goes up in the smaller city.[12]

If the direct effects dominate the indirect effects, we have $\widetilde{\Upsilon} > \Upsilon$ so that $\mathbb{P}_1$ increases and the large city becomes even larger as urban frictions are eliminated. The increase in population then leads to a productivity gain, which may offset the productivity drop at a given population size. As we show below, such a pattern indeed emerges in the quantified multi-city model (see Figures 1, 2, and 4): big cities like New York become even larger. Holding the initial population fixed, productivity goes down in New York, while it goes up once we take population changes into account, as shown in Figure 4. By the same argument, small cities may end up with a lower productivity due to their loss in population. Hence, eliminating urban frictions makes the productivity change in the economy as a whole ambiguous.

*No trade frictions.* Our second counterfactual experiment will be to eliminate trade frictions while leaving urban frictions unchanged. More specifically, we consider a scenario where consumers face the same trade costs for local and non-local varieties. This is equivalent to setting $\tau = t$, holding $\theta$ constant. As before, let $\widetilde{\Upsilon}$ be the value of $\Upsilon$ in the counterfactual scenario, while keeping city sizes fixed at the initial level. Noting that $h_1$ and $h_2$ remain constant, the change in $\Upsilon$ can now be written as

$$\text{sign}\left\{\widetilde{\Upsilon} - \Upsilon\right\} = \text{sign}\left\{h_1\left(\frac{1}{\widetilde{m}_1^d} - \frac{1}{m_1^d}\right) - h_2\left(\frac{1}{\widetilde{m}_2^d} - \frac{1}{m_2^d}\right)\right\}. \tag{33}$$

It can be shown that now *both* cutoffs decrease for given population sizes, i.e., $\widetilde{m}_1^d < m_1^d$ and $\widetilde{m}_2^d < m_2^d$. Both cities, therefore, experience a productivity gain. The first term in

[12]The reason is the following: the reduction of $\theta$ from any given positive value to zero raises aggregate labor supply $S_r$ in both cities. The increase is relatively stronger in the larger city ($S_1/S_2$ goes up), so that the relative wage $\omega$ increases. To offset this, the equilibrium cutoff must thus *increase* in the larger city and *decrease* in the smaller city.

brackets in (33) is thus positive and the second term is negative. Yet it can be shown that $\widetilde{\Upsilon} < \Upsilon$ holds if $\mu_2^{\max}/\mu_1^{\max} \leq (h_2/h_1)^{k+1}$. In other words, the large city becomes smaller if the two cities are not too different in terms of their technological possibilities. In the simple case where $\mu_2^{\max}/\mu_1^{\max} = 1$, the large city always becomes smaller as $h_2/h_1 > 1$. In contrast, the small city becomes larger and, consequently, experiences a stronger productivity gain than the large city. We show below that such a pattern also emerges in our quantified multi-city model (see Figures 5 and 6).[13]

# 4. Quantification

We now take our multi-city model to the data by estimating or calibrating its parameters. This procedure can be divided into two broad stages, namely the quantification of the *market equilibrium* and that of the *spatial equilibrium*, which we now explain in turn.

### *4.1 Market equilibrium*

The quantification of the market equilibrium consists of the following five steps:

1. Using the definition of total effective labor supply and data on commuting time, hours worked, and city size at the MSA level, we uniquely obtain the city-specific commuting technology parameters $\widehat{\theta}_r$ that constitute *urban frictions*.

2. Using the specification $\tau_{rs} \equiv d_{rs}^{\gamma}$, where $d_{rs}$ is the distance from $r$ to $s$, we estimate a gravity equation that relates the value of bilateral trade flows to distance. For a given value of the Pareto shape parameter $k$, we obtain the distance elasticity $\widehat{\gamma}$ that constitutes *trade frictions*.

3. The estimated distance elasticity, together with the value of $k$ and data on labor supply, value added per worker, and city size, allows us to uniquely back out the set of city-specific technological possibilities $\widehat{\mu}_r^{\max}$ and (relative) wages $\widehat{w}_r$ that are consistent with the market equilibrium conditions.[14]

[13] Other two-region NEG models with commuting costs (Tabuchi, 1998; Murata and Thisse, 2005) would come to qualitatively similar conclusions about how falling transport or commuting costs affect the spatial equilibrium. Helpman (1998) considers a fixed supply of land instead of commuting, but his model would also display a similar pattern as falling transport costs are dispersive, while greater abundance of land is agglomerative. Though useful for illustrative purposes, such two-region examples do not convey a sense of magnitude about the quantitative importance of spatial frictions in practice, however. Section 4 of this paper deals precisely with this issue.

[14] Even with urban costs, we can establish uniqueness in a similar way than in Behrens *et al.* (2014b). The proof is available upon request.

4. Using the set of city-specific technological possibilities thus obtained, we draw a large sample of firms from within the model to compute the difference between the simulated and observed establishment size distributions.

5. Iterating through steps 2 to 4, we search over the parameter space to find the value of the Pareto shape parameter $k$ that minimizes the sum of squared differences between the simulated and observed establishment size distributions.

Several details about this procedure and the data are relegated to the supplementary online appendix. As for the quantification results, our iterative procedure yields the Pareto shape parameter $\widehat{k} = 6.4$. Columns 1 and 2 of Table 1 below show that, despite having only a single degree of freedom, the simulated establishment size distribution fits the observed establishment size distribution well.

Turning to spatial frictions, we obtain an estimate for the commuting technology parameter that constitutes *urban frictions* for each MSA. As shown in Table 5 in the supplementary online appendix, the value of $\widehat{\theta}_r$ ranges from 0.0708 (Los Angeles-Long Beach-Santa Ana and New York-Northern New Jersey-Long Island) and 0.0867 (Chicago-Naperville-Joliet) to 0.9995 (Yuba City, CA) and 1.4824 (Hinesville-Fort Stewart, GA). Thus, big cities tend to have better commuting technologies per unit of distance.[15] For *trade frictions*, our estimation yields $\widehat{\gamma k} = 1.2918$ (with standard error 0.0271) which, given $\widehat{k} = 6.4$, implies $\widehat{\gamma} = 0.2018$.[16]

We then obtain the values of the technological possibilities $\widehat{\mu}_r^{\max}$, which may be viewed as a measure for MSA-level production amenities. Table 5 in the supplementary online appendix reports those values, along with the observed MSA populations scaled by their mean (i.e., $L_r/\overline{L}$) and average productivities ($\overline{M}_r$). From the quantification procedure we also obtain the wages $\widehat{w}_r$ that are consistent with the market equilibrium conditions, which we compare to the observed wages at the MSA level in Section 4.3. Ultimately, the quantification of the market equilibrium allows us to measure the indirect utility $\widehat{U}_r$ from (28) by using data on $h_r = S_r/L_r$ and $m_r^d$, as well as the estimate of $\widehat{\tau}_{rr}$.

[15]For any given distance $x$ from the CBD, a smaller $\theta$ implies that people spend less time to commute to the CBD. However, this does not necessarily mean that average commuting time is shorter in larger cities because of longer average commuting distances. Our finding that big cities tend to have better commuting technologies also holds when assuming a linear commuting technology as in Murata and Thisse (2005).

[16]We use OLS estimation with fixed effects as our benchmark. As a robustness check, we also consider the PPML fixed effects estimator by Santos Silva and Tenreyro (2006). The latter yields $\widehat{\gamma k} = 1.4659$ and $\widehat{k} = 8.5$ when redoing the iterative procedure. When it comes to the counterfactual analysis, however, it turns out that the PPML approach leads to virtually the same predictions as our benchmark.

### 4.2 *Spatial equilibrium*

Using the spatial equilibrium conditions (30), the expression of the indirect utility $\widehat{U}_r$, and data on observed amenities $A_r^o$, we obtain a measure for unobserved amenities $A_r^u$ and the relative weight of the indirect utility and amenities for individual location decisions that are consistent with the observed city-size distribution.

Setting $(U_1 + A_1)/\beta \equiv 0$ as a normalization, and using the observed $L_r$ for the 356 MSAs, the spatial equilibrium conditions $\mathbb{P}_r = L_r/L$ for $r = 2,3,\ldots,K$ can be *uniquely* solved for $(U_r + A_r)/\beta$.[17] We thus obtain the values of $(U_r + A_r)/\beta$ that replicate the observed city-size distribution as a spatial equilibrium. Let $\widehat{D}_r$ denote this solution satisfying

$$\mathbb{P}_r = \frac{\exp(\widehat{D}_r)}{\sum_{s=1}^{K}\exp(\widehat{D}_s)} = \frac{L_r}{L}, \quad \widehat{D}_1 = 0. \tag{34}$$

Having solved (34) for $\widehat{D}_r$, we then gauge the relative importance of the indirect utility $\widehat{U}_r$ and observed amenities $A_r^o$ in consumers' location choices by estimating a simple OLS regression as follows,

$$\widehat{D}_r = \alpha_0 + \alpha_1\widehat{U}_r + \alpha_2 A_r^o + \varepsilon_r, \tag{35}$$

which yields

$$\widehat{D}_r = \underset{(0.2644)}{-0.2194} + \underset{(0.5289)}{1.7481^{***}}\widehat{U}_r + \underset{(0.0199)}{0.0652^{***}}A_r^o + \widehat{\varepsilon}_r. \tag{36}$$

Consistent with theory, both indirect utility and observed amenities significantly influence the spatial distribution of population across MSAs, both coefficients being positive. The fitted residuals $\widehat{\varepsilon}_r$ can be interpreted as a measure of the unobserved part of the MSA amenities. We hence let $\widehat{A}_r^u \equiv \widehat{\varepsilon}_r$ which by construction is uncorrelated with $A_r^o$.

Notice that, to identify $\alpha_1$, we impose in our benchmark that $\varepsilon_r$ is orthogonal to $\widehat{U}_r$. As a robustness check we relax this assumption and allow the cities' unobserved amenities to be correlated with the indirect utility. More specifically, to estimate (35) we consider an instrumental variable approach similar to that in Rosenthal and Strange (2008), where $\widehat{U}_r$ is instrumented with geological variables measuring the suitability of a city for building constructions (see the supplementary online appendix for details). These variables are thus assumed to affect location decisions only via their impact on economic activity as measured by $\widehat{U}_r$. The corresponding 2SLS estimation attributes a larger weight to market interactions in governing individual location choices ($\widehat{\alpha}_1^{2SLS}$= 2.8416). In Section 6.2 we then apply the 2SLS estimates of (35) in our counterfactual analysis.

[17]See the supplementary online appendix for the proof of uniqueness.

Table 5 in the supplementary online appendix reports the observed and unobserved consumption amenities, as well as the production amenities in the benchmark case. Several points are worth emphasizing. First, in contrast to Roback (1982) type approaches, spatial patterns of MSA-level consumption and production amenities ($\widehat{A}^u_r$ and $\widehat{\mu}^{\max}_r$) are derived from a quantified spatial equilibrium framework where trade frictions are explicitly taken into account. Second, both observed and unobserved consumption amenities are positively correlated with city size, the correlation being stronger for the latter (0.7023) than for the former (0.1334). Third, while the correlation between $A^o_r$ and $\widehat{A}^u_r$ is zero by construction, there is also little correlation between technological possibilities and each type of consumption amenities (-0.0867 and 0.0713 for $A^o_r$ and $\widehat{A}^u_r$, respectively). This is consistent with the results by Chen and Rosenthal (2008) who find that good business locations in the US need not have good consumption amenities.

### 4.3 MSA- *and firm-level model fit*

Before turning to the counterfactual experiments, it is important to point out that our model can replicate several empirical facts, both at the MSA and firm levels, that have not been used in the quantification procedure. We briefly summarize some of those dimensions and again relegate several details of this model fit analysis to the supplementary online appendix.

First, since our key objective is to investigate the importance of urban and trade frictions, having an idea of how well our model captures empirical facts about these dimensions is particularly important.

*Urban frictions.* We first consider urban frictions by comparing the 'model-based' and observed aggregate land rents. The former can be obtained by making use of (13). The latter is, in turn, obtained by $\text{ALR}_r = \text{GMR}_r/(1 - \text{ownershare}_r)$, where GMR is the (aggregate) gross monthly rent.[18] The simple correlation between the model-based and observed aggregate land rents across MSAs is 0.9805, while the Spearman rank correlation

[18] The formula can be obtained as follows. First, the total amount of expenditure in housing services (ALR) is given by the sum of the gross monthly rent (GMR) and the equivalent rent value for houses that are owned (ERV). Data on GMR, which can be decomposed as (average rent) $\times$ (number of houses that are rented), is available. Now assume that GMR/(number of houses rented) $=$ ERV/(number of houses owned) holds in each city at equilibrium by arbitrage. We then obtain ALR $=$ GMR/(1 $-$ share of houses that are owned).

is 0.9379.[19] Alternatively, we can use $\text{ALR}_r = \text{ERV}_r/(\text{ownershare}_r)$, where $\text{ERV}_r$ is the equivalent rent value for houses that are owned. Under this alternative formula, the correlation between the model-based and observed aggregate land rents becomes 0.9624, while the Spearman rank correlation is 0.9129. In all cases, the correlations are high, thus suggesting that our model does a good job in capturing urban frictions across MSAs.[20]

*Trade frictions.* We next turn to trade frictions. Note that our estimate of the trade elasticity $\widehat{\gamma k}$ for the year 2007 closely matches the value of 1.348 reported by Hillberry and Hummels (2008) from estimation of a gravity equation at the 3-digit zip code level using the confidential CFS microdata. We can further assess to what extent our model can cope with existing micro evidence on the spatial structure of shipping patterns. As shown in the supplementary online appendix, both aggregate shipment values and the number of shipments predicted by our model fall off very quickly with distance – becoming very small beyond a threshold of about 200 miles – whereas price per unit first rises with distance and average shipment values do not display a clear pattern. These results are in line with those in Hillberry and Hummels (2008). Furthermore, we can also compare shipping shares and shipping distances by establishment size class predicted by our model, and the observed counterparts as reported by Holmes and Stevens (2012). Our model can qualitatively reproduce their observed shipment shares. It can also explain their finding that the mean distance shipped increases with establishment size.

Second, the correlation between actual relative wages and those predicted by our model is 0.7379 and thus reasonably high.

Third, the representative firm sample drawn from our quantified model can replicate the observed distribution of establishments across MSAs. Table 1 reports the mean, standard deviation, minimum, and maximum of the number of establishments (top part) and average establishment size (bottom part) at the MSA level, and the number of establishments is further broken down by employment size. The last column of Table 1

[19]To obtain the 'model-based' aggregate land rent, we set $R_r(\overline{x}_r) = 0$ in (13) for all cities since data on $R_r(\overline{x}_r)$ is not readily available. It is a priori unclear whether allowing for heterogeneity in $R_r(\overline{x}_r)$ raises the correlations between observed and model-based land rents that we report here. Note that we need not make any assumption on the value of $R_r(\overline{x}_r)$ when quantifying the model and running counterfactuals.

[20]One might argue that our simple monocentric city model is not the most appropriate specification as large MSAs are usually polycentric. To see how urban frictions relate to polycentricity, we compute a simple correlation between $\widehat{\theta}_r$ and the number of employment centers in each MSA for the year 2000 as identified by Arribas-Bel and Sanz Gracia (2010). The correlation is $-0.4282$, while the Spearman rank correlation is $-0.5643$, thus suggesting that our monocentric model with city-specific commuting technology captures the tendency that larger cities are more efficient for commuting as they allow for more employment centers, thereby reducing the average commuting distance through employment decentralization.

reports the correlation between the observed and our simulated data. As can be seen, the simple cross-MSA correlation for the total number of establishments is 0.7253, with a slightly larger rank correlation of 0.733. Furthermore, the correlations between the observed and the predicted numbers of medium-sized and large establishments across MSAs are high (between 0.889 and 0.9412).

Table 1: Cross-MSA distribution of establishment numbers and average size – summary for observed and simulated data.

| | Mean | | St.dev. | | Min | | Max | | Correlation |
|---|---|---|---|---|---|---|---|---|---|
| Variable | Model | Observed | Model | Observed | Model | Observed | Model | Observed | Model-Observed |
| # of establishments total | 18067.10 | 18067.09 | 16878.09 | 43138.45 | 1738 | 911 | 109210 | 541255 | 0.7253 |
| # of establishments size 1-19 | 15444.74 | 15461.97 | 12066.43 | 37449.79 | 1550 | 804 | 79181 | 478618 | 0.3824 |
| # of establishments size 20-99 | 2121.56 | 2162.09 | 6320.64 | 4728.28 | 49 | 93 | 52178 | 51310 | 0.9412 |
| # of establishments size 100-499 | 429.83 | 397.50 | 1729.44 | 922.34 | 14 | 13 | 24365 | 9951 | 0.8890 |
| # of establishments size 500+ | 70.94 | 45.52 | 132.67 | 113.75 | 2 | 1 | 1509 | 1376 | 0.9320 |
| Avg establishment size | 11.73 | 15.40 | 11.63 | 2.60 | 0.90 | 6.40 | 131.88 | 23.70 | 0.1716 |

*Notes:* Model values are computed from a representative sample of 6,431,886 establishments. See supplementary online appendix F.2 for a detailed description.

## 5. Counterfactuals

Having shown that our quantified model performs well in replicating several features of the data, we now use it for counterfactual analysis. Our aim is to assess the importance of spatial frictions for the US city-size distribution, for individual city sizes, as well as for the distributions of productivity and markups across MSAs. To this end we eliminate urban frictions or trade frictions (counterfactuals CF1 and CF2, respectively). In this section we discuss our benchmark results. We then check in Section 6 the robustness of our results when we allow for agglomeration economies, and for unobserved amenities to be correlated with the indirect utility.

### 5.1 No urban frictions

In the first counterfactual experiment (which we call 'no urban frictions'), we set all commuting-related frictions – and hence all land rents – to zero ($\widehat{\theta}_r = 0$ for all $r$) while keeping trade frictions $\widehat{\tau}_{rs}$, technological possibilities $\widehat{\mu}_r^{\max}$, consumption amenities ($A_r^o$ and $\widehat{A}_r^u$), and the location choice parameters $\widehat{\alpha}_0$, $\widehat{\alpha}_1$, and $\widehat{\alpha}_2$ constant.[21] This corresponds to a hypothetical world where only goods are costly to transport while living in cities does not impose any urban costs. Comparing the counterfactual equilibrium for this scenario to the initial spatial equilibrium is then a meaningful exercise, as it addresses to what extent the actual US economic geography is shaped by urban frictions.

[21] Although workers are mobile in our model, we can set urban frictions to zero without having degenerate equilibria with full agglomeration. The reason is that, as explained before, consumers' location choice probabilities are expressed as a logit so that no city disappears.

*City sizes.* Starting with city sizes, eliminating urban frictions leads to (gross) cross-MSA population movements of about 4 million people, i.e., 1.6% of the total MSA population in our sample. Figure 1 plots percentage changes in MSA population against the initial log MSA population. As can be seen, large cities would on average gain population, whereas small and medium-sized cities tend to lose. In other words, urban frictions limit the size of large cities. The size of New York, for example, would increase by about 8.5%. That is to say, urban frictions matter for the size of New York, as the city is 8.5% smaller than it would be in a hypothetical world without urban frictions. Some MSAs close to New York and Boston are affected even more by urban frictions. For example, New Haven-Milford, CT, is 12.1% smaller and Bridgeport-Stamford-Norwalk, CT, is even 15.9% smaller than it would be. The top panel of Figure 2 further indicates that the impacts of urban frictions follow a rich spatial pattern and are highly unevenly spread across MSAs.

Interestingly, although the sizes of individual cities would be substantially different in a world without urban frictions, the city-size distribution would be almost the same. This is shown in Figure 3. A standard rank-size rule regression reveals that the coefficient on log size rises slightly from $-0.9249$ to $-0.9178$, the change being statistically insignificant.[22] The hypothetical elimination of urban frictions would thus move single cities up or down in the urban hierarchy, but within a stable city-size distribution. We will discuss this stability in greater depth below in Section 5.3.

*Productivity.* Turning to average productivity, the middle panel of Figure 2 shows that the impact of urban frictions differs substantially across cities. New York's productivity is 0.76% higher in the counterfactual equilibrium. Urban frictions thus have a negative impact on productivity as they limit the size of New York. However, most MSAs would have a *lower* productivity level if urban frictions were eliminated, for example small cities like Monroe, MI, by 0.9%. This means that the presence of urban frictions in the real world leads to a higher productivity as population is retained in those cities. Computing the nation-wide productivity change, weighted by MSA population shares in the initial equilibrium, we find that eliminating urban frictions would increase average productivity by a mere 0.04%.

It is important to see that these results refer to the *long-run* impacts of eliminating urban frictions on productivity, as they include the effects of population movements. To gauge the contribution of labor mobility to these overall impacts, we disentangle the *short-run* effects, before the population reshufflings have taken place, from the long-run effects. The

[22]We follow Gabaix and Ibragimov (2011) and adjust the rank by subtracting 1/2. The standard deviation of the coefficient on the log of city size is 0.0086 for the initially observed city-size distribution.

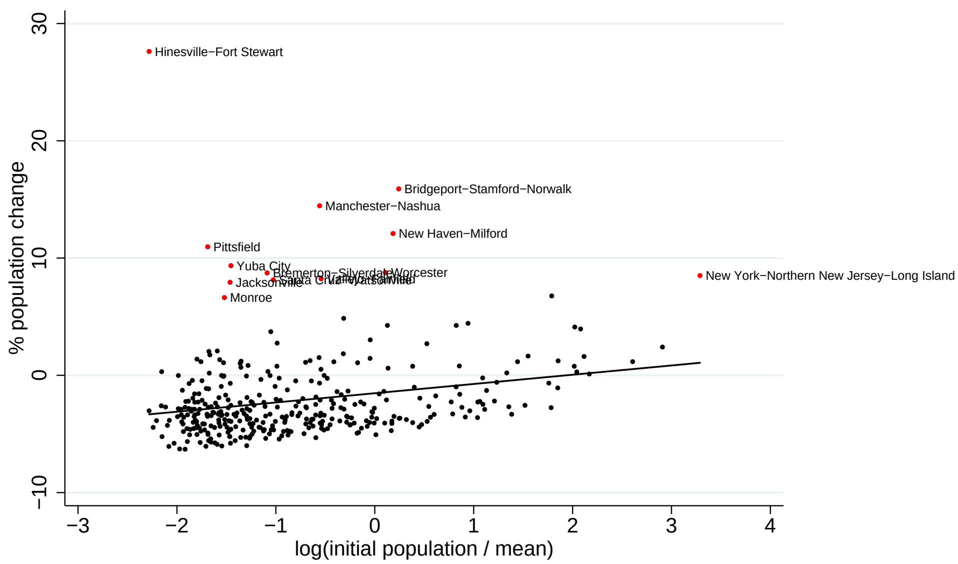


Figure 1: Changes in MSA populations and initial size (CF1)

left panel of Figure 4 illustrates the cutoff changes across MSAs when eliminating urban frictions, holding city sizes fixed at their initial levels. It shows that the cutoffs $m_r^d$ rise, on average, in larger cities. However, as can be seen from the right panel of Figure 4, the subsequent movements of population (which flows toward the larger cities), more than offset this initial change, thereby generating larger productivity gains in the bigger cities in the long-run equilibrium.[23] This decomposition of the short- and long-run effects can also be related to the comparative static results of Section 3.3. There, we have shown that the instantaneous impact of reducing urban frictions – keeping $L_r$ fixed – is to raise the cutoff in the large city and to lower it in the small city. This pattern can get reversed, however, once the population movements are taken into account.

