The Best Cities for Firms*

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Abstract

We examine the spatial distribution of jobs within firms to understand how city characteristics affect employment. Our approach allows us to control for firm-by-year fixed effects such that we can disentangle the potential shared fortunes of cities and the firms that operate there. Since there is a mechanical relationship between a city's population and employment in firms that produce nontradable output, we propose a new way of identifying firms producing tradables to better understand which city characteristics increase productivity. Our most robust findings are that physical city size and employment density drive employment even after controlling for firm selection. For tradable firms, we find employment increases with the industrial diversity of a city indicating that industrial diversity increases productivity. We find strikingly different patterns in the drivers of employment in nontradable firms suggesting that what drives population may differ from what drives productivity.

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1 Introduction

How to attract and retain employment to a city is a key concern of local policymakers. Many cities aim specifically to attract national or global corporations with tax incentives and aggressive courting rituals. Such place-based policies are costly and their effectiveness is sometimes questionable.[1] And yet, beyond direct incentives, little is understood about how cities make themselves attractive to employers. What can cities do to help firms create jobs, if anything?

In this paper, we tackle the question of the role of cities in firm growth by exploiting establishment-level data on employment within the same firm over time. To overcome the endogeneity of firms' initial location choices, we focus on large, multi-unit firms that have established operations with employment in multiple cities. We construct an index of the nontradability of a firm's output based on the spatial dispersion of its production. We then separate firms into those producing more or less tradable output. Conducting our analyses on firms producing more tradable output allows us to mitigate the influence of demand factors from within a city on our results. We exclude small cities from our estimations such that variation in a given firm's local employment does not materially affect aggregate city characteristics. We then identify the determinants of local productivity using within-firm heterogeneity in employment across cities over time.

We find that tradable firms have more employment in denser, larger, and more industrially diverse cities. In contrast, our estimates indicate that higher levels of local competition hinder tradable firm growth, likely by keeping firms from fully internalizing the benefits of any innovations (cf. Marshall-Arrow-Romer economies). We find the opposite pattern among nontradable firms highlighting that studies in-

[1]See discussions of place-based policies and the costs of cities' efforts to attract firms in, e.g., Bartik (1991), Austin et al. (2018), Neumark and Simpson (2015), Bartik (2020), and Slattery and Zidar (2020).

ferring the effects of city characteristics using all firms may incorrectly conclude that characteristics that drive population growth drive productivity growth.

Some of our results regarding the drivers of local productivity corroborate existing results in the urban economics literature that have not benefitted from the identification enabled by the availability of establishment-level employment data. In particular, we find that higher employment density and the physical size of a city increase employment. Within tradable firms, employment increases with industrial diversity consistent with prior findings summarized in, e.g., Combes and Gobillon (2015).

Several of our results only become apparent when we control for firm-by-year fixed effects, suggesting that firms' sorting across locations is a significant confounding factor in analyzing the spatial distribution of jobs. Similarly, we only recover the effects of some city characteristics on productivity after accounting for firms' past employment in those cities, indicating that adjustment costs are a key driver of firms' employment dynamics across locations.

The rest of the paper proceeds as follows. In the next section, we outline a framework relating an individual firm's employment decisions to a city's productivity and factor prices. In Section 3 describes our data and selection of firms. We present our results in Section 4. Section 5 offers concluding remarks.

2 Identifying the Drivers of City-Level Employment

The literature on agglomeration economies usually focuses on industry-level employment across cities (see, e.g., Glaeser et al., 1992; Henderson et al., 1995). Using industry-level employment as the outcome variable of interest creates an identification challenge. Since local industry employment is a linear combination of two common explanatory variables, local specialization and density, the effects of those variables cannot be independently identified (Combes and Gobillon, 2015).

To address this identification challenge we focus on local firm-level employment. Our choice of dependent variable further alleviates two related endogeneity concerns. First, the employment of an individual firm is unlikely to have a significant impact on city characteristics such as density, reducing the potential for reverse causality. Second, the granularity of our firm-level data allows us to include firm-by-year fixed effects. Those fixed effects capture unobserved, time-varying firm characteristics that drive firms' employment dynamics over time. We thus identify the effects of interest from cross-city variation in employment within firms, rather than between firms. In other words, the inclusion of firm-by-year fixed effects allows us to rule out that it is firm characteristics, rather than city characteristics, that drive our results. Importantly, we only focus on the locations in which firms have an established presence. This estimation approach allows us to account for the possibility that the most productive firms sort into the most productive locations when they first establish their operations.

In the remainder of this section, we outline the conceptual framework that we use to identify the drivers of city-level employment. To make ideas concrete, we outline a simple model to illustrate how city-level characteristics influence local employment. Then, we discuss the set of city characteristics whose impact on firms' employment decisions we assess in the data.