*Markups.* Turning to the long-run impact on markups, the bottom panel of Figure 2 reveals that this is the dimension where the largest changes take place. Markups would decrease everywhere, with reductions ranging from 5.3% to about 16%, but the more so for the most populated areas of the East and West coasts. As can be seen from (27), the reason for these large changes is twofold. First, eliminating urban frictions increases the effective labor supply per capita $h_r$ everywhere, which allows for more firms in each MSA and, therefore, for more competition. Second, there is an effect going through the cutoffs.

[23]Some simple OLS regressions of the change in $m_r^d$ in the short- and in the long-run on inital population yield: $\Delta m_r^d/m_r^d = -0.0821^{***} + 0.0127^{***} L_r$ in the short-run, and $\Delta m_r^d/m_r^d = 0.0817^{***} - 0.0194^{***} L_r$ in the long-run, thus showing the switch in the results depending on whether or not population is mobile.

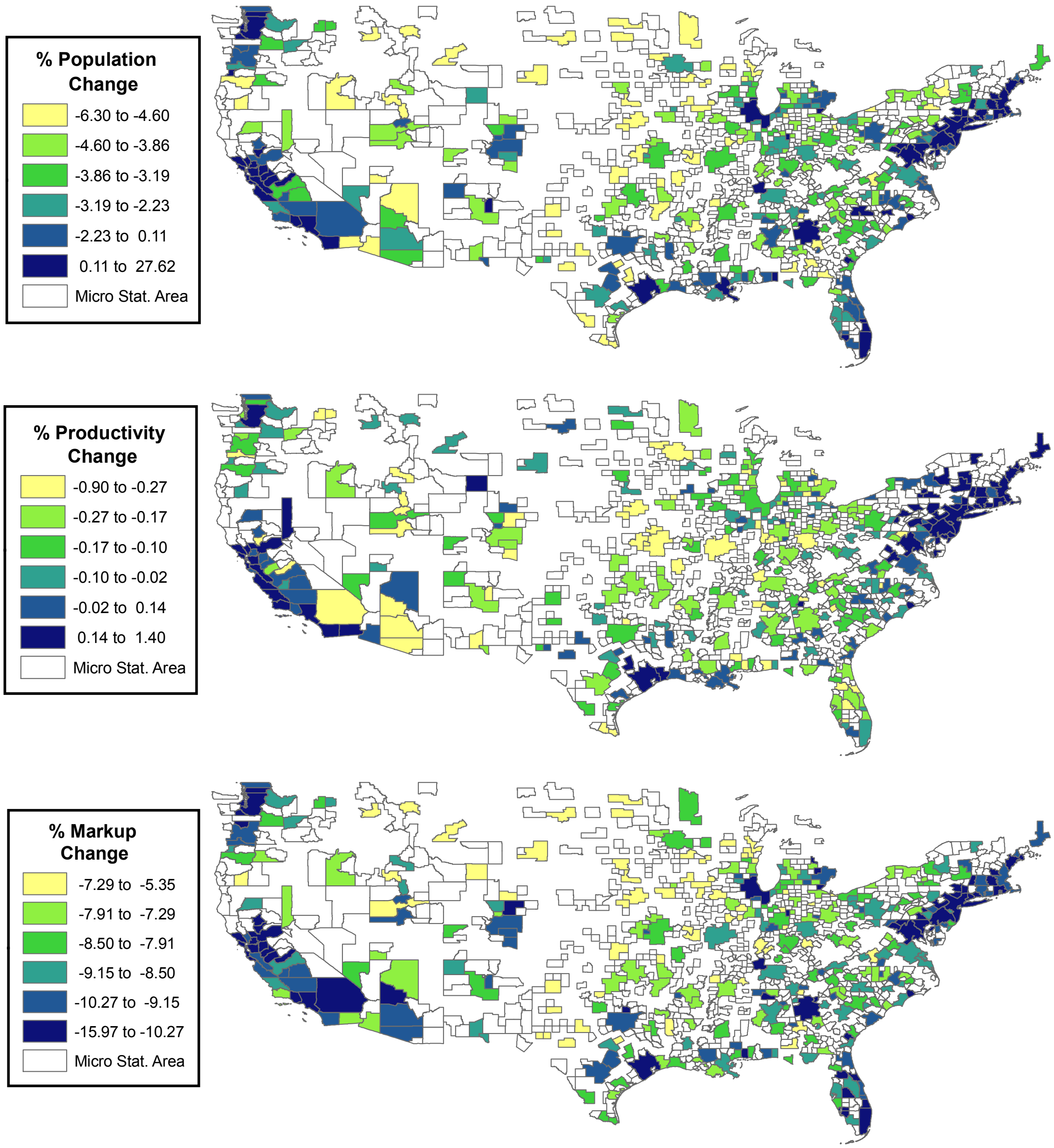


Figure 2: Spatial pattern of counterfactual changes in $L_r$, $1/m_r^d$ and $\overline{A}_r$ (CF1)

Some places see their cutoffs fall, especially larger cities which receive population inflows, and this puts additional pressure on markups there. In contrast, cutoffs increase in cities that lose population. However, even in those cities it turns out that markups decrease, as the pro-competitive effect due to higher effective labor supply per capita dominates the anti-competitive effect of the higher cutoff.

To summarize, even without urban frictions, the city-size distribution would remain fairly stable, despite the fact that larger cities tend to grow and smaller cities tend to shrink. Furthermore, the ‘no urban frictions’ case supports more firms, which reduces

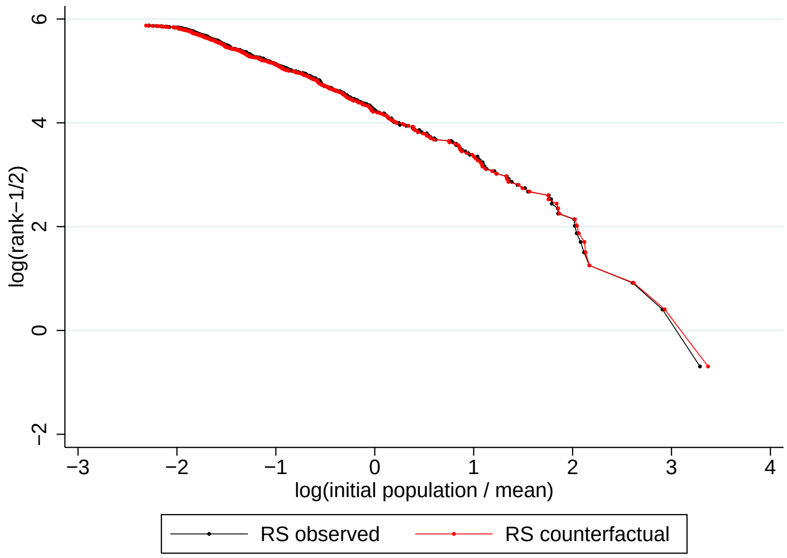


Figure 3: Rank-size rule, observed and counterfactual (CF1)

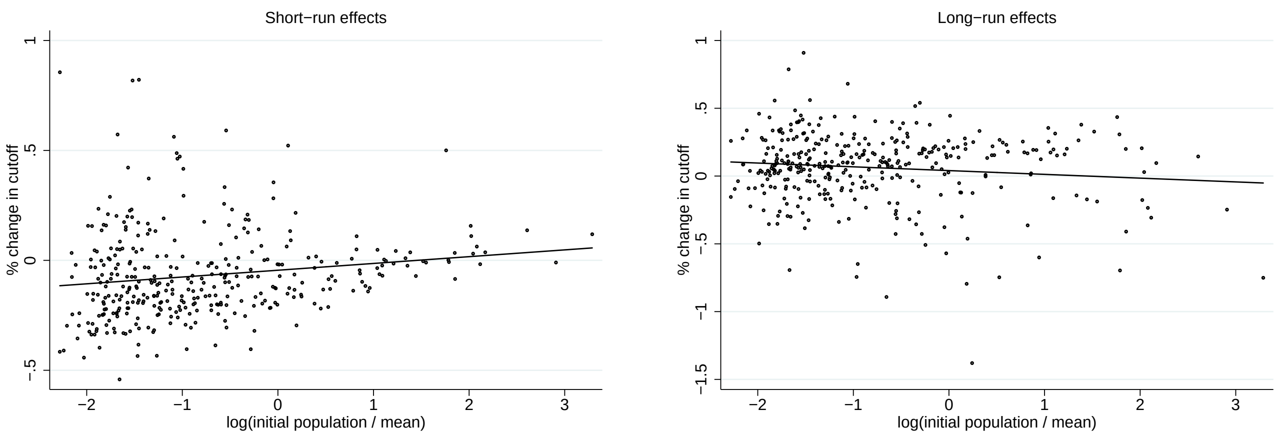


Figure 4: Difference in short- and long-run relationships between $\Delta m_r^d / m_r^d$ and $L_r$ (CF1)

markups and expands product diversity, though firms are not on average much more productive than in a world with urban frictions. The productivity gap between large and small cities would, however, widen.

### *5.2 No trade frictions*

How do trade frictions shape the US economic geography? To address this question, we set external trade costs from $s$ to $r$ equal to internal trade costs in $r$ ($\tau_{sr} = \tau_{rr}$ for all $r$ and $s$) in the second counterfactual experiment (which we call 'no trade frictions'). This

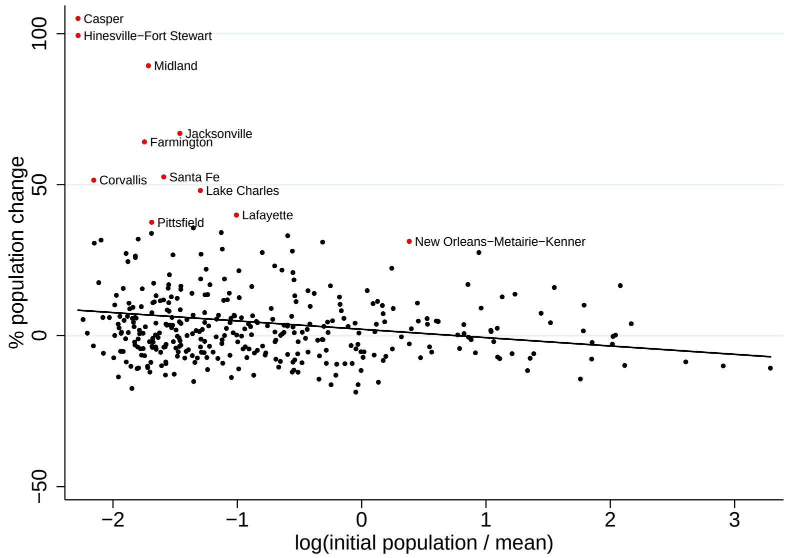


Figure 5: Changes in MSA populations and initial size (CF2)

experiment corresponds to a hypothetical world where consumers face the same trade costs for local and non-local varieties.[24]

*City sizes.* Starting with city sizes, eliminating trade frictions would lead to significant (gross) cross-MSA population movements of about 10.2 million people, i.e., 4.08% of the total MSA population in our sample. Some small and remote cities would gain substantially. For example, the population of Casper, WY, would grow by about 105% and that of Hinesville-Fort Stewart, GA, by about 99.4%. That is, trade frictions limit the size of small and remote cities substantially. Figure 5 plots the percentage changes in MSA population against the initial log MSA population. Consistent with the comparative static results of Section 3.3, in a world without trade frictions larger cities lose ground and individuals move, on average, to smaller cities to relax urban costs. These changes are depicted in the top panel of Figure 6. Although individual cities would be substantially affected by the fall in trade frictions, the city-size distribution remains again quite stable, as can be seen from Figure 7. The coefficient on log size drops from $-0.9249$ to $-0.9392$, yet this change is again statistically insignificant.

[24]Eaton and Kortum (2002) consider a similar counterfactual scenario in the context of international trade with a fixed population distribution. We have also experimented with setting $\tau_{rs} = \tau_{rr}$ for all $r$ and $s$, which corresponds to a hypothetical world where goods are as costly to trade between MSAs as within MSAs from the firms' perspective. The results are largely the same.

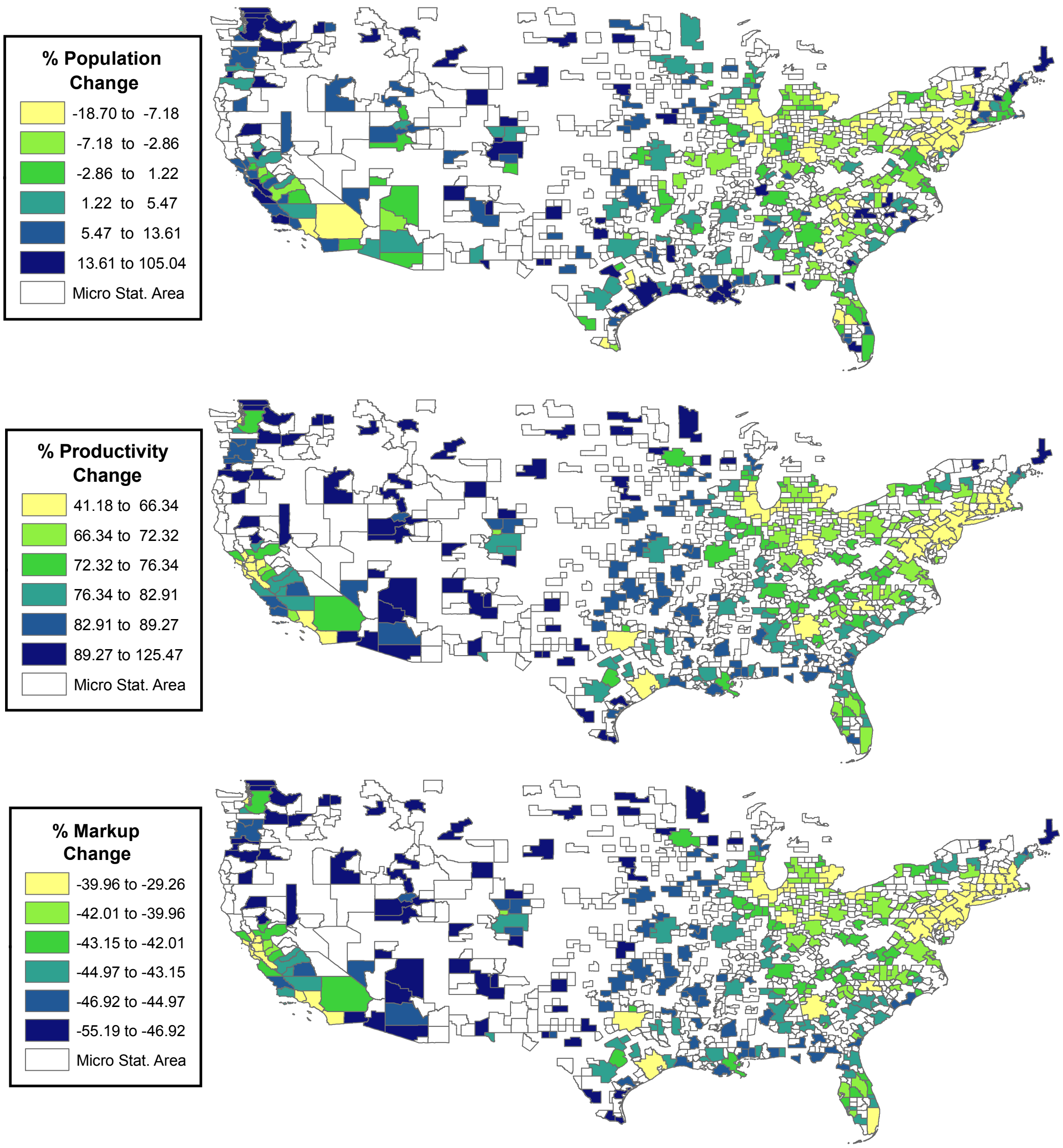


Figure 6: Spatial pattern of counterfactual changes in $L_r$, $1/m_r^d$ and $\overline{\Lambda}_r$ (CF2)

*Productivity.* Concerning the changes in average productivity, observe first that all MSAs gain. In other words, the existence of trade frictions in the real world causes productivity losses for the US economy. Yet, as can be seen from the middle panel of Figure 6, these impacts are unevenly spread across MSAs. If trade frictions were eliminated, some small cities would gain substantially (e.g., an increase of about 125.5% in Great Falls, MT), while large cities would gain significantly less: 41.18% in New York, 48.08% in Los Angeles, and 55.71% in Chicago. The first reason is linked to market access. Indeed, the more populated areas, e.g., those centered around California and New England, would be those

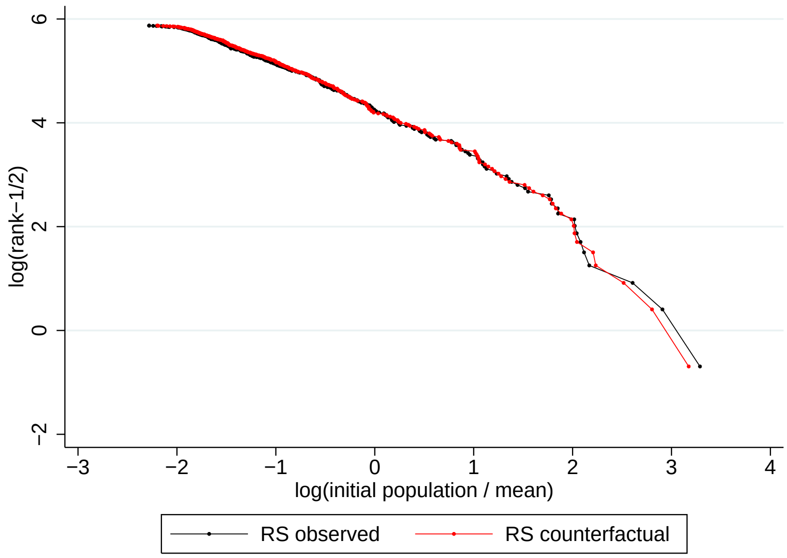


Figure 7: Rank-size rule, observed and counterfactual (CF2)

gaining the least from a reduction of trade frictions, as they already provide firms with a good access to a large local market. The second reason is that, as stated above, large cities tend to lose population, thereby reducing the productivity gains brought about by the fall in trade frictions. Computing the nation-wide productivity change, weighted by MSA population shares in the initial equilibrium, we find that eliminating trade frictions would increase average productivity by 67.59%. Thus, reducing spatial frictions for shipping goods would entail substantial aggregate productivity gains.

*Markups.* The bottom panel of Figure 6 reveals that markups would decrease considerably in a world without trade frictions, with reductions ranging from 29% to 55%. Such reductions are particularly strong in MSAs with poor market access, i.e., the center of the US and the areas close to the borders. Observe that the changes in markups – though substantial – are more compressed than the changes in productivity (the coefficient of variation for productivity changes is 0.18, while that for changes in markups is 0.09). The reason is the following. Eliminating trade frictions reduces cutoffs in all MSAs, but especially in small and remote ones. This puts downward pressure on markups. Yet, there is also an indirect effect through changes in effective labor supply $h_r$. An increase in $h_r$, which occurs in big cities that lose population, reduces markups more strongly than what is implied by the direct change only, while the decrease in $h_r$ that occurs in small and remote cities gaining population works in the opposite direction and dampens the markup reductions.

To summarize, without trade frictions, the city-size distribution would remain fairly stable, despite the fact that larger cities tend to shrink and smaller cities tend to grow. Furthermore, the 'no trade frictions' case allows for higher average productivity and lower markups by intensifying competition in all MSAs, and especially in small and remote ones. The productivity gap between large and small cities would, hence, shrink.

### 5.3 *How important are spatial frictions?*

Our paper is, to the best of our knowledge, the first to investigate the impact of both urban and trade frictions on the size distribution of cities.[25] A key novel insight of our analysis is that spatial frictions have a quite limited impact on that distribution. The rank-size rule would still hold with a statistically identical coefficient in a world without urban or trade frictions.

Note that our result on the stability of the city-size distribution contrasts with that of Desmet and Rossi-Hansberg (2013), who find that the size distribution tilts substantially when urban frictions are reduced. The difference in results can be understood as follows. In their analysis, the commuting friction parameter is common to all MSAs, whereas we allow commuting technologies to differ across cities. In our setting, big cities like New York or Los Angeles tend to have the best commuting technologies per unit of distance in the initial equilibrium, so that the impacts of setting $\widehat{\theta}_r = 0$ are relatively small there. By contrast, in Desmet and Rossi-Hansberg (2013), the commuting technology improves equally across all MSAs so that big cities get very large due to larger efficiency gains in commuting than in our case. Another key difference is that in Desmet and Rossi-Hansberg (2013), all consumers react in the same way to changes in utility and amenities, whereas those reactions are idiosyncratic in our model and, therefore, less extreme.

Although spatial frictions hardly affect the city-size distribution in our framework, they do matter for the sizes of individual cities within that stable distribution. Indeed, eliminating spatial frictions leads to aggregate (gross) inter-MSA reallocations of about 4–10 million people. Whether or not large or small cities gain population crucially depends on what type of spatial frictions is eliminated. Urban frictions limit the size of large cities, whereas trade frictions limit the size of small cities. As extensively discussed above, our approach is able to quantify those effects.

[25]The influential models on the city-size distribution by Gabaix (1999), Eeckhout (2004), Duranton (2007) and Rossi-Hansberg and Wright (2007) include urban costs but assume away trade costs. None of these papers analyzes how the city-size distribution is affected by urban frictions. The most closely related paper in that respect is Desmet and Rossi-Hansberg (2013). Yet, their framework is not suited to investigate the impact of trade frictions on the city-size distribution, as it also abstracts from trade costs.

Notice that we have so far considered *simultaneous* reductions in spatial frictions for all cities. We can also look at a *unilateral* reduction for a single city. Specifically, let us briefly consider two additional counterfactuals. In the first one, we only eliminate urban frictions for New York. In that case, New York grows by about 19.73% (i.e., by about 3.7 million people). In the second one, we set $\tau_{sr} = \tau_{rr}$ for all $s$ only when $r$ is New York. That is, we improve the market access to New York for all firms that are located elsewhere, while holding the market access of firms located in New York to other MSAs constant. In that case, New York shrinks remarkably by 15.57% (i.e., about 3 million people). Hence, a unilateral change in spatial frictions for a single city has a much larger impact on the size of that city. More generally, these results show that the *relative levels across cities* of both types of frictions matter a lot to understand the sizes of individual cities.

Finally, our experiments show that urban and trade frictions matter, though to a different extent, for the distributions of productivity and markups – and ultimately welfare – across MSAs. Eliminating trade frictions would lead to significant productivity gains and substantially reduced markups, both of which increase welfare. These changes are highly heterogeneous across space and tend to reduce differences in productivity and city sizes across MSAs. Concerning urban frictions, their elimination would not give rise to such significant productivity gains, but would still considerably intensify competition and generate lower markups by allowing for more firms in equilibrium.

## 6. Robustness checks

### *6.1 Agglomeration economies*

The recent literature shows that agglomeration economies, i.e., productivity gains due to larger or denser urban areas, are a prevalent feature of the spatial economy (see Rosenthal and Strange, 2004; Melo *et al.*, 2009). We have so far focused entirely on one channel: larger cities are more productive because of tougher firm selection. Yet, larger or denser cities can become more productive for various other reasons such as sharing–matching–learning externalities (Duranton and Puga, 2004; Behrens *et al.*, 2014a).

We illustrate a simple way to extend our framework to include agglomeration economies. Specifically, we allow the upper bound in each MSA ($m_r^{\max}$) to be a function of the population of that MSA. Agglomeration economies are thus modeled as a right-shift in the *ex ante* productivity distribution: upon entry, a firm in a larger MSA has a higher probability of getting a better productivity draw.[26] Starting from the baseline model, assume that technological possibilities $\mu_r^{\max}$ can be expressed as $\mu_r^{\max} = c \cdot L_r^{-k\xi} \cdot \psi_r^{\max}$, where $\xi$ is the size elasticity of the *ex ante* upper bound of the marginal labor requirement, and where $\psi_r^{\max}$ is an unobserved idiosyncratic measure of technological possibilities that is purged from agglomeration effects. We can then estimate the ex ante productivity advantage of large cities by running a simple log-log regression of $\widehat{\mu}_r^{\max}$ on MSA population and controls as follows:

$$\ln(\widehat{\mu}_r^{\max}) = \beta_0 + \beta_1 \ln L_r + X_r \mathbf{b} + \varepsilon_r,$$

where $L_r$ is the city's population, $X_r$ is a vector of city-specific controls, and $\varepsilon_r$ is an idiosyncratic error term with the usual properties.[27] The estimate $\widehat{\beta}_1$ of the key parameter is $-0.2843$, with standard error 0.1093. Since $\ln \mu_r^{\max}$ equals $k \ln m_r^{\max}$ plus a constant, the elasticity $\xi$ of $m_r^{\max}$ with respect to population is given by $0.2843/\widehat{k} = 0.0444$ which is the value we use in what follows. In words, doubling MSA population reduces the upper bound (and, equivalently, the mean by the properties of the Pareto distribution) of the *ex ante* marginal labor requirement of entrants by 4.44%.[28]

In the supplementary online appendix, we show how those agglomeration economies can be taken into account in the quantification of our model. We then run both counterfactuals ('no urban frictions' and 'no trade frictions') with the agglomeration economies specification. The results are summarized in the middle panel of Table 2 (labeled CF3 and CF4, respectively); and in the bottom panel for the case of the IV approach (labeled CF7 and CF8, respectively). As can be seen, the results change little compared to our specifications without agglomeration economies (reported in CF1, CF2, CF5, and CF6).

Note that our results are not incompatible with the ones by Combes *et al.* (2012), who argue that agglomeration economies are more important than selection effects. The reason is that their two identifying assumptions, namely a common productivity distribution for entrants in all cities and no income effects, are not satisfied in our model. Furthermore, their results are established for a cross-section of cities, *given spatial frictions*, whereas we consider *changes in spatial frictions*.

[26]Formally, the right-shift in the *ex ante* productivity distribution implies that the distribution in a larger MSA first-order stochastically dominates that in a smaller MSA. Observe that firm selection afterwards acts as a truncation, so that the *ex post* distribution is both right-shifted and truncated.

[27]To account for density effects, we control for the log of the city's surface in the regression. We also include a set of state-level fixed effects and cluster the standard errors at the state level. Some MSAs cover several states, in which case they have separate 'state' dummies.

[28]That figure, though computed for the ex ante distribution, lies within the consensus range of previous elasticity estimates for agglomeration economies measured using ex post productivity distributions (see, e.g., Rosenthal and Strange, 2004; Melo *et al.*, 2009).

Table 2: Summary of the counterfactuals.

| | | | | | | |
|---|---|---|---|---|---|---|
| **Baseline counterfactuals (OLS, no agglomeration economies)** | | | | | | |
| | No urban frictions (CF1) | | | No trade frictions (CF2) | | |
| | Mean | Std. dev. | Weighted mean | Mean | Std. dev. | Weighted mean |
| % change in average productivity ($\overline{M}_r$) | -0.06 | 0.26 | 0.04 | 78.50 | 14.26 | 67.59 |
| % change in population ($L_r$) | -2.15 | 3.60 | 0 | 4.30 | 15.28 | 0 |
| % change in average markup ($\overline{\Lambda}_r$) | -8.79 | 1.82 | -9.85 | -43.55 | 4.27 | -39.90 |
| % change in indirect utility ($V_r$) | 9.69 | 2.24 | 10.98 | 78.17 | 13.79 | 67.62 |
| RS coefficient | -0.9178 | | | -0.9392 | | |
| total population movement | 3,944,976 | | | 10,209,349 | | |
| **Robustness checks (OLS, with agglomeration economies)** | | | | | | |
| | No urban frictions (CF3) | | | No trade frictions (CF4) | | |
| | Mean | Std. dev. | Weighted mean | Mean | Std. dev. | Weighted mean |
| % change in average productivity ($\overline{M}_r$) | -0.15 | 0.34 | 0.04 | 78.82 | 14.72 | 67.65 |
| % change in population ($L_r$) | -2.25 | 3.82 | 0 | 4.61 | 16.64 | 0 |
| % change in average markup ($\overline{\Lambda}_r$) | -8.71 | 1.93 | -9.85 | -43.62 | 4.36 | -39.90 |
| % change in indirect utility ($V_r$) | 9.59 | 2.38 | 10.98 | 78.46 | 14.16 | 67.65 |
| RS coefficient | -0.9175 | | | -0.9395 | | |
| total population movement | 4,145,800 | | | 10,794,198 | | |
| **Robustness checks (2SLS, no agglomeration economies)** | | | | | | |
| | No urban frictions (CF5) | | | No trade frictions (CF6) | | |
| | Mean | Std. dev. | Weighted mean | Mean | Std. dev. | Weighted mean |
| % change in average productivity ($\overline{M}_r$) | -0.17 | 0.43 | 0.05 | 78.83 | 14.33 | 67.87 |
| % change in population ($L_r$) | -3.73 | 6.36 | 0 | 7.05 | 26.04 | 0 |
| % change in average markup ($\overline{\Lambda}_r$) | -8.69 | 1.95 | -9.86 | -43.61 | 4.21 | -40.03 |
| % change in indirect utility ($V_r$) | 9.57 | 2.41 | 11.00 | 78.34 | 13.60 | 67.95 |
| RS coefficient | -0.9120 | | | -0.9359 | | |
| total population movement | 6,989,034 | | | 16,098,780 | | |
| **Robustness checks (2SLS, with agglomeration economies)** | | | | | | |
| | No urban frictions (CF7) | | | No trade frictions (CF8) | | |
| | Mean | Std. dev. | Weighted mean | Mean | Std. dev. | Weighted mean |
| % change in average productivity ($\overline{M}_r$) | -0.35 | 0.66 | 0.05 | 79.35 | 15.11 | 67.98 |
| % change in population ($L_r$) | -4.04 | 7.17 | 0 | 7.92 | 30.23 | 0 |
| % change in average markup ($\overline{\Lambda}_r$) | -8.52 | 2.16 | -9.85 | -43.73 | 4.34 | -40.05 |
| % change in indirect utility ($V_r$) | 9.38 | 2.68 | 11.00 | 78.80 | 14.15 | 68.08 |
| RS coefficient | -0.9109 | | | -0.9388 | | |
| total population movement | 7,692,526 | | | 17,628,398 | | |

*Notes:* Weighted mean refers to the mean percentage change where the weights are given by the MSAs' initial population shares. The counterfactual scenarios CF3, CF4, CF7, and CF8 include the agglomeration economies specification. The counterfactual scenarios CF5, CF6, CF7, and CF8 use the results from the instrumental variable estimation of (35), see supplementary Appendix G.2. RS coefficient refers to the slope of the estimated rank-size relationship.

## *6.2 Instrumental variable regressions*

The quantification of our model suggests that amenities and regional attachment are important for shaping the city-size distribution. One may thus wonder how important the estimated value of $\alpha_1$ is for our qualitative and quantitative results. Recall that the value of $\alpha_1$ in (35) determines the relative weight of the indirect utility and amenities in individual location decisions, and any correlation between $\widehat{U}_r$ and unobserved amenities (the residual $\varepsilon_r$) will lead to a biased estimate of this weight. Hence, it could be the case that our relatively small population movements in response to shocks to spatial frictions are driven by too low an estimate of $\alpha_1$. To explore this possibility, we now use the estimates from the instrumental variable regression using geological instruments, which yields a higher sensitivity to economic determinants of location choices ($\widehat{\alpha}_1^{2SLS} = 2.8416$ instead of $\widehat{\alpha}_1^{OLS} = 1.7481$).[29] See Appendix G.2 for details.

[29] As we will see, the larger coefficient on indirect utility induces larger population movements under IV than under OLS. The qualitative results are, however, identical and the quantitative results other than population movement hardly change. Observe also that the correlation between population and unobserved amenities in the IV approach is 0.5520, which is smaller compared to 0.7023 in the OLS case.

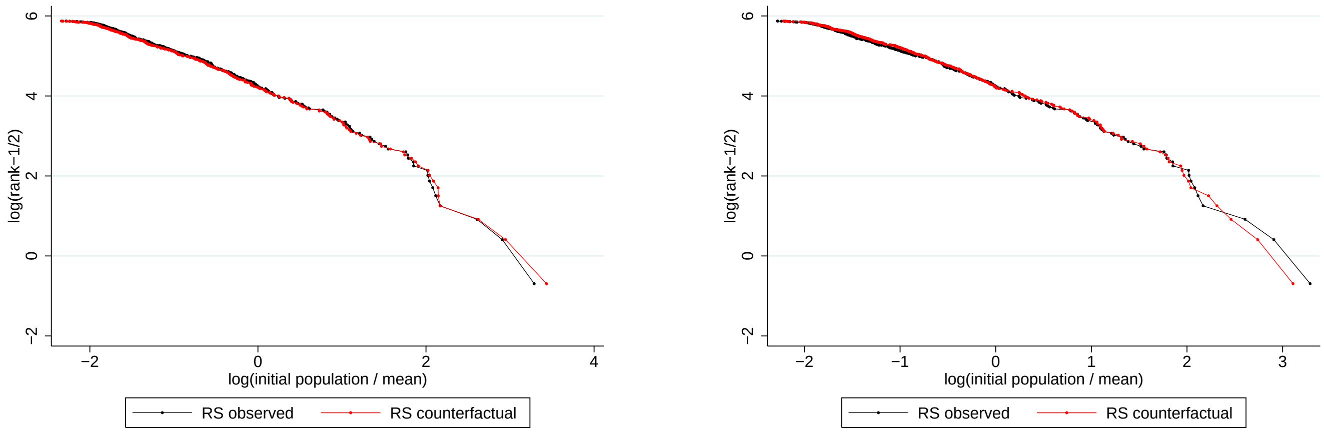


Figure 8: Rank-size rule, observed and counterfactual (CF5, left; and CF6, right)

Using this larger value of $\alpha_1$ and the associated smaller unobserved amenities, we run the same counterfactual experiments as before and look at how different the implied changes are. The results are summarized in the bottom panel of Table 2 (labeled CF5 and CF6).[30] As can be seen, in the IV counterfactual experiments there is a larger population reshuffling. More specifically, in the 'no urban frictions' counterfactual, roughly 75% more people relocate across cities compared to our benchmark, and roughly 60% more in the 'no trade frictions' case. Also the changes in individual city sizes span a much wider range than before. These findings are intuitive because a larger value of $\alpha_1$ makes agents more sensitive to differences in prices, wages, and consumption diversity across MSAs.

Despite these larger population movements, the city-size distribution remains fairly stable in both counterfactuals (see Figure 8). When urban frictions are eliminated, the Zipf coefficient changes from -0.9249 to -0.9120, implying a slightly higher population concentration in large cities. When 'trade frictions' are eliminated, the Zipf coefficient changes from -0.9249 to -0.9359, implying a slightly lower population concentration in large cities. Moreover, the predictions of how spatial frictions affect productivity and markups are very similar to our benchmark.

Our above findings suggest that our main results are robust, both qualitatively and to a large extent quantitatively, to higher values of $\alpha_1$. In particular, amenities do not matter for the city-size distribution to remain stable between the initial and counterfactual equilibria because that distribution is hardly affected even when we greatly reduce the importance of amenities relative to the indirect utility in consumers' location choices.

[30]For completeness, we also report results for the counterfactuals with both IV and agglomeration externalities (CF7 and CF8) in Table 2.

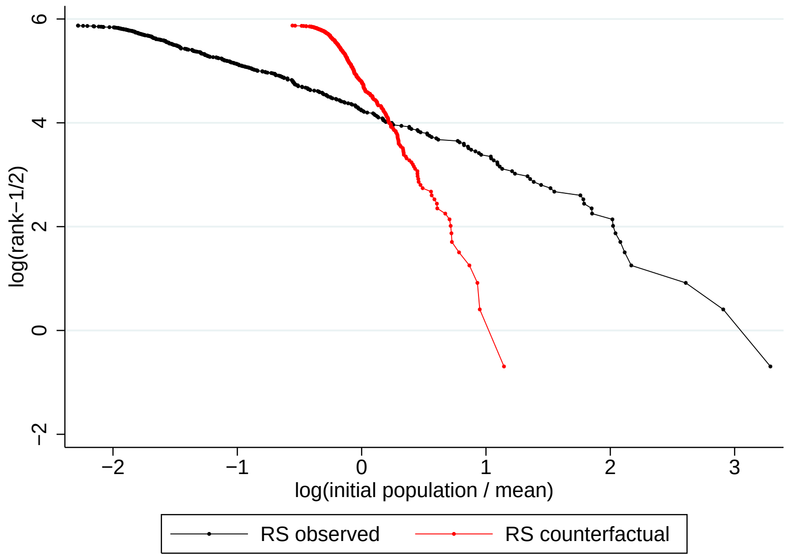


Figure 9: Changes in the city-size distribution (equal amenities case)

However, amenities do matter for replicating the observed initial city-size distribution. To see this, we briefly consider a similar counterfactual exercise as in Desmet and Rossi-Hansberg (2013) and set all unobserved amenities across cities equal to their mean, holding all spatial frictions fixed. Figure 9 shows that there would be a substantial tilt of the city-size distribution. The Zipf coefficient falls from -0.9249 to -3.6715, and about a half of the US MSA population move, leading to a much less unequal city-size distribution – large cities shrink and small cities grow.[31]

## 7. Conclusions

We have developed a novel general equilibrium model of a spatial economy with multiple cities and endogenous location decisions. Using 2007 US data at the state and MSA levels, we have quantified our model using all of its market and spatial equilibrium conditions, as well as a gravity equation for trade flows and a logit model for consumers' location choice probabilities. The quantified model performs well and is able to replicate – both at the MSA and firm levels – a number of empirical features that are linked to urban and trade frictions.

To assess the importance of spatial frictions, we have used our model to study two counterfactual scenarios. Those allow us to trace out the impacts of both trade and

[31] We also experimented with setting all technological possibilities equal to the mean. In that case, 5.57% of the population moves and there is no strong impact on the city-size distribution.

urban frictions on the city-size distribution, the sizes of individual cities, as well as on productivity and competition across space. A first key insight is that the city-size distribution is hardly affected by the presence of either trade or urban frictions. A second key insight is that, within the stable distribution, the sizes of individual cities can be affected substantially by changes in spatial frictions. Last, our third key insight is that the presence of spatial frictions reduces welfare via too high price-cost margins and, depending on the type of spatial frictions we consider, foregone productivity or reduced product diversity. These results are robust to the presence of agglomeration economies and to potential bias when estimating how individuals' location decisions are affected by changes in spatial frictions.

Our approach brings various strands of literature closer together. In particular, our model: (i) considers trade and urban frictions that are identified as being relevant by the NEG and urban economics literature; (ii) endogenizes productivity, markups, and product diversity, three aspects that loom large in the recent trade literature; (iii) allows to deal with heterogeneity along several dimensions (across space, across firms, across consumers); (iv) can be readily brought to data in very a self-contained way; and (v) replicates features of the data not used in the quantification stage. We believe that our framework provides a useful starting point for further general equilibrium counterfactual analysis involving various policy experiments.

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# Supplementary Online Appendix, not intended for publication

The Appendix is structured as follows: **Appendix A** shows how to derive the demand functions (2) and the firm-level variables (9) using the Lambert $W$ function. In **Appendix B** we provide integrals involving the Lambert $W$ function and derive the terms $\{\kappa_1, \kappa_2, \kappa_3, \kappa_4\}$ that are used in the paper. **Appendix C** contains proofs and computations for the single city case. In **Appendix D** we derive the equilibrium conditions (21)–(23) and provide further derivations for the multi-city case. **Appendix E** deals with the example with two cities. **Appendix F** provides details about the quantification procedure, the data used, and the different elements of model fit. **Appendix G** proves that the spatial equilibrium is uniquely determined in our quantification procedure, and presents the details of the instrumental variable approach. **Appendix H** describes the procedure for conducting counterfactual analysis with our quantified framework, while **Appendix I** spells out the procedure with agglomeration economies. Finally, **Appendix J** reports some additional results tables.

## Appendix A: Demand functions and firm-level variables.

*A.1. Derivation of the demand functions (2).* Letting $\lambda$ stand for the Lagrange multiplier, the first-order condition for an interior solution to the maximization problem (1) satisfies

$$\alpha \mathrm{e}^{-\alpha q_{sr}(i)} = \lambda p_{sr}(i), \quad \forall i \in \Omega_{sr} \tag{A-1}$$

and the budget constraint $\sum_s \int_{\Omega_{sr}} p_{sr}(k) q_{sr}(k) \mathrm{d}k = E_r$. Taking the ratio of (A-1) for $i \in \Omega_{sr}$ and $j \in \Omega_{vr}$ yields

$$q_{sr}(i) = q_{vr}(j) + \frac{1}{\alpha} \ln \left[ \frac{p_{vr}(j)}{p_{sr}(i)} \right] \quad \forall i \in \Omega_{sr}, \forall j \in \Omega_{vr}.$$

Multiplying this expression by $p_{vr}(j)$, integrating with respect to $j \in \Omega_{vr}$, and summing across all origins $v$ we obtain

$$q_{sr}(i) \sum_v \int_{\Omega_{vr}} p_{vr}(j) \mathrm{d}j = \underbrace{\sum_v \int_{\Omega_{vr}} p_{vr}(j) q_{vr}(j) \mathrm{d}j}_{\equiv E_r} + \frac{1}{\alpha} \sum_v \int_{\Omega_{vr}} \ln \left[ \frac{p_{vr}(j)}{p_{sr}(i)} \right] p_{vr}(j) \mathrm{d}j. \tag{A-2}$$

Using $\overline{p}_r \equiv (1/N_r^c)\sum_v \int_{\Omega_{vr}} p_{vr}(j)\mathrm{d}j$, expression (A-2) can be rewritten as follows:

$$\begin{aligned} q_{sr}(i) &= \frac{E_r}{N_r^c \bar{p}_r} - \frac{1}{\alpha}\ln p_{sr}(i) + \frac{1}{\alpha N_r^c \bar{p}_r}\sum_v \int_{\Omega_{vr}} \ln\left[p_{vr}(j)\right] p_{vr}(j)\mathrm{d}j \\ &= \frac{E_r}{N_r^c \bar{p}_r} - \frac{1}{\alpha}\ln\left[\frac{p_{sr}(i)}{N_r^c \bar{p}_r}\right] + \frac{1}{\alpha}\sum_v \int_{\Omega_{vr}} \ln\left[\frac{p_{vr}(j)}{N_r^c \bar{p}_r}\right]\frac{p_{vr}(j)}{N_r^c \bar{p}_r}\mathrm{d}j, \end{aligned}$$

which, given the definition of $\eta_r$, yields (2).

*A.2. Derivation of the firm-level variables (9) and properties of $W$.* Using $p_s^d = m_{rs}^x \tau_{rs} w_r$, the first-order conditions (6) can be rewritten as

$$\ln\left[\frac{m_{rs}^x \tau_{rs} w_r}{p_{rs}(m)}\right] = 1 - \frac{\tau_{rs} m w_r}{p_{rs}(m)}.$$

Taking the exponential of both sides and rearranging terms, we have

$$\mathrm{e}\frac{m}{m_{rs}^x} = \frac{\tau_{rs} m w_r}{p_{rs}(m)} \mathrm{e}^{\frac{\tau_{rs} m w_r}{p_{rs}(m)}}.$$

Noting that the Lambert $W$ function is defined as $\varphi = W(\varphi)\mathrm{e}^{W(\varphi)}$ and setting $\varphi = \mathrm{e}m/m_{rs}^x$, we obtain

$$W\left(\mathrm{e}\frac{m}{m_{rs}^x}\right) = \frac{\tau_{rs} m w_r}{p_{rs}(m)},$$

which implies $p_{rs}(m)$ as given in expression (9). The expression for the quantities $q_{rs}(m) = (1/\alpha)\left[1 - \tau_{rs} m w_r / p_{rs}(m)\right]$ and the expression for the operating profits $\pi_{rs}(m) = L_s q_{rs}(m)\left[p_{rs}(m) - \tau_{rs} m w_r\right]$ are then straightforward to compute.

Turning to the properties of the Lambert $W$ function, $\varphi = W(\varphi)\mathrm{e}^{W(\varphi)}$ implies that $W(\varphi) \geq 0$ for all $\varphi \geq 0$. Taking logarithms on both sides and differentiating yields

$$W'(\varphi) = \frac{W(\varphi)}{\varphi[W(\varphi)+1]} > 0$$

for all $\varphi > 0$. Finally, we have: $0 = W(0)\mathrm{e}^{W(0)}$, which implies $W(0) = 0$; and $\mathrm{e} = W(\mathrm{e})\mathrm{e}^{W(\mathrm{e})}$, which implies $W(\mathrm{e}) = 1$.