2.1 Model

Firms operate in multiple cities and each city potentially has a different productivity. Specifically, we conceive of firm i located in city c as producing output $Y_{i,c,t}$ using the technology

$$Y_{i,c,t} = \begin{cases} A_{c,t} f_{i,t} L_{i,c,t}^{\theta\alpha} K_{i,c,t}^{\theta(1-\alpha)} & \text{if } m_{i,c,t-j} \geq \overline{m} \\ 0 & \text{if } m_{i,c,t-j} < \overline{m} \end{cases}$$

where $A_{c,t}$ is city-level productivity, $f_{i,t}$ are firm-level productivity characteristics including capital not specific to city c, $L_{i,c,t}$ is the labor the firm uses in city c at time t, and $K_{i,c,t}$ is real estate the firm uses in city c at time t. Our specification of a common component of productivity for all firms operating in city c is similar to the state-specific productivity assumed by Fajgelbaum, Morales, Suárez Serrato, and Zidar (2018) and the local productivity posited by Glaeser et al. (1992).

We do not model why a firm operates in some cities and not others. Instead, we conceive of an unobservable historic city-firm characteristic, $m_{i,c,t-j}$, that led the firm to establish a presence in city c at time $t-j$ in the past. We then focus on the evolution of labor input in that firm-city pair over time. While a city's productivity may affect the firm's initial decision to establish operations in that location, there may also be historical reasons unrelated to a city's productivity that cause firms to have establishments in some cities and not others.[2]

The challenge for estimating the drivers of city-level productivity $A_{c,t}$ is that we do not observe $Y_{i,c,t}$. We can, however, observe employment in city c. This differs from many applications in the industrial organization literature wherein the challenge is that the researcher observes output but not *inputs* (e.g., Orr, 2022). We can observe labor input $L_{i,c,t}$ at the firm-city level, which will allow us to recover the drivers of $A_{c,t}$.

We limit our analyses to firms in tradable industries such that there is no variation across cities in the price of the firm's output. We thus normalize the output price to 1. We also assume the firm is a price-taker in input markets.

[2]See, e.g., Jansen and Winegar (2022) for how amenities influence where entrepreneurs locate.

Conditional on $m_{i,c,t-j} \geq \overline{m}$ and $f_{i,t}$, the firm chooses $L_{i,c,t}$ and $K_{i,c,t}$ to maximize

$$Y_{i,c,t} - w_{c,t}L_{i,c,t} - r_{c,t}K_{i,c,t}.$$

The first order conditions are

$$\begin{aligned} L_{i,c,t} &= \alpha\theta\frac{Y_{i,c,t}}{w_{c,t}} \\ K_{i,c,t} &= (1-\alpha)\theta\frac{Y_{i,c,t}}{r_{c,t}} \end{aligned}$$

such that optimal output, $Y^*_{i,c,t}$, is given by

$$Y^*_{i,c,t} = A_{c,t}^{\frac{1}{1-\theta}} f_{i,t}^{\frac{1}{1-\theta}} w_{c,t}^{-\frac{\theta\alpha}{1-\theta}} r_{c,t}^{-\frac{\theta(1-\alpha)}{1-\theta}} (\theta\alpha)^{\frac{\theta}{1-\theta}} (1-\alpha)^{\frac{(1-\alpha)\theta}{1-\theta}}$$

and optimal labor input, $L^*_{i,c,t}$ is

$$L^*_{i,c,t} = A_{c,t}^{\frac{1}{1-\theta}} f_{i,t}^{\frac{1}{1-\theta}} w_{c,t}^{-\frac{\theta\alpha+1-\theta}{1-\theta}} r_{c,t}^{-\frac{\theta(1-\alpha)}{1-\theta}} (\theta\alpha)^{\frac{1}{1-\theta}} (1-\alpha)^{\frac{(1-\alpha)\theta}{1-\theta}}. \tag{1}$$

We can take logs of equation (1) to get

$$log(L_{i,c,t}) = C + \frac{1}{1-\theta}log(A_{c,t}) + \frac{1}{1-\theta}log(f_{i,t}) - \frac{\theta\alpha+1-\theta}{1-\theta}log(w_{c,t}) - \frac{\theta(1-\alpha)}{1-\theta}log(r_{c,t}) \tag{2}$$

where C is a constant. City-level productivity, $A_{c,t}$, is in turn governed by observable productivity characteristics, $X^A_{c,t}$, and an unobservable component according to

$$A_{c,t} = X^A_{c,t}e^{\epsilon_{c,t}}.$$

In equilibrium, factor prices for labor and real estate capital depend on both $A_{c,t}$ and non-productivity related city characteristics. For example, workers may be willing to accept lower wages in cities that offer better amenities (see, e.g., Roback, 1982). Similarly, rents will be higher in cities where it is harder to build more real estate and may be higher in cities that offer workers higher amenities. To capture those relationships, we specify

$$w_{c,t} = (A_{c,t})^{\lambda_A}(X^w_{c,t})^{\lambda_w} \tag{3}$$

$$r_{c,t} = (A_{c,t})^{\kappa_A}(X^r_{c,t})^{\kappa_r} \tag{4}$$

where $X^w_{c,t}$ and $X^r_{c,t}$ are city characteristics that do not directly affect a city's total factor productivity but may do so through indirectly by influencing the prices of factor inputs.[3]