## Appendix B: Integrals involving the Lambert $W$ function.

To derive closed-form solutions for various expressions throughout the paper we need to compute integrals involving the Lambert $W$ function. This can be done by using the change in variables suggested by Corless *et al.* (1996, p.341). Let

$$z \equiv W\left(\mathrm{e}\frac{m}{I}\right), \quad \text{so that} \quad \mathrm{e}\frac{m}{I} = z\mathrm{e}^z, \quad \text{where} \quad I = m_r^d, m_{rs}^x.$$

The subscript $r$ can be dropped in the single city case. The change in variables then yields $\mathrm{d}m = (1+z)\mathrm{e}^{z-1} I \mathrm{d}z$, with the new integration bounds given by 0 and 1. Under our assumption of a Pareto distribution for productivity draws, the change in variables allows to rewrite integrals in simplified form.

*B.1.* First, consider the following expression, which appears when integrating firms' outputs:

$$\int_0^I m \left[1 - W\left(\mathrm{e}\frac{m}{I}\right)\right] \mathrm{d}G_r(m) = \kappa_1 \left(m_r^{\max}\right)^{-k} I^{k+1},$$

where $\kappa_1 \equiv k\mathrm{e}^{-(k+1)} \int_0^1 (1-z^2)\left(z\mathrm{e}^z\right)^k \mathrm{e}^z \mathrm{d}z > 0$ is a constant term which solely depends on the shape parameter $k$.

*B.2.* Second, the following expression appears when integrating firms' operating profits:

$$\int_0^I m \left[W\left(\mathrm{e}\frac{m}{I}\right)^{-1} + W\left(\mathrm{e}\frac{m}{I}\right) - 2\right] \mathrm{d}G_r(m) = \kappa_2 \left(m_r^{\max}\right)^{-k} I^{k+1},$$

where $\kappa_2 \equiv k\mathrm{e}^{-(k+1)} \int_0^1 (1+z)\left(z^{-1}+z-2\right)\left(z\mathrm{e}^z\right)^k \mathrm{e}^z \mathrm{d}z > 0$ is a constant term which solely depends on the shape parameter $k$.

*B.3.* Third, the following expression appears when deriving the (expenditure share) weighted average of markups:

$$\int_0^I m \left[W\left(\mathrm{e}\,\frac{m}{I}\right)^{-2} - W\left(\mathrm{e}\,\frac{m}{I}\right)^{-1}\right] \mathrm{d}G_r(m) = \kappa_3 \left(m_r^{\max}\right)^{-k} I^{k+1},$$

where $\kappa_3 \equiv k\mathrm{e}^{-(k+1)} \int_0^1 (z^{-2} - z^{-1})(1+z)(z\mathrm{e}^z)^k \mathrm{e}^z \mathrm{d}z > 0$ is a constant term which solely depends on the shape parameter $k$.

*B.4.* Finally, the following expression appears when integrating firms' revenues:

$$\int_0^I m \left[W\left(\mathrm{e}\,\frac{m}{I}\right)^{-1} - 1\right] \mathrm{d}G_r(m) = \kappa_4 \left(m_r^{\max}\right)^{-k} I^{k+1},$$

where $\kappa_4 \equiv k\mathrm{e}^{-(k+1)} \int_0^1 (z^{-1} - z)\left(z\mathrm{e}^z\right)^k \mathrm{e}^z \mathrm{d}z > 0$ is a constant term which solely depends on the shape parameter $k$. Using the expressions for $\kappa_1$ and $\kappa_2$, one can verify that $\kappa_4 = \kappa_1 + \kappa_2$.

## Appendix C: Equilibrium in the single city case.

*C.1. Existence and uniqueness of the equilibrium cutoff $m^d$.* To see that there exists a unique equilibrium cutoff $m^d$, we apply the Leibniz integral rule to the left-hand side of (14) and use $W(\mathrm{e}) = 1$ to obtain

$$\frac{\mathrm{e}L}{\alpha(m^d)^2}\int_0^{m^d} m^2\left(W^{-2}-1\right)W'\mathrm{d}G(m) > 0,$$

where the sign comes from $W' > 0$ and $W^{-2} \geq 1$ for $0 \leq m \leq m^d$. Hence, the left-hand side of (14) is strictly increasing. This uniquely determines the equilibrium cutoff $m^d$, because

$$\lim_{m^d\to 0}\int_0^{m^d} m\left(W^{-1}+W-2\right)\mathrm{d}G(m) = 0 \quad \text{and} \quad \lim_{m^d\to \infty}\int_0^{m^d} m\left(W^{-1}+W-2\right)\mathrm{d}G(m) = \infty.$$

*C.2. Indirect utility in the single city.* To derive the indirect utility, we first compute the (unweighted) average price across all varieties. Multiplying both sides of (6) by $p(i)$, integrating over $\Omega$, and using (3), we obtain:

$$\overline{p} = \overline{m}w + \frac{\alpha E}{N}$$

where $\overline{m} \equiv (1/N)\int_\Omega m(j)\mathrm{d}j$ denotes the average marginal labor requirement of the surviving firms. Using $\overline{p}$, expression (4) can be rewritten as

$$U = \frac{N}{k+1} - \frac{S}{L}\frac{\alpha}{m^d}, \tag{A-3}$$

where we use $E = (S/L)w$, $p^d = m^d w$ and $\overline{m} = [1/G(m^d)]\int_0^{m^d} m\mathrm{d}G(m) = [k/(k+1)]m^d$. When combined with (17) and (18), we obtain the expression for $U$ as given in (19).

*C.3. Single-peakedness of the indirect utility in the single city case.* We now show that $U$ is single-peaked with respect to $L$. To this end, we rewrite the indirect utility (20) as $U = b(S/L)L^{1/(k+1)}$, where $b$ is a positive constant capturing $k$, $\alpha$, and $\mu^{\max}$, and then consider a log-transformation, $\ln U = \ln b + \ln S - [k/(k+1)]\ln L$. It then follows that

$$\frac{\partial \ln U}{\partial \ln L} = \frac{LS'}{S} - \frac{k}{k+1}.$$

To establish single-peakedness, we need to show that

$$\frac{LS'}{S} = \frac{\theta^2(L/\pi)}{2\left(\mathrm{e}^{\theta\sqrt{L/\pi}} - 1 - \theta\sqrt{L/\pi}\right)}$$

cuts the horizontal line $k/(k+1) \in (0,1)$ only once from above. Notice that $LS'/S \to 1$ as $L \to 0$, whereas $LS'/S \to 0$ as $L \to \infty$. Single-peakedness therefore follows if

$$\frac{\mathrm{d}}{\mathrm{d}L}\left(\frac{LS'}{S}\right) = -\frac{2+\theta\sqrt{L/\pi}+\mathrm{e}^{\theta\sqrt{L/\pi}}\left(\theta\sqrt{L/\pi}-2\right)}{(4/\theta^2)\left[\sqrt{\pi}\left(\mathrm{e}^{\theta\sqrt{L/\pi}}-1\right)-\theta\sqrt{L}\right]^2} < 0, \quad \forall L.$$

For this to be the case, the numerator must be positive. Let $y \equiv \theta\sqrt{L/\pi} > 0$. Then we can show that $H(y) \equiv 2 + y + \mathrm{e}^y(y-2) > 0$ for all $y > 0$. Obviously, $H(0) = 0$. So, if $H' > 0$ for all $y > 0$, the proof is complete. It is readily verified that $H' = 1 + y\mathrm{e}^y - \mathrm{e}^y > 0$ is equivalent to $\mathrm{e}^{-y} > 1 - y$, which is true for all $y > 0$ by convexity of $\mathrm{e}^{-y}$ (observe that $1 - y$ is the tangent to $\mathrm{e}^{-y}$ at $y = 0$ and that a convex function is everywhere above its tangent).

## Appendix D: Equilibrium in the urban system.

*D.1. Equilibrium conditions using the Lambert W function.* By definition, the zero expected profit condition for each firm in city $r$ is given by

$$\sum_s L_s \int_0^{m_{rs}^x} \left[p_{rs}(m) - \tau_{rs} m w_r\right] q_{rs}(m) \mathrm{d}G_r(m) = F w_r. \tag{D-1}$$

Furthermore, each labor market clears in equilibrium, which requires that

$$N_r^E \left[\sum_s L_s \tau_{rs} \int_0^{m_{rs}^x} m q_{rs}(m) \mathrm{d}G_r(m) + F\right] = S_r. \tag{D-2}$$

Last, in equilibrium trade must be balanced for each city

$$N_r^E \sum_{s \neq r} L_s \int_0^{m_{rs}^x} p_{rs}(m) q_{rs}(m) \mathrm{d}G_r(m) = L_r \sum_{s \neq r} N_s^E \int_0^{m_{sr}^x} p_{sr}(m) q_{sr}(m) \mathrm{d}G_s(m). \tag{D-3}$$

We now restate the foregoing conditions (D-1)–(D-3) in terms of the Lambert $W$ function.

First, using (9), the labor market clearing condition can be rewritten as follows:

$$N_r^E \left\{\frac{1}{\alpha} \sum_s L_s \tau_{rs} \int_0^{m_{rs}^x} m \left[1 - W\left(\mathrm{e}\frac{m}{m_{rs}^x}\right)\right] \mathrm{d}G_r(m) + F\right\} = S_r. \tag{D-4}$$

Second, plugging (9) into (D-1), zero expected profits require that

$$\frac{1}{\alpha} \sum_s L_s \tau_{rs} \int_0^{m_{rs}^x} m \left[W\left(\mathrm{e}\frac{m}{m_{rs}^x}\right)^{-1} + W\left(\mathrm{e}\frac{m}{m_{rs}^x}\right) - 2\right] \mathrm{d}G_r(m) = F. \tag{D-5}$$

Last, the trade balance condition is given by

$$N_r^E w_r \sum_{s\neq r} L_s \tau_{rs} \int_0^{m_{rs}^x} m \left[ W\left( \mathrm{e}\, \frac{m}{m_{rs}^x} \right)^{-1} - 1 \right] \mathrm{d}G_r(m)$$

$$= L_r \sum_{s\neq r} N_s^E \tau_{sr} w_s \int_0^{m_{sr}^x} m \left[ W\left( \mathrm{e}\, \frac{m}{m_{sr}^x} \right)^{-1} - 1 \right] \mathrm{d}G_s(m). \tag{D-6}$$

Applying the city-specific Pareto distribution $G_r(m) = (m/m_r^{\max})^k$ to (D-4)–(D-6) yields, using the results of Appendix B, expressions (21)–(23) given in the main text.

*D.2. The mass of varieties consumed in the urban system.* Using $N_r^c$ as defined in (8), and the external cutoff and the mass of entrants as given by (7) and (24), and making use of the Pareto distribution, we obtain:

$$N_r^c = \frac{\kappa_2}{\kappa_1+\kappa_2} \left( m_r^d \right)^k \sum_s \frac{S_s}{F(m_s^{\max})^k} \left( \frac{\tau_{rr}}{\tau_{sr}} \frac{w_r}{w_s} \right)^k = \frac{\alpha}{\kappa_1+\kappa_2} \frac{\left( m_r^d \right)^k}{\tau_{rr}} \sum_s S_s \tau_{rr} \left( \frac{\tau_{rr}}{\tau_{sr}} \frac{w_r}{w_s} \right)^k \frac{\kappa_2}{\alpha F(m_s^{\max})^k}.$$

Using the definition of $\mu_s^{\max}$, and noting that the summation in the foregoing expression appears in the equilibrium relationship (25), we can then express the mass of varieties consumed in city $r$ as given in (26).

*D.3. The weighted average of markups in the urban system.* Plugging (9) into the definition (27), the weighted average of markups in the urban system can be rewritten as

$$\overline{\Lambda}_r = \frac{1}{\alpha E_r \sum_s N_s^E G_s(m_{sr}^x)} \sum_s N_s^E \tau_{sr} w_s \int_0^{m_{sr}^x} m \left( W^{-2} - W^{-1} \right) \mathrm{d}G_s(m),$$

where the argument $\mathrm{e}m/m_{sr}^x$ of the Lambert $W$ function is suppressed to alleviate notation. As shown in Appendix B, the integral term is given by $\kappa_3 (m_s^{\max})^{-k} (m_{sr}^x)^{k+1} = \kappa_3 G_s(m_{sr}^x) m_{sr}^x$. Using this, together with (7) and $E_r = (S_r/L_r) w_r$, yields the expression in (27).

*D.4. Indirect utility in the urban system.* To derive the indirect utility, we first compute the (unweighted) average price across all varieties sold in each market. Multiplying both sides of (6) by $p_{rs}(i)$, integrating over $\Omega_{rs}$, and summing the resulting expressions across $r$, we obtain:

$$\overline{p}_s \equiv \frac{1}{N_s^c} \sum_r \int_{\Omega_{rs}} p_{rs}(j) \mathrm{d}j = \frac{1}{N_s^c} \sum_r \tau_{rs} w_r \int_{\Omega_{rs}} m_r(j) \mathrm{d}j + \frac{\alpha E_s}{N_s^c},$$

where the first term is the average of marginal delivered costs. Under the Pareto distribution, $\int_{\Omega_{sr}} m_s(j)\mathrm{d}j = N_s^E \int_0^{m_{sr}^x} m\mathrm{d}G_s(m) = [k/(k+1)]m_{sr}^x N_s^E G_s(m_{sr}^x)$. Hence, the (unweighted) average price can be rewritten for city $r$ as follows

$$\overline{p}_r = \frac{1}{N_r^c}\sum_s \tau_{sr} w_s \left(\frac{k}{k+1}\right) m_{sr}^x N_s^E G_s(m_{sr}^x) + \frac{\alpha E_r}{N_r^c} = \left(\frac{k}{k+1}\right) p_r^d + \frac{\alpha E_r}{N_r^c}, \tag{D-7}$$

where we have used (8) and $p_r^d = \tau_{sr} w_s m_{sr}^x$. Plugging (D-7) into (4) and using (7), the indirect utility is then given by

$$U_r = \frac{N_r^c}{k+1} - \frac{\alpha}{\tau_{rr}} \frac{S_r}{L_r m_r^d},$$

which together with (26) and (27) yields (28).

## Appendix E: The case with two cities.

*E.1. Market equilibrium in the two city case.* Recall that $\tau_{12} = \tau_{21} = \tau$, $\tau_{11} = \tau_{22} = t$, and $\tau \geq t$ by assumption. For given city sizes $L_1$ and $L_2$, the market equilibrium is given by a system of three equations (22)–(24) with three unknowns (the two internal cutoffs $m_1^d$ and $m_2^d$, and the relative wage $\omega \equiv w_1/w_2$) as follows:

$$\mu_1^{\max} = L_1 t \left(m_1^d\right)^{k+1} + L_2 \tau \left(\frac{t}{\tau}\frac{1}{\omega} m_2^d\right)^{k+1} \tag{E-1}$$

$$\mu_2^{\max} = L_2 t \left(m_2^d\right)^{k+1} + L_1 \tau \left(\frac{t}{\tau}\omega m_1^d\right)^{k+1} \tag{E-2}$$

$$\omega^{2k+1} = \frac{\rho}{\sigma}\left(\frac{m_2^d}{m_1^d}\right)^{k+1}, \tag{E-3}$$

where $\rho \equiv \mu_2^{\max}/\mu_1^{\max}$ and $\sigma \equiv h_2/h_1 = (S_2/L_2)/(S_1/L_1)$.

When $\tau > t$, equations (E-1) and (E-2) can be uniquely solved for the cutoffs as a function of $\omega$:

$$(m_1^d)^{k+1} = \frac{\mu_1^{\max}}{L_1 t}\,\frac{1-\rho(t/\tau)^k \omega^{-(k+1)}}{1-(t/\tau)^{2k}} \quad \text{and} \quad (m_2^d)^{k+1} = \frac{\mu_2^{\max}}{L_2 t}\,\frac{1-\rho^{-1}(t/\tau)^k \omega^{k+1}}{1-(t/\tau)^{2k}}. \tag{E-4}$$

Substituting the cutoffs (E-4) into (E-3) yields, after some simplification, the following expression:

$$\text{LHS} \equiv \omega^k = \rho\,\frac{S_1}{S_2}\,\frac{\rho - (t/\tau)^k\,\omega^{k+1}}{\omega^{k+1} - \rho\,(t/\tau)^k} \equiv \text{RHS}. \tag{E-5}$$

The RHS of (E-5) is non-negative if and only if $\underline{\omega} < \omega < \overline{\omega}$, where $\underline{\omega} \equiv \rho^{1/(k+1)} (t/\tau)^{k/(k+1)}$ and $\overline{\omega} \equiv \rho^{1/(k+1)} (\tau/t)^{k/(k+1)}$. Furthermore, the RHS is strictly decreasing in $\omega \in (\underline{\omega}, \overline{\omega})$ with $\lim_{\omega \to \underline{\omega}+} \text{RHS} = \infty$ and $\lim_{\omega \to \overline{\omega}-} \text{RHS} = 0$. Since the LHS of (E-5) is strictly increasing in $\omega \in (0, \infty)$, there exists a unique equilibrium relative wage $\omega^* \in (\underline{\omega}, \overline{\omega})$. The internal cutoffs are then uniquely determined by (E-4).

When $\tau = t$, we can also establish the uniqueness of $\omega$, $m_1^d$ and $m_2^d$. The proof is relegated to E.4. (i).

*E.2. Market equilibrium: $L_1 > L_2$ implies $\omega > 1$ and $m_1^d < m_2^d$.* Assume that $\overline{h}_1 = \overline{h}_2 = \overline{h}$, $\theta_1 = \theta_2 = \theta$, and $\rho = 1$. Observe that $L_1/L_2 = 1$ implies $S_1/S_2 = 1$, so that the unique equilibrium wage is $\omega^* = 1$ by (E-5) if the two cities are equally large. Now suppose that city 1 is larger than city 2, $L_1/L_2 > 1$, which implies $S_1/S_2 > 1$. Then, the equilibrium relative wage satisfies $\omega^* > 1$ because an increase in $S_1/S_2$ raises the RHS of (E-5) without affecting the LHS. Finally, expression (E-3), together with the foregoing assumption, yields $\omega^{2k+1} = (1/\sigma) \left(m_2^d/m_1^d\right)^{k+1}$. As $L_1 > L_2$ implies $\omega > 1$ and $\sigma > 1$ (recall that $h \equiv S/L$ is decreasing in $L$), it follows that $m_1^d < m_2^d$. Hence, the unique market equilibrium is such that the larger city has the higher wage and the lower cutoff. Note that the proof relies on (E-5), which is obtained under $\tau > t$. However, we can establish the same properties for $\tau = t$ by using the expressions in E.4. (i) below.

*E.3. Spatial equilibrium: No urban frictions.* We have claimed that the third and the fourth term in (32) are negative because $m_1^d < \widetilde{m}_1^d < \widetilde{m}_2^d < m_2^d$. To verify these inequalities, notice at first that the reduction in $\theta$ from any given positive value to zero raises $S_1/S_2$. This is straightforward to prove: In a world with urban frictions (where $\theta > 0$), and given that $\overline{h}_1 = \overline{h}_2 = \overline{h}$ and $\theta_1 = \theta_2 = \theta$, the term $S_1/S_2$ is given by

$$\frac{S_1}{S_2} = \frac{1 - \left(1 + \theta\sqrt{L_1/\pi}\right) \mathrm{e}^{-\theta\sqrt{L_1/\pi}}}{1 - \left(1 + \theta\sqrt{L_2/\pi}\right) \mathrm{e}^{-\theta\sqrt{L_2/\pi}}}. \tag{E-6}$$

In a world without urban frictions ($\theta = 0$), we have $\widetilde{S}_1 = L_1\overline{h}$ and $\widetilde{S}_2 = L_2\overline{h}$, so that $\widetilde{S}_1/\widetilde{S}_2 = L_1/L_2$. Letting $y_r \equiv \theta\sqrt{L_r/\pi} > 0$, proving that $L_1/L_2$ is larger than the term $S_1/S_2$ given in (E-6) is equivalent to proving that $y_1^2/\left(1 - \mathrm{e}^{-y_1} - y_1\mathrm{e}^{-y_1}\right) > y_2^2/\left(1 - \mathrm{e}^{-y_2} - y_2\mathrm{e}^{-y_2}\right)$. We thus need to show that $y^2/(1 - \mathrm{e}^{-y} - y\mathrm{e}^{-y})$ is increasing because $y_1 > y_2$. By differentiating, we have the derivative

$$\frac{y\mathrm{e}^{-y}}{(1 - \mathrm{e}^{-y} - y\mathrm{e}^{-y})^2} Y, \quad \text{where} \quad Y \equiv 2\mathrm{e}^y - [(y+1)^2 + 1].$$

Noting that $Y = 0$ at $y = 0$ and $Y' = 2[\mathrm{e}^y - (y+1)] > 0$ for all $y > 0$, we know that the derivative is positive for all $y > 0$. Hence, $\widetilde{S}_1/\widetilde{S}_2 = L_1/L_2 > S_1/S_2$. The elimination of urban frictions thus raises $S_1/S_2$, and thereby the relative wage $\omega$ by shifting up the RHS of (E-5). We hence observe *wage divergence*. The expressions in (E-4) then indeed imply $m_1^d < \widetilde{m}_1^d < \widetilde{m}_2^d < m_2^d$ as $\omega$ increases.

*E.4. Spatial equilibrium: No trade frictions.* Our aim is to show the condition for $\widetilde{\Upsilon} < \Upsilon$ to hold in (33), and we proceed in two steps. First, we show that the elimination of trade frictions implies a lower cutoff in both regions. Second, we show under which conditions the elimination of trade frictions lead to a decrease in $\mathbb{P}_1$.

(i) Setting $\tau = t$, the market equilibrium conditions (E-1)–(E-3) can be rewritten as

$$\frac{\mu_1^{\max}}{t} = L_1 X_1 + L_2 \frac{X_2}{\Omega} \tag{E-7}$$

$$\frac{\mu_2^{\max}}{t} = L_2 X_2 + L_1 \Omega X_1 \tag{E-8}$$

$$\Omega = \left(\frac{\rho}{\sigma}\frac{X_2}{X_1}\right)^{\frac{k+1}{2k+1}}, \tag{E-9}$$

where $X_1 \equiv (m_1^d)^{k+1}$, $X_2 \equiv (m_2^d)^{k+1}$, and $\Omega \equiv \omega^{k+1}$. From (E-7) and (E-8), we thus have $\Omega\mu_1^{\max}/t = \mu_2^{\max}/t = L_1\Omega X_1 + L_2 X_2$. Hence, $\Omega = \rho$ must hold when $\tau = t$, and $\omega$ is uniquely determined. We know by (E-9) that $X_2 = (\sigma/\rho)\Omega^{\frac{2k+1}{k+1}} X_1 = \sigma\rho^{\frac{k}{k+1}} X_1$. Plugging this expression into (E-7) yields the unique counterfactual cutoffs

$$\widetilde{X}_1 = (\widetilde{m}_1^d)^{k+1} = \frac{\mu_1^{\max}/(L_1 t)}{1 + \sigma\rho^{-\frac{1}{k+1}}(L_2/L_1)} \quad \text{and} \quad \widetilde{X}_2 = (\widetilde{m}_2^d)^{k+1} = \frac{\mu_2^{\max}/(L_2 t)}{1 + \sigma^{-1}\rho^{\frac{1}{k+1}}(L_1/L_2)}. \tag{E-10}$$

Establishing that $\widetilde{X}_1 < X_1$, i.e., that $\widetilde{m}_1^d < m_1^d$ requires

$$\begin{aligned}
&\frac{1 - \rho(t/\tau)^k \omega^{-(k+1)}}{1 - (t/\tau)^{2k}} > \frac{1}{1 + \sigma\rho^{-\frac{1}{k+1}}(L_2/L_1)} \\
\Rightarrow\quad & \sigma\rho^{-\frac{1}{k+1}}\left(\frac{L_2}{L_1}\right)\left[1 - \rho\left(\frac{t}{\tau}\right)^k \omega^{-(k+1)}\right] > \left(\frac{t}{\tau}\right)^k \left[\rho\omega^{-(k+1)} - \left(\frac{t}{\tau}\right)^k\right] \\
\Rightarrow\quad & \rho^{-\frac{1}{k+1}}\left(\frac{S_2}{S_1}\right)\omega^{-(k+1)}\left[\omega^{k+1} - \rho\left(\frac{t}{\tau}\right)^k\right] > \left(\frac{t}{\tau}\right)^k \omega^{-(k+1)}\left[\rho - \left(\frac{t}{\tau}\right)^k \omega^{k+1}\right] \\
\Rightarrow\quad & \rho\rho^{-\frac{1}{k+1}}\left(\frac{\tau}{t}\right)^k > \rho\left(\frac{S_1}{S_2}\right)\frac{\rho - (t/\tau)^k\omega^{k+1}}{\omega^{k+1} - \rho(t/\tau)^k} = \omega^k,
\end{aligned}$$

where the last equality holds by (E-5). We thus need to prove $\rho^{k/(k+1)}(\tau/t)^k > \omega^k$ or $\rho^{1/(k+1)}(\tau/t) > \omega$, which is straightforward since $\rho^{1/(k+1)}(\tau/t) > \rho^{1/(k+1)}(\tau/t)^{k/(k+1)} \equiv \overline{\omega} > \omega$. Hence, $\widetilde{m}_1^d < m_1^d$ must hold. Using a similar approach, it can be shown that $\widetilde{m}_2^d < m_2^d$. The elimination of trade frictions thus leads to lower cutoffs in *both* regions.

(ii) Now we want to show under which conditions we have $\widetilde{\Upsilon} < \Upsilon$ in (33). Let $\Delta m_r^d \equiv m_r^d - \widetilde{m}_r^d > 0$. Then, proving $h_1(1/\widetilde{m}_1^d - 1/m_1^d) < h_2(1/\widetilde{m}_2^d - 1/m_2^d)$ is equivalent to proving that

$$\frac{h_1 \Delta m_1^d}{m_1^d \widetilde{m}_1^d} < \frac{h_2 \Delta m_2^d}{m_2^d \widetilde{m}_2^d} \quad \Leftrightarrow \quad \frac{m_1^d \widetilde{m}_1^d \Delta m_2^d}{m_2^d \widetilde{m}_2^d \Delta m_1^d} \frac{h_2}{h_1} > 1. \tag{E-11}$$

This can be done by the following steps. First, we prove cutoff convergence, i.e., $\widetilde{m}_2^d/\widetilde{m}_1^d < m_2^d/m_1^d$. Using (E-10), the counterfactual cutoff ratio is given by $(\widetilde{m}_2^d/\widetilde{m}_1^d)^{k+1} = \sigma\rho^{k/(k+1)}$, whereas using (E-4), the cutoff ratio with trade frictions is

$$\left(\frac{m_2^d}{m_1^d}\right)^{k+1} = \frac{L_1}{L_2} \frac{1}{\omega^{-(k+1)}} \frac{\rho - (t/\tau)^k \omega^{k+1}}{\omega^{k+1} - \rho(t/\tau)^k} = \frac{L_1}{L_2} \frac{1}{\omega^{-(k+1)}} \frac{\omega^k}{\rho} \frac{S_2}{S_1} = \frac{\sigma}{\rho} \omega^{2k+1},$$

where we use (E-5) to obtain the second equality. Taking their difference, showing that $\widetilde{m}_2^d/\widetilde{m}_1^d < m_2^d/m_1^d$ boils down to showing that $\rho^{1/(k+1)} < \omega$ at the market equilibrium. This can be done by evaluating (E-5) at $\omega = \rho^{1/(k+1)}$. The LHS is equal to $\rho^{k/(k+1)}$, which falls short of the RHS given by $\rho S_1/S_2$ (because $\rho \geq 1$, $k \geq 1$, and $S_1/S_2 > 1$). Since the LHS is increasing and the RHS is decreasing, it must be that $\rho^{1/(k+1)} < \omega^*$. Thus, we have proved $\widetilde{m}_2^d/\widetilde{m}_1^d < m_2^d/m_1^d$ . Turning to the second step, this cutoff convergence then implies

$$\frac{m_2^d}{m_1^d} > \frac{\widetilde{m}_2^d}{\widetilde{m}_1^d} \quad \Rightarrow \quad \frac{m_1^d}{m_2^d} \frac{\Delta m_2^d}{\Delta m_1^d} > 1 \quad \Rightarrow \quad \left(\frac{m_1^d}{m_2^d} \frac{\widetilde{m}_1^d}{\widetilde{m}_2^d} \frac{\Delta m_2^d}{\Delta m_1^d} \frac{h_2}{h_1}\right) \frac{\widetilde{m}_2^d}{\widetilde{m}_1^d} \frac{h_1}{h_2} > 1. \tag{E-12}$$

Recall from (E-11) that we ultimately want to prove that $\left(\frac{m_1^d}{m_2^d} \frac{\widetilde{m}_1^d}{\widetilde{m}_2^d} \frac{\Delta m_2^d}{\Delta m_1^d} \frac{h_2}{h_1}\right) > 1$. A sufficient condition for this to be satisfied, given condition (E-12), is that $(\widetilde{m}_2^d/\widetilde{m}_1^d)(h_1/h_2) \leq 1$, i.e., that $[\sigma\rho^{k/(k+1)}]^{1/(k+1)}(1/\sigma) = [\rho^{1/(k+1)}/\sigma]^{k/(k+1)} \leq 1$. This is the case if $\rho^{1/(k+1)} \leq \sigma$. In words, the elimination of trade frictions leads to a decrease in the size of the large city if the two cities are not too different in terms of their technological possibilities. In the simple case where $\rho = 1$, the large city always becomes smaller as $\sigma > 1$.

## Appendix F: Quantification – Data, procedure, and model fit.

*F.1. Data.* We summarize the data used for the quantification of our model.

*i)* MSA *data*

We construct a dataset for 356 MSAs (see Table 5 below for a full list). The bulk of our MSA-level data comes from the 2007 American Community Survey (ACS) of the US Census, from the Bureau of Economic Analysis (BEA), and from the Bureau of Labor Statistics (BLS). The geographical coordinates of each MSA are computed as the centroid of its constituent counties' geographical coordinates. The latter are obtained from the 2000 US Census Gazetteer county geography file, and the MSA-level aggregation is carried out using the county-to-MSA concordance tables for 2007. We then construct our measure of distance between two MSAs as $d_{rs} = \cos^{-1}\big(\sin(\mathrm{lat}_r)\sin(\mathrm{lat}_s) + \cos(|\mathrm{lon}_r - \mathrm{lon}_s|)\cos(\mathrm{lat}_r)\times \cos(\mathrm{lat}_s)\big) \times 6{,}378.137$ using the great circle formula, where $\mathrm{lat}_r$ and $\mathrm{lon}_r$ are the geographical coordinates of the MSA. The internal distance of an MSA is defined as $d_{rr} \equiv (2/3)\sqrt{\mathrm{surface}_r/\pi}$ as in Redding and Venables (2004). All MSA surface measures are given in square kilometers and include only land surface of the MSA's forming counties. That data is obtained from the 2000 US Census Gazetteer, and is aggregated from the county to the MSA level.

We further obtain total gross domestic product by MSA from the BEA metropolitan GDP files. Total employment at the MSA level is obtained from the 2007 BLS employment flat files (we use aggregate values for 'All occupations'). Using gross domestic product, total employment, and the average number of hours worked, we construct our measure of average MSA productivity (GDP per employee), which can be used as a proxy for $1/m_r^d$ under the Pareto distribution. Wages at the MSA level for 2007 are computed as total labor expenses (compensation of employees plus employer contributions for employee pension and insurance funds plus employer contributions for government social insurance) divided by total MSA employment. Data to compute total labor expenses is provided by the BEA.

*ii) Amenity data*

County-level data on natural amenities refer to the year 1999 and are provided by the US Department of Agriculture (USDA). The USDA data includes six measures of climate, topography, and water area that reflect environmental attributes usually valued by people. In our benchmark OLS estimation of (35), we use the standardized amenity score from that data as a proxy for our observed amenities $A_r^o$. We aggregate the county-level amenities up to the MSA level by using the county-to-MSA concordance table and by weighting each county by its share in the total MSA land surface.

In the instrumental variable approach (described in more detail in Appendix G.2 below) we additionally use information from the United States Geological Survey (USGS) to compute three measures: the fraction of an MSA underlain by sedimentary rock; the fraction of an MSA designated as seismic hazard; and the fraction designated as landslide hazard (see Rosenthal and Strange, 2008). These variables, as well as their squared terms, are used as instruments for $\widehat{U}_r$. Moreover, when conducting the 2SLS estimation of (35), we include a full battery of state dummies.

*iii) Urban frictions data*
Data is taken from the 2007 ACS which provides total MSA population, average weekly hours worked and average one-way commuting time in minutes. Those pieces of information are used to compute the aggregate labor supply $\overline{h}_r L_r$, and the effective labor supply $S_r$.

*iv) Trade frictions data*
Finally, we use aggregate bilateral trade flows $X_{rs}$ from the 2007 Commodity Flow Survey (CFS) of the Bureau of Transportation Statistics (BTS) for the lower 48 contiguous US states, as these are the states containing the MSAs that will be used in our analysis. We work at the state level since MSA trade flows from the CFS public files can only be meaningfully exploited for a relatively small sample of large 'CFS regions'. The distance between $r$ and $s$ in kilometers is computed using the great circle formula given above. In that case, $\text{lat}_r$ and $\text{lon}_r$ denote the coordinates of the capital of state $r$, measured in radians, which are taken from Anderson and van Wincoop's (2003) dataset.

*F.2. Quantification procedure: Market equilibrium.* As explained in the main text, the quantification procedure for the market equilibrium consists of five steps that we now explain in detail.

*i) Urban frictions $\theta_r$*
To obtain the city-specific commuting technology parameters $\widehat{\theta}_r$ that constitute urban frictions, we rewrite equation (12) as

$$L_r \frac{h_r}{\overline{h}_r} = \frac{2\pi}{\theta_r^2} \left[1 - \left(1 + \theta_r \sqrt{L_r/\pi}\right) \mathrm{e}^{-\theta_r \sqrt{L_r/\pi}}\right], \tag{F-1}$$

where we use $S_r = L_r h_r$. We compute $h_r$ as the average number of hours worked per week in MSA $r$. The gross labor supply per capita, $\overline{h}_r$, which is the endowment of hours available for work and commuting, is constructed as the sum of $h_r$ and hours per week spent by workers in each MSA for travel-to-work commuting in 2007. Given $h_r$, $\overline{h}_r$, as well as city size $L_r$, the above equation can be uniquely solved for the city-specific commuting parameter $\widehat{\theta}_r$. Table 5 below provides the values for the 356 MSAs.

*ii) Trade frictions $\tau_{rs}$*

To estimate the distance elasticity $\widehat{\gamma}$ that constitutes trade frictions, we consider the value of sales from $r$ to $s$:

$$X_{rs} = N_r^E L_s \int_0^{m_{rs}^x} p_{rs}(m) q_{rs}(m) \mathrm{d}G_r(m). \tag{F-2}$$

Using (7), (9), (24), and the result from Appendix B.4, we then obtain the following gravity equation: $X_{rs} = S_r L_s \tau_{rs}^{-k} \tau_{ss}^{k+1} (w_s/w_r)^{k+1} w_r \left(m_s^d\right)^{k+1} (\mu_r^{\max})^{-1}$. Turning to the specification of trade costs $\tau_{rs}$, we stick to standard practice and assume that $\tau_{rs} \equiv d_{rs}^{\gamma}$, where $d_{rs}$ stands for the distance from $r$ to $s$. The gravity equation can then be rewritten in log-linear stochastic form:

$$\ln X_{rs} = \text{const.} - k\gamma \ln d_{rs} + I_{rs}^0 + \zeta_r^1 + \zeta_s^2 + \varepsilon_{rs}, \tag{F-3}$$

where all terms specific to the origin and the destination are collapsed into fixed effects $\zeta_r^1$ and $\zeta_s^2$, where $I_{rs}^0$ is a zero-flow dummy, and $\varepsilon_{rs}$ is an error term with the usual properties for OLS consistency.[32] Using aggregate bilateral trade flows $X_{rs}$ in 2007 for the 48 contiguous US states that cover all MSAs used in the subsequent analysis, we estimate the gravity equation on state-to-state trade flows. Given a value of $k$, we then obtain an estimate of the distance elasticity $\widehat{\gamma}$ that constitutes trade frictions.

*iii) Market equilibrium conditions $(w_r, \mu_r^{\max})$*

Observe that expressions (22) and (25) can be rewritten as:

$$\mu_r^{\max} = \sum_s L_s \tau_{rs} \left( m_s^d \frac{\tau_{ss}}{\tau_{rs}} \frac{w_s}{w_r} \right)^{k+1} \tag{F-4}$$

$$\frac{S_r}{L_r} \frac{1}{\left(m_r^d\right)^{k+1}} = \sum_s S_s \tau_{rr} \left( \frac{\tau_{sr}}{\tau_{rr}} \frac{w_s}{w_r} \right)^{-k} \frac{1}{\mu_s^{\max}}. \tag{F-5}$$

Ideally, we would use data on technological possibilities $\mu_r^{\max}$ to solve for the wages and cutoffs. Yet, $\mu_r^{\max}$ is unobservable. We thus solve for wages and technological possibilities $(\widehat{w}_r, \widehat{\mu}_r^{\max})$, given the values of $m_r^d$. More specifically, from data on GDP of MSA $r$ and the total number of hours worked in that MSA (hours worked per week times total employment) we compute the average MSA productivity $\overline{M}_r$ (GDP per employee), which can be used as a proxy for $1/m_r^d$ under the Pareto distribution. Using the value of $k$, the cutoffs $m_r^d$, the city-specific commuting technologies $\widehat{\theta}_r$, the observed MSA populations $L_r$, as well as trade frictions $\widehat{\tau}_{rs} = d_{rs}^{\widehat{\gamma}}$, we can solve (F-4) and (F-5) for the wages

[32] There are 179 'zero flows' out of 2,304 in the data, i.e., 7.7% of the sample. We control for them by using a standard dummy-variable approach, where $I_{rs}^0$ takes value 1 if $X_{rs} = 0$ and 0 otherwise.

and unobserved technological possibilities $(\widehat{w}_r, \widehat{\mu}_r^{\max})$ that are consistent with the market equilibrium.

*iv) Firm size distribution and Pareto shape parameter $k$*

The quantification procedure described thus far has assumed a given value of the shape parameter $k$. To estimate $k$ structurally, we proceed as follows. First, given a value of $k$, we can compute trade frictions $\widehat{\tau}_{rs}$ and the wages and cutoffs $(\widehat{w}_r, \widehat{\mu}_r^{\max})$ as described before. This, together with the internal cutoff $m_r^d$ computed from data, yields the external cutoffs $\widehat{m}_{rs}^x$ by (7). With that information in hand, we can compute the share $\widehat{\nu}_r$ of surviving firms in each MSA as follows:

$$\widehat{\nu}_r \equiv \frac{\widehat{N}_r^p}{\sum_s \widehat{N}_s^p}, \quad \text{where} \quad \widehat{N}_r^p = \widehat{N}_r^E G_r\left(\max_s \widehat{m}_{rs}^x\right) = \frac{\alpha}{\kappa_1+\kappa_2} S_r \left(\widehat{\mu}_r^{\max}\right)^{-1}\left(\max_s \widehat{m}_{rs}^x\right)^k$$

denotes the number of firms operating in MSA $r$. The total effective labor supply $S_r$ is computed as described above in *i)*. Note that $\widehat{\nu}_r$ is independent of the unobservable constant scaling $\alpha/(\kappa_1+\kappa_2)$ that multiplies the number of firms.

Second, we draw a large sample of firms from our calibrated MSA-level productivity distributions $\widehat{G}_r(m) = (m/\max_s\{m_{rs}^x\})^k$. For that sample to be representative, we draw firms in MSA $r$ in proportion to its share $\widehat{\nu}_r$. For each sampled firm with marginal labor requirement $m$ in MSA $r$, we can compute its employment as follows:[33]

$$\text{employment}_r(m) = m\sum_s \widehat{\chi}_{rs} L_s q_{rs}(m) = \frac{m}{\alpha}\sum_s \widehat{\chi}_{rs} L_s\left[1 - W\left(\mathrm{e}\frac{m}{\widehat{m}_{rs}^x}\right)\right],$$

where $\widehat{\chi}_{rs} = 1$ if $m < \widehat{m}_{rs}^x$ (the establishment can sell to MSA $s$) and zero otherwise (the establishment cannot sell to MSA $s$). Since we can identify employment only up to some positive constant (which depends on the unobservable $\alpha$) we choose, without loss of generality, that coefficient such that the average employment per firm in our sample of establishments matches the observed average employment in the 2007 CBP. Doing so allows us to readily compare the generated and observed data as we can sort the sampled firms into the same size bins as those used for the observed firms. We use four standard employment size bins from the CBP: $\iota = \{1\text{–}19, 20\text{–}99, 100\text{–}499, 500+\}$ employees. Let $N_{(\iota)}^{\text{SIM}}$ and $N_{(\iota)}^{\text{CBP}}$ denote the number of firms in each size bin $\iota$ in our sample and in the CBP, respectively. Let also $N^{\text{SIM}}$ and $N^{\text{CBP}}$ denote our sample size and the observed number of establishments in the CBP. Given a value of $k$, the following statistic is a natural measure

[33] We exclude the labor used for shipping goods and the sunk initial labor requirement.

Table 3: Shipment shares and shipping distances – summary for observed and simulated data.

| Employment | Number of establishments | | Shipment shares by distance shipped to destination < 100 miles | | 100–500 miles | | > 500 miles | | Mean distance shipped | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Observed | Model | Observed | Model | Observed | Model | Observed | Model | Observed | Model | Model (wgt) |
| All | 6,431,884 | 6,431,886 | 0.261 | 0.506 | 0.288 | 0.277 | 0.348 | 0.217 | 529.6 | 71.98 | 739.8 |
| 1–19 | 5,504,463 | 5,498,328 | 0.561 | 0.984 | 0.204 | 0.016 | 0.194 | 0.000 | 327.2 | 38.5 | 61.2 |
| 20–99 | 769,705 | 755,275 | 0.382 | 0.835 | 0.288 | 0.162 | 0.276 | 0.004 | 423.8 | 157.9 | 194.4 |
| 100–499 | 141,510 | 153,021 | 0.254 | 0.420 | 0.318 | 0.440 | 0.342 | 0.139 | 520.4 | 556.0 | 740.3 |
| 500+ | 16,206 | 25,255 | 0.203 | 0.079 | 0.272 | 0.332 | 0.388 | 0.590 | 588.6 | 1450.6 | 1519.1 |

*Notes:* Shipping distance and shipping share columns are adapted from calculations by Holmes and Stevens (2012, Table 1) who use confidential Census microdata from the 1997 Commodity Flow Survey. The small difference (of 2 units) between the observed and model total number of establishments is due to rounding in our sampling procedure. The last column reports distances shipped weighted by establishments' sales shares in total sales.

of the goodness-of-fit of the simulated establishment-size distribution:

$$\text{SS}(k) = \sum_{\iota=1}^{4} \left[ \frac{N_{(\iota)}^{\text{SIM}}}{N^{\text{SIM}}} - \frac{N_{(\iota)}^{\text{CBP}}}{N^{\text{CBP}}} \right]^2, \tag{F-6}$$

the value of which depends on the chosen $k$. It is clear from (F-6) that we can choose any large sample size $N^{\text{SIM}}$ since it would not affect the ratio $N_{(\iota)}^{\text{SIM}}/N^{\text{SIM}}$. Without loss of generality, we choose the sample size such that the total number of simulated firms operating matches the observed total number of establishments ($N^{\text{SIM}} = N^{\text{CBP}}$). There are 6,431,884 establishments across our 356 MSAs in the 2007 CBP, and we sample the same number of firms from our quantified model.[34] We finally choose $k$ by minimizing $\text{SS}(k)$.

*F.3. Model fit.* We now provide details about our model fit with respect to trade frictions. Figure 10 below is analogous to Figures 1-3 in Hillberry and Hummels (2008) who provide micro evidence on the spatial structure of firms' shipping patterns. The figure reports kernel regressions of various predicted shipment characteristics on distance. Specifically, we consider that the value of sales from an establishment in city $r$ to city $s$ represents one shipment characterized by an origin MSA, a destination MSA, a shipping value, a unit price, and a shipping distance. We then draw a representative sample of 40,000 establishments from all MSAs, which yields a total of $40{,}000 \times 356^2$ potential shipments.[35] Most of these shipments do of course not occur, and there are only 243,784 positive shipments in our sample. As in Hillberry and Hummels (2008), we then use a Gaussian kernel with optimal bandwidth and calculated on 100 points.

We illustrate the results for distances greater than about 10 miles (the minimum in our sample) and up to slightly below 3,000 miles (the maximum in our sample). Note that

[34] Doing so allows for a direct comparison of $N_{(\iota)}^{\text{SIM}}$ and $N_{(\iota)}^{\text{CBP}}$ for each $\iota$. The very small differences in the aggregate numbers in Tables 1 and 3 are due to rounding as the number of firms has to be an integer.

[35] The sample size is immaterial for our results provided that it is large enough. Given that the number of shipments is substantially larger than the number of firms, drawing a large sample of 6.5 million firms as before proves computationally infeasible.

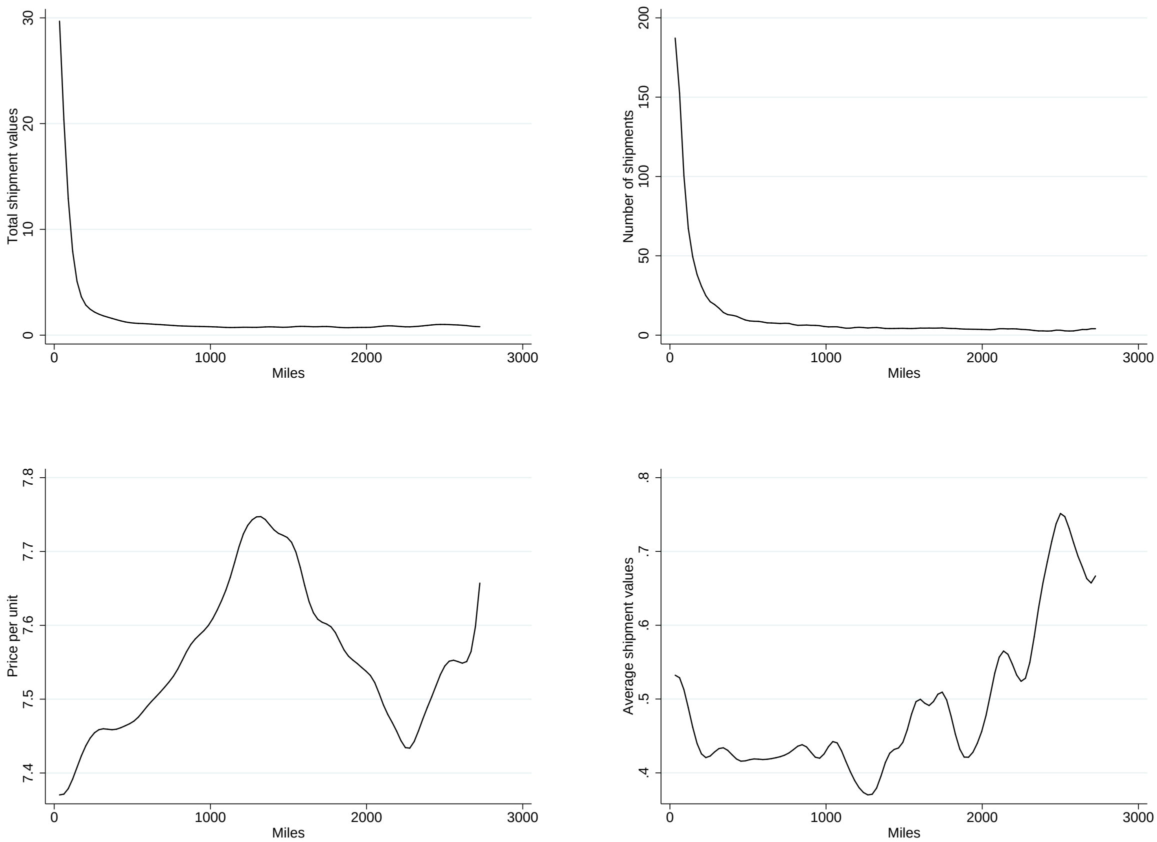


Figure 10: Micro-fit for cross-MSA establishment-level shipments (kernel regressions on distance)

we have less variation in distances than Hillberry and Hummels (2008) who use either 3-digit or 5-digit zip code level data instead of MSA data. In line with the micro evidence presented in Hillberry and Hummels (2008), we find that both aggregate shipment values and the number of shipments predicted by our model fall off very quickly with distance – becoming very small beyond a threshold of about 200 miles – whereas price per unit first rises with distance and average shipment values do not display a clear pattern.

Next, we compare shipping shares and shipping distances by establishment size class predicted by our model, and their empirically observed counterparts. The former are obtained as follows. First, for each establishment with labor requirement $m$ in MSA $r$, we compute the value of its sales:

$$\text{sales}_r(m) = \sum_s \chi_{rs} L_s p_{rs}(m) q_{rs}(m) = \frac{\widehat{w}_r m}{\alpha} \sum_s \chi_{rs} L_s d_{rs}^{\widehat{\gamma}} [W(\text{e}m/\widehat{m}_{rs}^x)^{-1} - 1].$$

We then classify all 6,431,886 establishments in our sample by employment size class, and disaggregate the value of sales for each establishment by distance shipped to compute the shares reported in Table 3.[36] The observed patterns in Table 3 come from Holmes and Stevens (2012) who use confidential CFS microdata from 1997 to compute the shares of shipping values by distance as well as average shipping distances. As can be seen, our model can qualitatively reproduce the observed shipment shares, and it can also explain the tendency that the mean distance shipped increases with establishment size.

## Appendix G: Spatial equilibrium.

*G.1. Unique solution for $D_r$.* Letting $D_r = (U_r + A_r)/\beta$, the spatial equilibrium condition can be written as

$$\frac{\exp(D_r)}{\sum_{s=1}^{K}\exp(D_s)} = \frac{L_r}{\sum_{s=1}^{K} L_s}, \quad \text{with } D_1 = 0. \tag{G-1}$$

Taking the ratio for regions $r$ and 1, we have

$$\frac{\exp(D_r)}{\exp(D_1)} = \exp(D_r) = \frac{L_r}{L_1}, \quad \forall r. \tag{G-2}$$

Hence, $D_r$ is uniquely determined as $D_r = \ln(L_r/L_1)$ for all $r$.

*G.2. Instrumental variable approach.* In the IV approach to estimating (35), the second-stage specification is as follows:

$$\widehat{D}_r = \alpha_0 + \alpha_1 \widehat{U}_r^{\text{instr}} + \alpha_2 A_r^o + \xi_{s(r)} + \varepsilon_r, \tag{G-3}$$

where $A_r^o$ is the USDA amenity score (observed amenities); and where $\xi_{s(r)}$ (with MSA $r$ belonging to state $s$) are state fixed effects (some MSAs cover several states, in which case they have separate 'state' dummies). We cluster standard errors at the state level. Here, $\widehat{U}_r^{\text{instr}}$ is the instrumented value of utility of MSA $r$, which is obtained from the following first-stage regression

$$\begin{aligned}\widehat{U}_r \;=\; & \beta_0 + \beta_1 \text{SEDIM\_ROCK}_r + \beta_2 \text{LANDSLIDE}_r + \beta_3 \text{SEISMIC\_HAZARD}_r \\ & + \beta_4 \text{SEDIM\_ROCK}_r^2 + \beta_5 \text{LANDSLIDE}_r^2 + \beta_6 \text{SEISMIC\_HAZARD}_r^2 + \beta_7 A_r^o + \xi_{s(r)} + \varepsilon_r,\end{aligned} \tag{G-4}$$

where $\text{SEDIM\_ROCK}_r$, $\text{LANDSLIDE}_r$ and $\text{SEISMIC\_HAZARD}_r$ are the three geological instruments as described in Appendix F.1.

The results from the 2SLS regression are reported in Table 4. As one can see, our instruments are strong and the second-stage coefficient on the instrumented utility is significant at the 1% level.

[36] Since we work with shares, the unobservable scaling parameter $\alpha$ does not affect our results.

Table 4: IV estimation results.

| | Coefficient | p-value |
|---|---|---|
| **Second stage** | | |
| $\widehat{U}_r$ (instrumented) | 2.8416*** | 0.0050 |
| | (1.0166) | |
| Natural amenities score | 0.0404** | 0.2940 |
| | (0.0384) | |
| State fixed effects | Yes | |
| Second-stage centered $R^2$ | 0.3575 | |
| Second-stage uncentered $R^2$ | 0.5506 | |
| **First stage** | | |
| Sedimentary rock | 0.0990 | 0.4050 |
| | 0.1183 | |
| Sedimentary rock squared | −0.0326 | 0.7680 |
| | (0.1102) | |
| Landslide | −0.0081 | 0.9240 |
| | (0.0841) | |
| Landslide squared | −0.0036 | 0.8870 |
| | (0.0249) | |
| Seismic hazard | −0.0053 | 0.0940 |
| | (0.0031) | |
| Seismic hazard squared | 0.0002*** | 0.0000 |
| | (0.0000) | |
| Natural amenities score | 0.0078* | 0.0890 |
| | (0.0046) | |
| State fixed effects | Yes | |
| First-stage centered $R^2$ | 0.4727 | |
| First-stage uncentered $R^2$ | 0.9775 | |
| Number of excluded instruments | 6 | |
| Kleibergen-Paap $LM$ statistic | 6.147 | |
| Kleibergen-Paap $F$ statistic | 16.37 | |
| Cragg-Donald Wald $F$ statistic | 3.91 | |

*Notes:* Cluster robust standard errors (by state) in parentheses. Regressions for $N = 356$ observations. ***, **, and * denote coefficient significant at 1%, 5%, and 10%, respectively.

With these estimates in hand, we then decompose $\widehat{D}_r$ as follows:

$$\widehat{D}_r = \widehat{\alpha}_1^{2SLS}\widehat{U}_r + \underbrace{\widehat{\alpha}_0^{2SLS} + \widehat{\alpha}_2^{2SLS}A_r^o + \widehat{\xi}_{s(r)}}_{\text{observed amenities}} + \underbrace{\widehat{\varepsilon}_r^*}_{\text{unobserved amenities}} \tag{G-5}$$

where $\widehat{\varepsilon}_r^*$ is a residual allowing the right-hand side to match the left-hand side. We hold $\widehat{\alpha}_1^{2SLS}$ and both observed and unobserved amenities in (G-5) constant during the counterfactual experiments and use the changes in $\widehat{U}_r$ to construct the changes in $\widehat{D}_r$.

## Appendix H: Numerical procedure for counterfactual analysis.

For simplicity, we only explain the procedure for the 'no urban frictions' case, as it works analogously for the 'no trade frictions' scenario. First, we let $\widehat{\theta}_r = 0$ for all $r$ and keep the initial population distribution fixed. This parameter change induces changes in the indirect utility levels. Let $\widetilde{U}_r^0$ denote the new counterfactual utility in MSA $r$, evaluated at the initial population and $\widehat{\theta}_r = 0$. Second, we replace $\widehat{U}_r$ with its new counterfactual value $\widetilde{U}_r^0$ to obtain $\widetilde{D}_r^0 = \widehat{\alpha}_0 + \widehat{\alpha}_1\widetilde{U}_r^0 + \widehat{\alpha}_2 A_r^o + \widehat{A}_r^u$. The spatial equilibrium conditions (34) will then, in general, no longer be satisfied, and hence city sizes must change.

We thus consider the following iterative adjustment procedure to find the new counterfactual spatial equilibrium:

1. Given the values of $\widetilde{D}_r^0$, induced by the change in spatial frictions, the new choice probabilities are uniquely determined as follows:

$$\widetilde{\mathbb{P}}_r^0 = \frac{\exp(\widetilde{D}_r^0)}{\sum_s \exp(\widetilde{D}_s^0)}, \tag{H-1}$$

which yields a unique new population distribution $\widetilde{L}_r^0 = L\widetilde{\mathbb{P}}_r^0$ for all $r = 1,...,K$.

2. Given the intial $\widehat{\mu}_r^{\max}$, the new population distribution $\widetilde{L}_r^0$ for all $r = 1,...,K$, as well as the counterfactual value for the commuting technology parameter $\widehat{\theta}_r = 0$, the market equilibrium conditions are uniquely solved for the new (relative) wages and cutoffs $\{\widetilde{w}_r^1, (\widetilde{m}_r^d)^1\}$. Expression (28) then yields new utility levels $\widetilde{U}_r^1$.

3. Using $\widetilde{D}_r^1 = \widehat{\alpha}_0 + \widehat{\alpha}_1\widetilde{U}_r^1 + \widehat{\alpha}_2 A_r^o + \widehat{A}_r^u$, the choice probabilities can be updated as in (H-1), which yields a new population distribution $\widetilde{L}_r^1 = L\widetilde{\mathbb{P}}_r^1$ for all $r = 1,...,K$.

4. We iterate over steps 2–3 until convergence of the population distribution to obtain $\{\widetilde{L}_r, \widetilde{w}_r, \widetilde{m}_r^d\}$ for all $r = 1,...,K$.

## Appendix I: Agglomeration economies.

We compute $\widehat{\mu}_r^{\max}$ in the initial equilibrium. Call it $\widehat{\mu}_r^{\max,0}$. Assume now that the population of MSA $r$ changes from $L_r^0$ to $L_r^1$. The new $\widehat{\mu}_r^{\max}$ is then given by $\widehat{\mu}_r^{\max,1} = c \cdot (L_r^1)^{-k\xi} \cdot \widehat{\psi}_r^{\max}$. Hence, it is easy to see that, given the initial estimates $\widehat{\mu}_r^{\max,0}$ we have $\widehat{\mu}_r^{\max,1} = \widehat{\mu}_r^{\max,0}\left(L_r^1/L_r^0\right)^{-k\xi}$. Thus, we can integrate agglomeration economies in a straightforward way into our framework by replacing $\widehat{\mu}_r^{\max}$ by $\widehat{\mu}_r^{\max}\left(L_r^1/L_r^0\right)^{-k\xi}$ in the market equilibrium conditions (F-4) and (F-5) when running the counterfactuals:

$$\widehat{\mu}_r^{\max}\left(\frac{L_r^1}{L_r^0}\right)^{-k\xi} = \sum_s L_s^1 \tau_{rs}\left(m_s^d \frac{\tau_{ss}}{\tau_{rs}}\frac{w_s}{w_r}\right)^{k+1} \tag{I-1}$$

$$\frac{S_r^1}{L_r^1}\frac{1}{(m_r^d)^{k+1}} = \sum_s S_s^1 \tau_{rr}\left(\frac{\tau_{sr}}{\tau_{rr}}\frac{w_s}{w_r}\right)^{-k}\frac{1}{\widehat{\mu}_s^{\max}\left(\frac{L_s^1}{L_s^0}\right)^{-k\xi}}. \tag{I-2}$$

# Appendix J: Additional results tables.

Table 5: MSA variables and descriptive statistics for the initial equilibrium.

| FIPS | MSA name | State | $L_r/\overline{L}$ | $\widehat{\mu}_r^{\max}$ | $\overline{M}_r$ | $\widehat{\theta}_r$ | $A_r^o$ | $\widehat{A}_r^u$ |
|---|---|---|---|---|---|---|---|---|
| 10180 | Abilene | TX | 0.2268 | 6.8852 | 1.1412 | 0.3925 | 1.3141 | -0.6556 |
| 10420 | Akron | OH | 0.9956 | 17.4352 | 1.1254 | 0.2473 | -2.2749 | 1.0062 |
| 10500 | Albany | GA | 0.2336 | 28.3000 | 0.9842 | 0.4608 | -0.0435 | -0.4451 |
| 10580 | Albany-Schenectady-Troy | NY | 1.2149 | 15.6558 | 1.1952 | 0.2015 | -0.2432 | 1.1317 |
| 10740 | Albuquerque | NM | 1.1889 | 11.6475 | 1.1914 | 0.2232 | 3.7322 | 0.9275 |
| 10780 | Alexandria | LA | 0.2133 | 14.7747 | 1.0459 | 0.5445 | -0.2067 | -0.5842 |
| 10900 | Allentown-Bethlehem-Easton | PA-NJ | 1.1444 | 22.9469 | 1.1892 | 0.3088 | 0.3026 | 0.9760 |
| 11020 | Altoona | PA | 0.1787 | 28.9660 | 0.9424 | 0.5223 | -0.8600 | -0.7009 |
| 11100 | Amarillo | TX | 0.3449 | 7.1209 | 1.1381 | 0.3277 | 1.6304 | -0.2289 |
| 11180 | Ames | IA | 0.1207 | 0.7978 | 1.3453 | 0.6556 | -3.5400 | -1.1175 |
| 11300 | Anderson | IN | 0.1869 | 6.1621 | 1.1301 | 0.8718 | -3.4700 | -0.6463 |
| 11340 | Anderson | SC | 0.2562 | 16.3593 | 1.0337 | 0.5571 | 0.7100 | -0.4872 |
| 11460 | Ann Arbor | MI | 0.4983 | 2.9986 | 1.3345 | 0.2977 | -2.1900 | 0.1721 |
| 11500 | Anniston-Oxford | AL | 0.1610 | 13.1516 | 1.0181 | 0.5613 | 0.2200 | -0.9536 |
| 11540 | Appleton | WI | 0.3104 | 9.1579 | 1.0961 | 0.3684 | -2.7304 | -0.0904 |
| 11700 | Asheville | NC | 0.5756 | 31.3698 | 1.0427 | 0.3163 | 2.1012 | 0.2978 |
| 12020 | Athens-Clarke County | GA | 0.2668 | 15.4460 | 1.0768 | 0.4865 | -1.0511 | -0.3069 |
| 12060 | Atlanta-Sandy Springs-Marietta | GA | 7.5152 | 7.9312 | 1.4838 | 0.1174 | 0.2253 | 2.7880 |
| 12100 | Atlantic City-Hammonton | NJ | 0.3853 | 4.3460 | 1.2672 | 0.3301 | -0.0400 | -0.2364 |
| 12220 | Auburn-Opelika | AL | 0.1858 | 14.1079 | 1.0001 | 0.6358 | -0.2400 | -0.7240 |
| 12260 | Augusta-Richmond County | GA-SC | 0.7524 | 23.6409 | 1.1035 | 0.2920 | -0.0192 | 0.6829 |
| 12420 | Austin-Round Rock | TX | 2.2752 | 5.6156 | 1.3675 | 0.1860 | 1.6141 | 1.5231 |
| 12540 | Bakersfield | CA | 1.1257 | 8.3291 | 1.3486 | 0.2453 | 4.8400 | 0.6741 |
| 12580 | Baltimore-Towson | MD | 3.7983 | 12.0935 | 1.3507 | 0.1519 | -0.3557 | 2.1378 |
| 12620 | Bangor | ME | 0.2118 | 5.6207 | 1.1110 | 0.5506 | -0.5200 | -0.5302 |
| 12700 | Barnstable Town | MA | 0.3163 | 2.9345 | 1.1726 | 0.4759 | 1.5200 | -0.4993 |
| 12940 | Baton Rouge | LA | 1.0962 | 3.7242 | 1.3720 | 0.2569 | -0.6186 | 0.9311 |
| 12980 | Battle Creek | MI | 0.1945 | 7.2642 | 1.1375 | 0.4982 | -2.7300 | -0.6453 |
| 13020 | Bay City | MI | 0.1531 | 6.5755 | 1.0662 | 0.7995 | -1.5300 | -0.9167 |
| 13140 | Beaumont-Port Arthur | TX | 0.5356 | 8.3601 | 1.1884 | 0.2801 | 0.9407 | 0.1728 |
| 13380 | Bellingham | WA | 0.2748 | 1.1589 | 1.3356 | 0.4955 | 5.2600 | -0.7955 |
| 13460 | Bend | OR | 0.2193 | 2.3869 | 1.2328 | 0.4620 | 6.1000 | -1.0336 |
| 13740 | Billings | MT | 0.2131 | 7.1640 | 1.0636 | 0.3735 | 2.4532 | -0.6830 |
| 13780 | Binghamton | NY | 0.3508 | 56.9535 | 0.9409 | 0.3785 | -0.9289 | 0.0588 |
| 13820 | Birmingham-Hoover | AL | 1.5777 | 5.8973 | 1.3723 | 0.2055 | 0.5780 | 1.2351 |
| 13900 | Bismarck | ND | 0.1470 | 12.2467 | 0.9710 | 0.4403 | -1.6258 | -0.7564 |
| 13980 | Blacksburg-Christiansburg-Radford | VA | 0.2244 | 10.1677 | 1.1161 | 0.5208 | 0.5141 | -0.5979 |
| 14020 | Bloomington | IN | 0.2616 | 14.7889 | 1.1155 | 0.5467 | -0.4507 | -0.3408 |
| 14060 | Bloomington-Normal | IL | 0.2338 | 2.4247 | 1.3554 | 0.3871 | -3.5700 | -0.4375 |
| 14260 | Boise City-Nampa | ID | 0.8367 | 10.6193 | 1.1636 | 0.2399 | 2.2919 | 0.6976 |
| 14460 | Boston-Cambridge-Quincy | MA-NH | 6.3819 | 2.7007 | 1.6266 | 0.1098 | 0.1444 | 2.4955 |
| 14500 | Boulder | CO | 0.4132 | 0.6188 | 1.5305 | 0.3373 | 5.8200 | -0.6755 |
| 14540 | Bowling Green | KY | 0.1651 | 12.3177 | 1.0554 | 0.5611 | -0.2160 | -0.8510 |
| 14740 | Bremerton-Silverdale | WA | 0.3370 | 1.2068 | 1.4377 | 0.7249 | 2.6100 | -0.6981 |
| 14860 | Bridgeport-Stamford-Norwalk | CT | 1.2742 | 0.0329 | 2.5112 | 0.2506 | 2.2500 | -0.2081 |
| 15180 | Brownsville-Harlingen | TX | 0.5512 | 55.3719 | 0.8101 | 0.3178 | 2.4600 | 0.3482 |
| 15260 | Brunswick | GA | 0.1449 | 13.3594 | 1.0310 | 0.6313 | 1.3530 | -1.0593 |
| 15380 | Buffalo-Niagara Falls | NY | 1.6061 | 15.4178 | 1.1271 | 0.1730 | -0.6399 | 1.4505 |
| 15500 | Burlington | NC | 0.2069 | 16.5166 | 1.0109 | 0.6324 | -0.9600 | -0.6176 |
| 15540 | Burlington-South Burlington | VT | 0.2952 | 2.2778 | 1.2371 | 0.4271 | -0.1238 | -0.3845 |
| 15940 | Canton-Massillon | OH | 0.5797 | 27.4059 | 1.0334 | 0.3382 | -1.4796 | 0.4955 |
| 15980 | Cape Coral-Fort Myers | FL | 0.8407 | 2.0378 | 1.3203 | 0.3210 | 5.2300 | 0.1676 |
| 16220 | Casper | WY | 0.1021 | 0.0797 | 1.8677 | 0.4917 | 2.4900 | -1.9697 |
| 16300 | Cedar Rapids | IA | 0.3599 | 6.3374 | 1.1933 | 0.3126 | -3.3035 | 0.0590 |
| 16580 | Champaign-Urbana | IL | 0.3145 | 14.7922 | 1.1461 | 0.3848 | -4.3383 | 0.0884 |
| 16620 | Charleston | WV | 0.4327 | 6.2623 | 1.2677 | 0.3322 | -0.7294 | 0.0286 |
| 16700 | Charleston-North Charleston-Summerville | SC | 0.8970 | 8.8536 | 1.1909 | 0.2777 | 0.5686 | 0.7409 |
| 16740 | Charlotte-Gastonia-Concord | NC-SC | 2.3512 | 0.6377 | 1.8070 | 0.1561 | 0.1000 | 1.3196 |
| 16820 | Charlottesville | VA | 0.2744 | 7.2636 | 1.2334 | 0.4341 | -0.0364 | -0.4526 |
| 16860 | Chattanooga | TN-GA | 0.7326 | 8.8814 | 1.2192 | 0.2830 | 0.2832 | 0.5342 |
| 16940 | Cheyenne | WY | 0.1229 | 2.1311 | 1.2574 | 0.5112 | 3.0500 | -1.4960 |
| 16980 | Chicago-Naperville-Joliet | IL-IN-WI | 13.5596 | 7.6522 | 1.5622 | 0.0867 | -2.1021 | 3.4958 |
| 17020 | Chico | CA | 0.3115 | 5.1269 | 1.1704 | 0.5341 | 5.1100 | -0.5608 |
| 17140 | Cincinnati-Middletown | OH-KY-IN | 3.0376 | 14.2620 | 1.2956 | 0.1438 | -0.7916 | 2.0448 |
| 17300 | Clarksville | TN-KY | 0.3727 | 1.4179 | 1.4612 | 0.5319 | 0.0733 | -0.3729 |
| 17420 | Cleveland | TN | 0.1582 | 3.0055 | 1.2491 | 0.7279 | 0.8781 | -1.1302 |
| 17460 | Cleveland-Elyria-Mentor | OH | 2.9846 | 7.3233 | 1.3479 | 0.1352 | -1.4310 | 1.9676 |
| 17660 | Coeur d'Alene | ID | 0.1914 | 8.3418 | 0.9814 | 0.6066 | 3.5000 | -0.9011 |
| 17780 | College Station-Bryan | TX | 0.2895 | 47.5407 | 0.9761 | 0.4095 | 0.8622 | -0.2296 |
| 17820 | Colorado Springs | CO | 0.8671 | 7.0613 | 1.2141 | 0.2838 | 5.3867 | 0.3780 |
| 17860 | Columbia | MO | 0.2311 | 16.7125 | 1.0091 | 0.4196 | 0.1054 | -0.4706 |
| 17900 | Columbia | SC | 1.0194 | 22.2288 | 1.1406 | 0.2385 | 0.5017 | 0.9371 |
| 17980 | Columbus | GA-AL | 0.4025 | 8.7851 | 1.1704 | 0.3100 | -0.2353 | -0.0490 |

Table 5 (continued).

| FIPS | MSA name | State | $L_r/\overline{L}$ | $\widehat{\mu}_r^{\max}$ | $\overline{M}_r$ | $\widehat{\theta}_r$ | $A_r^o$ | $\widehat{A}_r^u$ |
|---|---|---|---|---|---|---|---|---|
| 18020 | Columbus | IN | 0.1064 | 2.9595 | 1.2043 | 0.4856 | -2.3800 | -1.3775 |
| 18140 | Columbus | OH | 2.4975 | 11.5892 | 1.3067 | 0.1398 | -1.9162 | 1.8984 |
| 18580 | Corpus Christi | TX | 0.5899 | 5.0627 | 1.1707 | 0.2746 | 2.8551 | 0.1577 |
| 18700 | Corvallis | OR | 0.1159 | 0.1014 | 1.6653 | 0.7211 | 3.1000 | -1.8133 |
| 19060 | Cumberland | MD-WV | 0.1414 | 56.7425 | 0.9012 | 0.7389 | 1.0076 | -0.9889 |
| 19100 | Dallas-Fort Worth-Arlington | TX | 8.7483 | 3.2987 | 1.6484 | 0.0923 | 0.6857 | 2.8079 |
| 19140 | Dalton | GA | 0.1908 | 15.8567 | 1.0122 | 0.3339 | 0.4652 | -0.8035 |
| 19180 | Danville | IL | 0.1156 | 13.3585 | 1.0646 | 0.7748 | -3.2100 | -1.0515 |
| 19260 | Danville | VA | 0.1506 | 34.1566 | 0.9627 | 0.6804 | -0.3000 | -0.8908 |
| 19340 | Davenport-Moline-Rock Island | IA-IL | 0.5355 | 8.2798 | 1.2047 | 0.2759 | -2.6893 | 0.4377 |
| 19380 | Dayton | OH | 1.1895 | 14.1872 | 1.1840 | 0.1988 | -2.1260 | 1.1962 |
| 19460 | Decatur | AL | 0.2125 | 3.5335 | 1.2627 | 0.6612 | 0.7910 | -0.8247 |
| 19500 | Decatur | IL | 0.1548 | 2.7975 | 1.2112 | 0.4092 | -2.7900 | -0.9344 |
| 19660 | Deltona-Daytona Beach-Ormond Beach | FL | 0.7124 | 22.2777 | 1.0226 | 0.3743 | 3.4500 | 0.3884 |
| 19740 | Denver-Aurora | CO | 3.4326 | 2.2957 | 1.5781 | 0.1477 | 4.1942 | 1.7018 |
| 19780 | Des Moines-West Des Moines | IA | 0.7782 | 2.2274 | 1.3921 | 0.2050 | -2.0346 | 0.6429 |
| 19820 | Detroit-Warren-Livonia | MI | 6.3602 | 8.3299 | 1.4224 | 0.1089 | -1.6704 | 2.7501 |
| 20020 | Dothan | AL | 0.1986 | 49.5100 | 0.8991 | 0.4212 | -0.4149 | -0.5370 |
| 20100 | Dover | DE | 0.2168 | 1.9540 | 1.3732 | 0.5895 | -0.0700 | -0.8842 |
| 20220 | Dubuque | IA | 0.1315 | 5.7814 | 1.0783 | 0.3977 | -0.7900 | -1.1171 |
| 20260 | Duluth | MN-WI | 0.3905 | 18.6402 | 1.0958 | 0.3678 | -0.8127 | 0.1938 |
| 20500 | Durham | NC | 0.6828 | 0.8200 | 1.6361 | 0.2552 | 0.0966 | 0.1845 |
| 20740 | Eau Claire | WI | 0.2247 | 12.7566 | 1.0431 | 0.4796 | -2.6695 | -0.3365 |
| 20940 | El Centro | CA | 0.2304 | 19.7182 | 1.0788 | 0.4081 | 6.4500 | -0.8598 |
| 21060 | Elizabethtown | KY | 0.1589 | 3.7636 | 1.2184 | 0.5914 | -0.8465 | -1.0560 |
| 21140 | Elkhart-Goshen | IN | 0.2818 | 9.4337 | 1.0857 | 0.2901 | -2.7200 | -0.2450 |
| 21300 | Elmira | NY | 0.1253 | 16.7836 | 0.9593 | 0.6243 | -1.1300 | -1.0690 |
| 21340 | El Paso | TX | 1.0459 | 2.2083 | 1.2705 | 0.2441 | 4.4600 | 0.5021 |
| 21500 | Erie | PA | 0.3973 | 18.7253 | 1.0133 | 0.3204 | -0.5700 | 0.0764 |
| 21660 | Eugene-Springfield | OR | 0.4891 | 13.2218 | 1.0718 | 0.3197 | 4.2900 | 0.0543 |
| 21780 | Evansville | IN-KY | 0.4979 | 8.0962 | 1.2141 | 0.2898 | -1.6375 | 0.2844 |
| 22020 | Fargo | ND-MN | 0.2739 | 4.1400 | 1.1461 | 0.3067 | -4.5908 | -0.0388 |
| 22140 | Farmington | NM | 0.1743 | 0.2874 | 1.6723 | 0.5778 | 2.8300 | -1.3307 |
| 22180 | Fayetteville | NC | 0.4968 | 0.7242 | 1.5255 | 0.3601 | -0.9161 | -0.1293 |
| 22220 | Fayetteville-Springdale-Rogers | AR-MO | 0.6203 | 13.9314 | 1.1278 | 0.2715 | 0.8552 | 0.4160 |
| 22380 | Flagstaff | AZ | 0.1814 | 41.4362 | 1.0685 | 0.4704 | 4.9300 | -0.8937 |
| 22420 | Flint | MI | 0.6189 | 11.2936 | 1.1285 | 0.4086 | -1.9000 | 0.4963 |
| 22500 | Florence | SC | 0.2829 | 14.4850 | 1.0690 | 0.4358 | -0.2137 | -0.3219 |
| 22520 | Florence-Muscle Shoals | AL | 0.2038 | 22.0682 | 0.9977 | 0.6420 | 0.8059 | -0.6681 |
| 22540 | Fond du Lac | WI | 0.1411 | 5.1570 | 1.1492 | 0.6231 | -1.9200 | -1.0104 |
| 22660 | Fort Collins-Loveland | CO | 0.4094 | 9.8391 | 1.1367 | 0.3890 | 5.6200 | -0.3039 |
| 22900 | Fort Smith | AR-OK | 0.4124 | 21.2879 | 1.0816 | 0.3342 | 1.6228 | -0.0124 |
| 23020 | Fort Walton Beach-Crestview-Destin | FL | 0.2584 | 0.3985 | 1.5286 | 0.4967 | 2.0100 | -0.9455 |
| 23060 | Fort Wayne | IN | 0.5838 | 20.3049 | 1.0802 | 0.2692 | -3.0754 | 0.5929 |
| 23420 | Fresno | CA | 1.2803 | 22.9506 | 1.1604 | 0.2171 | 6.0300 | 0.8406 |
| 23460 | Gadsden | AL | 0.1469 | 27.7629 | 0.9140 | 0.7121 | 0.9600 | -1.0397 |
| 23540 | Gainesville | FL | 0.3660 | 7.8664 | 1.1250 | 0.3731 | 2.0892 | -0.2095 |
| 23580 | Gainesville | GA | 0.2565 | 4.7162 | 1.1488 | 0.6287 | 0.9600 | -0.6703 |
| 24020 | Glens Falls | NY | 0.1835 | 53.2073 | 0.9276 | 0.6495 | -0.3136 | -0.6305 |
| 24140 | Goldsboro | NC | 0.1617 | 4.7743 | 1.1284 | 0.6350 | -1.4100 | -0.9470 |
| 24220 | Grand Forks | ND-MN | 0.1391 | 7.5933 | 1.0521 | 0.4540 | -4.2873 | -0.6426 |
| 24300 | Grand Junction | CO | 0.1980 | 14.4225 | 1.0036 | 0.5205 | 2.2600 | -0.7599 |
| 24340 | Grand Rapids-Wyoming | MI | 1.1058 | 14.8202 | 1.1985 | 0.2091 | -2.1226 | 1.1623 |
| 24500 | Great Falls | MT | 0.1164 | 3.0799 | 1.0900 | 0.5633 | 2.2000 | -1.3183 |
| 24540 | Greeley | CO | 0.3470 | 11.1165 | 1.1707 | 0.6195 | 1.7000 | -0.2422 |
| 24580 | Green Bay | WI | 0.4287 | 7.7067 | 1.1493 | 0.2912 | -1.3945 | 0.1489 |
| 24660 | Greensboro-High Point | NC | 0.9944 | 12.2863 | 1.2010 | 0.2038 | -0.2512 | 0.8794 |
| 24780 | Greenville | NC | 0.2455 | 8.4053 | 1.1029 | 0.4570 | -1.9108 | -0.3848 |
| 24860 | Greenville-Mauldin-Easley | SC | 0.8739 | 29.0690 | 1.0696 | 0.2293 | 1.3467 | 0.7392 |
| 25060 | Gulfport-Biloxi | MS | 0.3296 | 3.7705 | 1.2257 | 0.4062 | 0.1310 | -0.3076 |
| 25180 | Hagerstown-Martinsburg | MD-WV | 0.3718 | 29.3045 | 1.0342 | 0.6204 | 0.3042 | -0.0839 |
| 25260 | Hanford-Corcoran | CA | 0.2119 | 4.4956 | 1.2082 | 0.5882 | 3.4800 | -0.9992 |
| 25420 | Harrisburg-Carlisle | PA | 0.7529 | 15.7008 | 1.1804 | 0.2220 | -0.0004 | 0.5819 |
| 25500 | Harrisonburg | VA | 0.1674 | 3.5773 | 1.2622 | 0.4938 | 1.2500 | -1.0739 |
| 25540 | Hartford-West Hartford-East Hartford | CT | 1.6929 | 0.6312 | 1.8030 | 0.1934 | 1.4760 | 0.8809 |
| 25620 | Hattiesburg | MS | 0.1967 | 14.5668 | 1.0382 | 0.6026 | -0.2014 | -0.6437 |
| 25860 | Hickory-Lenoir-Morganton | NC | 0.5132 | 43.2249 | 0.9904 | 0.3150 | 1.5055 | 0.2302 |
| 25980 | Hinesville-Fort Stewart | GA | 0.1022 | 0.0097 | 2.3505 | 1.4824 | 0.8063 | -2.4818 |
| 26100 | Holland-Grand Haven | MI | 0.3690 | 4.6934 | 1.1913 | 0.4246 | -0.0400 | -0.1742 |
| 26300 | Hot Springs | AR | 0.1372 | 11.9767 | 0.9892 | 0.7581 | 1.6400 | -1.1335 |
| 26380 | Houma-Bayou Cane-Thibodaux | LA | 0.2863 | 2.3685 | 1.3317 | 0.4086 | 0.3192 | -0.5579 |
| 26420 | Houston-Sugar Land-Baytown | TX | 8.0123 | 0.7875 | 1.9559 | 0.1036 | 0.8426 | 2.4951 |
| 26580 | Huntington-Ashland | WV-KY-OH | 0.4043 | 18.9859 | 1.0797 | 0.3638 | -0.1699 | 0.0365 |
| 26620 | Huntsville | AL | 0.5504 | 4.8277 | 1.2477 | 0.2864 | -0.9066 | 0.2760 |
| 26820 | Idaho Falls | ID | 0.1700 | 14.9270 | 0.9584 | 0.6242 | 1.7783 | -0.8152 |
| 26900 | Indianapolis-Carmel | IN | 2.4131 | 6.4117 | 1.3983 | 0.1453 | -2.5367 | 1.8239 |
| 26980 | Iowa City | IA | 0.2093 | 3.0028 | 1.2468 | 0.4185 | -2.9476 | -0.5311 |
| 27060 | Ithaca | NY | 0.1439 | 7.6229 | 1.0802 | 0.5491 | -0.2800 | -0.9925 |
| 27100 | Jackson | MI | 0.2321 | 5.6531 | 1.1899 | 0.6124 | -2.4500 | -0.4931 |
| 27140 | Jackson | MS | 0.7603 | 9.3264 | 1.1970 | 0.2701 | -0.6024 | 0.6792 |
| 27180 | Jackson | TN | 0.1604 | 8.0248 | 1.0716 | 0.4913 | -1.6345 | -0.8225 |
| 27260 | Jacksonville | FL | 1.8519 | 6.0828 | 1.3004 | 0.1930 | 2.0244 | 1.3020 |
| 27340 | Jacksonville | NC | 0.2317 | 0.1526 | 1.6719 | 0.6158 | 0.7400 | -1.3510 |
| 27500 | Janesville | WI | 0.2272 | 17.1165 | 1.0296 | 0.5567 | -2.6200 | -0.3910 |
| 27620 | Jefferson City | MO | 0.2074 | 21.2752 | 1.0394 | 0.4518 | 0.3296 | -0.5943 |

Table 5 (continued).

| FIPS | MSA name | State | $L_r/\overline{L}$ | $\widehat{\mu}_r^{\max}$ | $\overline{M}_r$ | $\widehat{\theta}_r$ | $A_r^o$ | $\widehat{A}_r^u$ |
|---|---|---|---|---|---|---|---|---|
| 27740 | Johnson City | TN | 0.2755 | 15.4626 | 1.0432 | 0.4448 | 1.5055 | -0.4559 |
| 27780 | Johnstown | PA | 0.2064 | 47.5556 | 0.9152 | 0.5599 | -0.2300 | -0.5483 |
| 27860 | Jonesboro | AR | 0.1657 | 19.0537 | 1.0048 | 0.4910 | -2.2503 | -0.6718 |
| 27900 | Joplin | MO | 0.2438 | 33.7469 | 0.9232 | 0.4025 | -1.3200 | -0.2872 |
| 28020 | Kalamazoo-Portage | MI | 0.4602 | 10.9030 | 1.1573 | 0.3422 | -1.3239 | 0.2034 |
| 28100 | Kankakee-Bradley | IL | 0.1576 | 66.9572 | 0.9281 | 0.7130 | -3.3000 | -0.6326 |
| 28140 | Kansas City | MO-KS | 2.8265 | 9.2978 | 1.3318 | 0.1388 | -1.3222 | 2.0201 |
| 28420 | Kennewick-Pasco-Richland | WA | 0.3260 | 1.7999 | 1.2862 | 0.4454 | 0.7491 | -0.3261 |
| 28660 | Killeen-Temple-Fort Hood | TX | 0.5268 | 2.1655 | 1.4005 | 0.3488 | 1.5578 | -0.0822 |
| 28700 | Kingsport-Bristol-Bristol | TN-VA | 0.4323 | 20.7011 | 1.0819 | 0.3835 | 0.3622 | 0.0800 |
| 28740 | Kingston | NY | 0.2589 | 38.4944 | 1.0444 | 0.7757 | 0.7000 | -0.4394 |
| 28940 | Knoxville | TN | 0.9702 | 10.7076 | 1.1830 | 0.2284 | 1.0960 | 0.7774 |
| 29020 | Kokomo | IN | 0.1421 | 4.4454 | 1.1801 | 0.4794 | -4.4522 | -0.9032 |
| 29100 | La Crosse | WI-MN | 0.1864 | 15.4794 | 0.9862 | 0.4276 | -1.1484 | -0.6119 |
| 29140 | Lafayette | IN | 0.2736 | 6.6786 | 1.2283 | 0.4269 | -3.4119 | -0.2047 |
| 29180 | Lafayette | LA | 0.3652 | 0.3936 | 1.5540 | 0.3333 | -0.9092 | -0.4845 |
| 29340 | Lake Charles | LA | 0.2732 | 0.2160 | 1.7799 | 0.4158 | 0.1230 | -0.8452 |
| 29460 | Lakeland-Winter Haven | FL | 0.8182 | 41.3451 | 1.0056 | 0.3320 | 3.9800 | 0.5254 |
| 29540 | Lancaster | PA | 0.7096 | 23.6630 | 1.1151 | 0.2773 | 0.4500 | 0.4974 |
| 29620 | Lansing-East Lansing | MI | 0.6498 | 8.5097 | 1.2380 | 0.3102 | -3.3358 | 0.6664 |
| 29700 | Laredo | TX | 0.3319 | 40.7539 | 0.9025 | 0.3942 | 1.1200 | -0.0710 |
| 29740 | Las Cruces | NM | 0.2830 | 14.1950 | 1.0495 | 0.4945 | 4.7700 | -0.5204 |
| 29820 | Las Vegas-Paradise | NV | 2.6143 | 5.7538 | 1.3678 | 0.1449 | 4.8600 | 1.4990 |
| 29940 | Lawrence | KS | 0.1616 | 9.0883 | 1.0225 | 0.6893 | 0.3600 | -0.9008 |
| 30020 | Lawton | OK | 0.1620 | 1.7247 | 1.2588 | 0.4717 | 2.2900 | -1.2620 |
| 30140 | Lebanon | PA | 0.1821 | 21.6701 | 1.0004 | 0.6784 | -0.6600 | -0.7918 |
| 30340 | Lewiston-Auburn | ME | 0.1521 | 6.7201 | 1.0069 | 0.6650 | -0.3200 | -0.9631 |
| 30460 | Lexington-Fayette | KY | 0.6366 | 7.4339 | 1.2161 | 0.2408 | -2.0342 | 0.5128 |
| 30620 | Lima | OH | 0.1498 | 6.3170 | 1.0933 | 0.4620 | -2.3700 | -0.9154 |
| 30700 | Lincoln | NE | 0.4160 | 6.3780 | 1.1229 | 0.2917 | -2.8183 | 0.2242 |
| 30780 | Little Rock-North Little Rock-Conway | AR | 0.9487 | 8.6504 | 1.2323 | 0.2235 | -0.0673 | 0.8521 |
| 30860 | Logan | UT-ID | 0.1724 | 17.5016 | 0.9483 | 0.6184 | 2.2845 | -0.8079 |
| 30980 | Longview | TX | 0.2899 | 3.1890 | 1.2889 | 0.4235 | 1.0970 | -0.5565 |
| 31020 | Longview | WA | 0.1430 | 5.9983 | 1.1138 | 0.8130 | 4.5400 | -1.3338 |
| 31100 | Los Angeles-Long Beach-Santa Ana | CA | 18.3301 | 4.3306 | 1.6868 | 0.0708 | 10.0712 | 2.8862 |
| 31140 | Louisville/Jefferson County | KY-IN | 1.7564 | 14.2754 | 1.2532 | 0.1752 | -0.7687 | 1.5113 |
| 31180 | Lubbock | TX | 0.3804 | 12.8002 | 1.0110 | 0.3094 | 1.7950 | -0.0905 |
| 31340 | Lynchburg | VA | 0.3468 | 21.0406 | 1.0961 | 0.4312 | 0.4764 | -0.1345 |
| 31420 | Macon | GA | 0.3272 | 31.5646 | 1.0212 | 0.3784 | 0.9051 | -0.1751 |
| 31460 | Madera | CA | 0.2086 | 6.7275 | 1.2184 | 0.8123 | 6.0000 | -1.0943 |
| 31540 | Madison | WI | 0.7910 | 4.1702 | 1.3437 | 0.2343 | -0.4945 | 0.6170 |
| 31700 | Manchester-Nashua | NH | 0.5727 | 0.1167 | 1.9944 | 0.5151 | 0.0700 | -0.3611 |
| 31900 | Mansfield | OH | 0.1789 | 33.4517 | 0.9223 | 0.4979 | -2.8800 | -0.5658 |
| 32580 | McAllen-Edinburg-Mission | TX | 1.0115 | 78.4494 | 0.8243 | 0.2479 | 0.4600 | 1.0886 |
| 32780 | Medford | OR | 0.2837 | 7.3664 | 1.0610 | 0.3762 | 4.5000 | -0.5412 |
| 32820 | Memphis | TN-MS-AR | 1.8230 | 5.5326 | 1.3539 | 0.1653 | -0.7140 | 1.4824 |
| 32900 | Merced | CA | 0.3495 | 3.4046 | 1.3438 | 0.6661 | 4.5100 | -0.5673 |
| 33100 | Miami-Fort Lauderdale-Pompano Beach | FL | 7.7064 | 5.1829 | 1.4740 | 0.1063 | 5.2315 | 2.4562 |
| 33140 | Michigan City-La Porte | IN | 0.1563 | 21.9162 | 1.0128 | 0.6279 | -1.8700 | -0.8200 |
| 33260 | Midland | TX | 0.1800 | 0.0677 | 1.7699 | 0.3498 | 1.4200 | -1.5392 |
| 33340 | Milwaukee-Waukesha-West Allis | WI | 2.1987 | 5.9256 | 1.3133 | 0.1410 | -1.7072 | 1.6745 |
| 33460 | Minneapolis-St. Paul-Bloomington | MN-WI | 4.5673 | 4.2763 | 1.4626 | 0.1133 | -2.1830 | 2.4717 |
| 33540 | Missoula | MT | 0.1504 | 2.8725 | 1.1210 | 0.4512 | 1.7400 | -1.0344 |
| 33660 | Mobile | AL | 0.5757 | 9.1311 | 1.0984 | 0.3067 | 1.5200 | 0.2423 |
| 33700 | Modesto | CA | 0.7278 | 6.4113 | 1.2548 | 0.4128 | 7.2100 | 0.0268 |
| 33740 | Monroe | LA | 0.2453 | 9.2380 | 1.0825 | 0.4184 | 0.3390 | -0.5074 |
| 33780 | Monroe | MI | 0.2187 | 2.0031 | 1.3360 | 0.9408 | -1.4300 | -0.7490 |
| 33860 | Montgomery | AL | 0.5210 | 12.6484 | 1.1449 | 0.3087 | 0.4625 | 0.2498 |
| 34060 | Morgantown | WV | 0.1677 | 4.0622 | 1.2569 | 0.6007 | -0.5645 | -0.9222 |
| 34100 | Morristown | TN | 0.1916 | 17.5432 | 0.9983 | 0.6252 | 1.4428 | -0.8147 |
| 34580 | Mount Vernon-Anacortes | WA | 0.1657 | 0.7668 | 1.4170 | 0.7719 | 4.9400 | -1.4000 |
| 34620 | Muncie | IN | 0.1643 | 21.3999 | 0.9605 | 0.5363 | -2.6000 | -0.6699 |
| 34740 | Muskegon-Norton Shores | MI | 0.2483 | 10.5424 | 1.0442 | 0.4962 | -0.4000 | -0.4569 |
| 34820 | Myrtle Beach-North Myrtle Beach-Conway | SC | 0.3558 | 14.1273 | 1.0296 | 0.3492 | 0.8800 | -0.1685 |
| 34900 | Napa | CA | 0.1887 | 0.7977 | 1.5290 | 0.6025 | 7.5300 | -1.5827 |
| 34940 | Naples-Marco Island | FL | 0.4496 | 0.8553 | 1.5056 | 0.3608 | 5.0000 | -0.4961 |
| 34980 | Nashville-Davidson–Murfreesboro–Franklin | TN | 2.1660 | 8.8103 | 1.3395 | 0.1761 | -0.8913 | 1.6814 |
| 35300 | New Haven-Milford | CT | 1.2037 | 0.3565 | 1.8353 | 0.3373 | 2.5200 | 0.3149 |
| 35380 | New Orleans-Metairie-Kenner | LA | 1.4669 | 0.3827 | 1.8005 | 0.1997 | 0.3337 | 0.8483 |
| 35620 | New York-Northern New Jersey-Long Island | NY-NJ-PA | 26.7870 | 2.3289 | 1.9622 | 0.0708 | 0.7740 | 3.7219 |
| 35660 | Niles-Benton Harbor | MI | 0.2272 | 4.2225 | 1.2195 | 0.4910 | -0.3000 | -0.7112 |
| 35980 | Norwich-New London | CT | 0.3806 | 2.5282 | 1.3620 | 0.3834 | 2.4300 | -0.4626 |
| 36100 | Ocala | FL | 0.4625 | 26.5691 | 1.0121 | 0.4508 | 2.5900 | 0.0392 |
| 36140 | Ocean City | NJ | 0.1373 | 1.0674 | 1.3332 | 0.6085 | 0.0700 | -1.4334 |
| 36220 | Odessa | TX | 0.1845 | 1.7012 | 1.1914 | 0.4434 | 2.5000 | -1.1410 |
| 36260 | Ogden-Clearfield | UT | 0.7379 | 7.3733 | 1.1369 | 0.3433 | 4.0883 | 0.3479 |
| 36420 | Oklahoma City | OK | 1.6984 | 8.9525 | 1.2684 | 0.1702 | 0.1199 | 1.4212 |
| 36500 | Olympia | WA | 0.3396 | 2.6762 | 1.2006 | 0.5266 | 3.3200 | -0.5078 |

# Table 5 (continued).

| FIPS | MSA name | State | $L_r/\overline{L}$ | $\widehat{\mu}_r^{\max}$ | $\overline{M}_r$ | $\widehat{\theta}_r$ | $A_r^o$ | $\widehat{A}_r^u$ |
|---|---|---|---|---|---|---|---|---|
| 36540 | Omaha-Council Bluffs | NE-IA | 1.1815 | 4.6939 | 1.3147 | 0.1726 | -1.6836 | 1.1351 |
| 36740 | Orlando-Kissimmee | FL | 2.8935 | 9.3348 | 1.2989 | 0.1484 | 3.6792 | 1.6530 |
| 36780 | Oshkosh-Neenah | WI | 0.2308 | 3.4099 | 1.1577 | 0.3631 | -1.3700 | -0.5731 |
| 36980 | Owensboro | KY | 0.1596 | 5.0431 | 1.1735 | 0.4904 | -0.9396 | -0.9497 |
| 37100 | Oxnard-Thousand Oaks-Ventura | CA | 1.1366 | 1.0892 | 1.5986 | 0.3101 | 11.1700 | -0.0195 |
| 37340 | Palm Bay-Melbourne-Titusville | FL | 0.7633 | 7.0268 | 1.1556 | 0.3242 | 3.9300 | 0.3194 |
| 37460 | Panama City-Lynn Haven | FL | 0.2335 | 3.9684 | 1.1138 | 0.4859 | 2.1500 | -0.7925 |
| 37620 | Parkersburg-Marietta-Vienna | WV-OH | 0.2287 | 20.4051 | 1.0463 | 0.4824 | -0.0229 | -0.5302 |
| 37700 | Pascagoula | MS | 0.2164 | 3.3176 | 1.2155 | 0.6623 | 0.1912 | -0.7469 |
| 37860 | Pensacola-Ferry Pass-Brent | FL | 0.6455 | 10.5757 | 1.1044 | 0.3574 | 2.0978 | 0.3456 |
| 37900 | Peoria | IL | 0.5285 | 6.0365 | 1.2920 | 0.2890 | -2.5036 | 0.3764 |
| 37980 | Philadelphia-Camden-Wilmington | PA-NJ-DE-MD | 8.2969 | 5.0519 | 1.6274 | 0.1023 | -0.6748 | 2.8345 |
| 38060 | Phoenix-Mesa-Scottsdale | AZ | 5.9500 | 13.0025 | 1.3310 | 0.1114 | 4.3136 | 2.4388 |
| 38220 | Pine Bluff | AR | 0.1445 | 18.4953 | 1.0257 | 0.5508 | -1.2731 | -0.8725 |
| 38300 | Pittsburgh | PA | 3.3537 | 10.5364 | 1.3663 | 0.1425 | 0.4012 | 2.0415 |
| 38340 | Pittsfield | MA | 0.1848 | 0.0590 | 2.1213 | 0.7997 | 0.8100 | -1.5454 |
| 38540 | Pocatello | ID | 0.1247 | 18.4792 | 0.9326 | 0.5365 | 1.9030 | -1.1149 |
| 38860 | Portland-South Portland-Biddeford | ME | 0.7305 | 0.3729 | 1.6948 | 0.3868 | 0.9595 | 0.1744 |
| 38900 | Portland-Vancouver-Beaverton | OR-WA | 3.0966 | 2.5795 | 1.4937 | 0.1534 | 2.8130 | 1.7475 |
| 38940 | Port St. Lucie | FL | 0.5696 | 4.4925 | 1.2049 | 0.4656 | 5.1827 | -0.0890 |
| 39100 | Poughkeepsie-Newburgh-Middletown | NY | 0.9537 | 57.5790 | 1.0783 | 0.3958 | 0.0107 | 0.8914 |
| 39140 | Prescott | AZ | 0.3027 | 55.8791 | 0.9866 | 0.5665 | 5.2100 | -0.4084 |
| 39300 | Providence-New Bedford-Fall River | RI-MA | 2.2790 | 1.8282 | 1.5584 | 0.2242 | 1.2849 | 1.3694 |
| 39340 | Provo-Orem | UT | 0.7023 | 15.6423 | 1.1251 | 0.3378 | 3.0296 | 0.5132 |
| 39380 | Pueblo | CO | 0.2200 | 33.0571 | 0.9327 | 0.5804 | 2.1100 | -0.5738 |
| 39460 | Punta Gorda | FL | 0.2176 | 4.7904 | 1.1345 | 0.6776 | 5.1000 | -1.0319 |
| 39540 | Racine | WI | 0.2777 | 2.6053 | 1.2397 | 0.5556 | -0.5100 | -0.5717 |
| 39580 | Raleigh-Cary | NC | 1.4914 | 4.1913 | 1.3699 | 0.2143 | -0.6762 | 1.1883 |
| 39660 | Rapid City | SD | 0.1712 | 10.5487 | 1.0612 | 0.4558 | -0.3579 | -0.7024 |
| 39740 | Reading | PA | 0.5722 | 12.9659 | 1.1918 | 0.3670 | -0.7300 | 0.2974 |
| 39820 | Redding | CA | 0.2554 | 5.9179 | 1.1467 | 0.4672 | 5.6900 | -0.7588 |
| 39900 | Reno-Sparks | NV | 0.5841 | 6.1702 | 1.2543 | 0.2685 | 6.7038 | -0.0559 |
| 40060 | Richmond | VA | 1.7268 | 11.1761 | 1.3350 | 0.1846 | -0.9568 | 1.4730 |
| 40140 | Riverside-San Bernardino-Ontario | CA | 5.8104 | 104.4265 | 1.1829 | 0.1695 | 4.3817 | 2.5456 |
| 40220 | Roanoke | VA | 0.4222 | 22.5390 | 1.0696 | 0.3012 | 0.9380 | 0.0199 |
| 40340 | Rochester | MN | 0.2578 | 7.1786 | 1.1296 | 0.3375 | -3.3458 | -0.2406 |
| 40380 | Rochester | NY | 1.4670 | 9.7948 | 1.2412 | 0.1746 | -0.6948 | 1.3292 |
| 40420 | Rockford | IL | 0.5015 | 16.7848 | 1.0660 | 0.3553 | -2.7901 | 0.3797 |
| 40580 | Rocky Mount | NC | 0.2073 | 6.0239 | 1.1722 | 0.4688 | -1.7475 | -0.6464 |
| 40660 | Rome | GA | 0.1361 | 17.3345 | 0.9911 | 0.6475 | 0.3300 | -1.0785 |
| 40900 | Sacramento–Arden-Arcade–Roseville | CA | 2.9770 | 4.8303 | 1.4313 | 0.1708 | 5.4091 | 1.5526 |
| 40980 | Saginaw-Saginaw Township North | MI | 0.2880 | 16.5948 | 1.0391 | 0.3910 | -3.3300 | -0.0839 |
| 41060 | St. Cloud | MN | 0.2642 | 12.5971 | 1.0450 | 0.4347 | -3.0004 | -0.1386 |
| 41100 | St. George | UT | 0.1905 | 23.2639 | 0.9521 | 0.4957 | 2.5700 | -0.7385 |
| 41140 | St. Joseph | MO-KS | 0.1756 | 10.6024 | 1.0856 | 0.5409 | -1.4641 | -0.7059 |
| 41180 | St. Louis | MO-IL | 3.9914 | 19.9079 | 1.2643 | 0.1312 | -0.4277 | 2.3707 |
| 41420 | Salem | OR | 0.5505 | 9.5532 | 1.1035 | 0.3850 | 3.4215 | 0.1330 |
| 41500 | Salinas | CA | 0.5803 | 1.2221 | 1.5755 | 0.3426 | 9.2400 | -0.5045 |
| 41540 | Salisbury | MD | 0.1703 | 13.6356 | 1.0504 | 0.6063 | -0.3934 | -0.8133 |
| 41620 | Salt Lake City | UT | 1.5660 | 5.5353 | 1.3497 | 0.1645 | 3.3545 | 1.1401 |
| 41660 | San Angelo | TX | 0.1539 | 11.3999 | 1.0347 | 0.5001 | 1.5945 | -0.9984 |
| 41700 | San Antonio | TX | 2.8340 | 12.2914 | 1.2660 | 0.1656 | 2.1287 | 1.8188 |
| 41740 | San Diego-Carlsbad-San Marcos | CA | 4.2351 | 1.5943 | 1.6748 | 0.1332 | 9.7800 | 1.4266 |
| 41780 | Sandusky | OH | 0.1101 | 4.8876 | 1.0852 | 0.5651 | -0.9100 | -1.3725 |
| 41860 | San Francisco-Oakland-Fremont | CA | 5.9848 | 0.3531 | 2.0490 | 0.1203 | 7.3604 | 1.6192 |
| 41940 | San Jose-Sunnyvale-Santa Clara | CA | 2.5677 | 0.1447 | 2.1759 | 0.1526 | 5.5612 | 0.8121 |
| 42020 | San Luis Obispo-Paso Robles | CA | 0.3736 | 2.4081 | 1.3821 | 0.3809 | 7.8700 | -0.6538 |
| 42060 | Santa Barbara-Santa Maria-Goleta | CA | 0.5754 | 0.8643 | 1.5674 | 0.2810 | 10.9700 | -0.5659 |
| 42100 | Santa Cruz-Watsonville | CA | 0.3584 | 0.6286 | 1.5617 | 0.6419 | 8.4900 | -1.0716 |
| 42140 | Santa Fe | NM | 0.2035 | 0.1706 | 1.6987 | 0.6477 | 3.0200 | -1.2264 |
| 42220 | Santa Rosa-Petaluma | CA | 0.6612 | 1.8173 | 1.4210 | 0.3670 | 7.9300 | -0.2054 |
| 42260 | Bradenton-Sarasota-Venice | FL | 0.9783 | 8.0869 | 1.1622 | 0.2326 | 4.7123 | 0.5228 |
| 42340 | Savannah | GA | 0.4688 | 9.2001 | 1.1068 | 0.3385 | 0.7595 | 0.0822 |
| 42540 | Scranton–Wilkes-Barre | PA | 0.7822 | 62.6807 | 1.0069 | 0.2540 | 0.3497 | 0.7451 |
| 42660 | Seattle-Tacoma-Bellevue | WA | 4.7113 | 1.1719 | 1.7037 | 0.1332 | 4.6088 | 1.8885 |
| 42680 | Sebastian-Vero Beach | FL | 0.1877 | 1.2555 | 1.2826 | 0.6381 | 4.7200 | -1.2862 |
| 43100 | Sheboygan | WI | 0.1630 | 3.2650 | 1.1820 | 0.4794 | -0.3700 | -1.0073 |
| 43300 | Sherman-Denison | TX | 0.1689 | 20.5729 | 1.0063 | 0.7441 | 0.7800 | -0.9061 |
| 43340 | Shreveport-Bossier City | LA | 0.5518 | 0.5061 | 1.6557 | 0.2672 | 0.4263 | -0.0654 |
| 43580 | Sioux City | IA-NE-SD | 0.2033 | 6.7056 | 1.1070 | 0.3518 | -1.6477 | -0.5531 |
| 43620 | Sioux Falls | SD | 0.3234 | 0.9176 | 1.4228 | 0.3194 | -3.1981 | -0.1810 |
| 43780 | South Bend-Mishawaka | IN-MI | 0.4508 | 5.9962 | 1.2356 | 0.3487 | -2.3182 | 0.1576 |
| 43900 | Spartanburg | SC | 0.3923 | 11.2840 | 1.0951 | 0.3525 | 0.5200 | -0.1066 |
| 44060 | Spokane | WA | 0.6494 | 3.8173 | 1.1601 | 0.2893 | 1.3300 | 0.3953 |
| 44100 | Springfield | IL | 0.2941 | 14.5944 | 1.0630 | 0.3680 | -2.6215 | -0.1150 |
| 44140 | Springfield | MA | 0.9719 | 48.7269 | 1.0487 | 0.2673 | -0.0296 | 0.9868 |
| 44180 | Springfield | MO | 0.5980 | 42.4428 | 0.9814 | 0.3118 | -0.1019 | 0.5377 |
| 44220 | Springfield | OH | 0.2000 | 20.6803 | 0.9762 | 0.6353 | -2.0300 | -0.5560 |
| 44300 | State College | PA | 0.2059 | 5.6983 | 1.2306 | 0.4912 | -0.4000 | -0.6733 |
| 44700 | Stockton | CA | 0.9552 | 9.1216 | 1.2154 | 0.3999 | 4.7700 | 0.4709 |
| 44940 | Sumter | SC | 0.1480 | 5.4151 | 1.1225 | 0.6486 | 0.4500 | -1.1196 |
| 45060 | Syracuse | NY | 0.9187 | 11.6878 | 1.1814 | 0.2285 | -1.0878 | 0.9094 |

Table 5 (continued).

| FIPS | MSA name | State | $L_r/\overline{L}$ | $\widehat{\mu}_r^{\max}$ | $\overline{M}_r$ | $\widehat{\theta}_r$ | $A_r^o$ | $\widehat{A}_r^u$ |
|---|---|---|---|---|---|---|---|---|
| 45220 | Tallahassee | FL | 0.5016 | 15.0466 | 1.0808 | 0.3650 | 1.8418 | 0.1910 |
| 45300 | Tampa-St. Petersburg-Clearwater | FL | 3.8779 | 17.9295 | 1.1870 | 0.1303 | 4.0087 | 1.9781 |
| 45460 | Terre Haute | IN | 0.2411 | 20.4346 | 1.0643 | 0.5363 | -2.2437 | -0.3093 |
| 45500 | Texarkana | TX | 0.1911 | 11.9339 | 1.0554 | 0.4806 | 0.3401 | -0.7535 |
| 45780 | Toledo | OH | 0.9267 | 18.0928 | 1.1349 | 0.2156 | -2.2985 | 0.9937 |
| 45820 | Topeka | KS | 0.3256 | 22.9574 | 1.0514 | 0.3978 | -1.2054 | -0.0417 |
| 45940 | Trenton-Ewing | NJ | 0.5203 | 1.6191 | 1.4344 | 0.3137 | -0.8000 | -0.1181 |
| 46060 | Tucson | AZ | 1.3768 | 24.1671 | 1.1242 | 0.2328 | 4.0400 | 1.0965 |
| 46140 | Tulsa | OK | 1.2895 | 5.5205 | 1.3491 | 0.1913 | 0.4138 | 1.0760 |
| 46220 | Tuscaloosa | AL | 0.2922 | 7.7286 | 1.1972 | 0.3964 | 0.5956 | -0.3554 |
| 46340 | Tyler | TX | 0.2829 | 3.5960 | 1.2186 | 0.4075 | 0.7200 | -0.5192 |
| 46540 | Utica-Rome | NY | 0.4198 | 76.1905 | 0.9437 | 0.3637 | -1.6177 | 0.3300 |
| 46660 | Valdosta | GA | 0.1853 | 33.3007 | 0.9361 | 0.4890 | 0.4906 | -0.6906 |
| 46700 | Vallejo-Fairfield | CA | 0.5817 | 2.3184 | 1.3973 | 0.5800 | 5.8800 | -0.2641 |
| 47020 | Victoria | TX | 0.1620 | 1.9775 | 1.3235 | 0.5431 | 0.7132 | -1.1395 |
| 47220 | Vineland-Millville-Bridgeton | NJ | 0.2214 | 18.9165 | 1.0652 | 0.5472 | 0.3800 | -0.6868 |
| 47260 | Virginia Beach-Norfolk-Newport News | VA-NC | 2.3615 | 6.6554 | 1.3267 | 0.1646 | 0.7721 | 1.5923 |
| 47300 | Visalia-Porterville | CA | 0.6001 | 20.2186 | 1.1325 | 0.3309 | 5.6500 | 0.1024 |
| 47380 | Waco | TX | 0.3248 | 14.4336 | 1.0447 | 0.3399 | 0.7600 | -0.2405 |
| 47580 | Warner Robins | GA | 0.1865 | 2.0361 | 1.2082 | 0.5774 | -0.0400 | -0.9647 |
| 47900 | Washington-Arlington-Alexandria | DC-VA-MD-WV | 7.5546 | 2.1874 | 1.7644 | 0.1175 | -0.5658 | 2.6267 |
| 47940 | Waterloo-Cedar Falls | IA | 0.2325 | 4.0817 | 1.2037 | 0.3123 | -3.6928 | -0.3363 |
| 48140 | Wausau | WI | 0.1850 | 8.5505 | 1.0743 | 0.4457 | -3.3000 | -0.5433 |
| 48260 | Weirton-Steubenville | WV-OH | 0.1745 | 12.5561 | 1.0666 | 0.6507 | -0.4289 | -0.8395 |
| 48300 | Wenatchee | WA | 0.1526 | 2.5064 | 1.2836 | 0.6415 | 1.1223 | -1.0532 |
| 48540 | Wheeling | WV-OH | 0.2071 | 27.1680 | 1.0011 | 0.5045 | -0.0508 | -0.6087 |
| 48620 | Wichita | KS | 0.8491 | 7.0330 | 1.2276 | 0.2070 | -0.5189 | 0.7748 |
| 48660 | Wichita Falls | TX | 0.2109 | 3.6100 | 1.2650 | 0.4866 | -0.0733 | -0.7295 |
| 48700 | Williamsport | PA | 0.1663 | 37.1189 | 0.9883 | 0.5359 | 0.3300 | -0.8261 |
| 48900 | Wilmington | NC | 0.4833 | 4.2397 | 1.2504 | 0.3689 | 0.8620 | 0.0454 |
| 49020 | Winchester | VA-WV | 0.1725 | 8.0065 | 1.2012 | 0.8358 | 0.2643 | -0.9449 |
| 49180 | Winston-Salem | NC | 0.6594 | 3.7013 | 1.3302 | 0.2738 | -0.3283 | 0.3418 |
| 49340 | Worcester | MA | 1.1124 | 1.7596 | 1.5552 | 0.4121 | 0.2400 | 0.7079 |
| 49420 | Yakima | WA | 0.3318 | 3.8343 | 1.2424 | 0.4012 | 1.4800 | -0.2958 |
| 49620 | York-Hanover | PA | 0.5994 | 20.5103 | 1.1115 | 0.4145 | -0.5800 | 0.3817 |
| 49660 | Youngstown-Warren-Boardman | OH-PA | 0.8125 | 37.2035 | 1.0470 | 0.2679 | -2.2828 | 0.9348 |
| 49700 | Yuba City | CA | 0.2337 | 1.2193 | 1.4215 | 0.9995 | 3.3821 | -1.0057 |
| 49740 | Yuma | AZ | 0.2713 | 45.4247 | 0.9541 | 0.3985 | 4.2400 | -0.5236 |

*Notes:* See Appendix F.2 for additional details on computations.

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