To recover the full effect of $X^A_{c,t}$ on employment, we insert (3) and (4) into (2) to get

$$log\left(L_{i,c,t}\right) = \gamma_A log\left(X^A_{c,t}\right) + \gamma_{i,t} + \gamma_w log\left(X^w_{c,t}\right) + \gamma_k log\left(X^r_{c,t}\right) + u_{i,c,t} \tag{5}$$

where $u_{i,c,t}$ is a function of the parameters θ, α, λ_A, κ_A, and $\epsilon_{c,t}$.

Our empirical analyses are focused on the estimation of Eq. (5) in the data. As is standard, we require $E\left(u_{i,c,t}|X^A_{c,t}, X^w_{c,t}, X^r_{c,t}\right) = 0$ to recover unbiased estimates of γ_A, γ_w, and γ_k. The greatest identification threats are that 1) $\epsilon_{c,t}$ is correlated with amenities that attract workers who contribute more to productivity, such that $\left(E\left(\epsilon_{c,t}|X^w_{c,t}\right) \neq 0\right)$, and 2) cities with higher productivity enact more land use restrictions, such that $E\left(u_{i,c,t}|X^r_{c,t}\right) \neq 0$ (Davidoff, 2016). To address these concerns, we include controls for physical geography and land use restrictiveness directly in our estimating equation.

[3] In the language of Roback (1982), $X^w_{c,t}$ and $X^r_{c,t}$ are city characteristics that don't affect the cost function, i.e., $C_s = 0$.

2.2 City Characteristics

In our empirical analyses, we consider two types of city characteristics: those that directly influence city productivity and those that influence it indirectly by affecting the prices of factor inputs (wages and rents). We outline each set of characteristics in turn.

2.2.1 City Productivity Characteristics

The set of productivity-related city characteristics ($X_{c,t}^{A}$) that we examine in the data is informed by the existing literature on the empirics of agglomeration economies. Combes and Gobillon (2015) provide an extensive survey of the local determinants of agglomeration effects.

The first determinant that we consider is the size of the local economy. Following Ciccone and Hall (1996) and Rosenthal and Strange (2008), we measure the size of the local economy as employment density, defined as total employment in a city, scaled by the total land area of that city. We focus on employment density, instead of population density, because employment better captures the magnitude of local economic activity (Combes and Gobillon, 2015). We use employment density instead of raw local employment to reduce the impacts on our estimations of potential mis-measurement in the size of the local economy (Briant et al., 2010). We consider the total land area of cities alongside their employment density to distinguish between productivity gains stemming from higher employment (density) and a larger spatial scale of the city (Combes and Gobillon, 2015).

Next, we consider two variables that capture the industrial composition of the local economy, namely, specialization and diversity. The industrial specialization of a city can give rise to localization economies that are based on the accumulation of knowledge from communications between local firms in the same industry (Porter, 1990). Such effects have been termed Marshall-Arrow-Romer (MAR) economies, reflecting their intellectual origins. We define specialization at the city-level following Duranton and Puga (2000) as

$$Specialization_{c,t} = \max\left(\frac{Employment_{c,s,t}}{Employment_{s,t}}\right) \tag{6}$$

where $Employment_{c,s,t}$ is the share of industry s in total employment of city c at time t, and $Employment_{s,t}$ is the share of industry s in total employment nationwide at time t. We note that local employment density and specialization may both have a positive impact on city-level productivity as they reflect, respectively, urbanization economies and localization economies (Combes, 2000).

The industrial diversity of a city can give rise to urbanization economies that are driven by the sharing of knowledge and innovations between firms from different local industries (Jacobs, 1969). To capture those effects, we define diversity at the city-level similar to Duranton and Puga (2000) as

$$Diversity_{c,t} = \frac{1}{\sum_s (Employment_{c,s,t} - Employment_{s,t})^2} \tag{7}$$

where $Employment_{c,s,t}$ and $Employment_{s,t}$ are defined as in Eq. (6). Combes et al. (2004) argue that measures of diversity which sum over local industries s are highly sensitive to the number of locally active industries. To identify the effect of diversity on city-level productivity more accurately, they propose considering the number of locally active industries alongside the diversity measure.

The distribution of local economic activity across the firms in a city may also generate localization economies. Jacobs (1969) and Porter (1990) posit that local competition supports city productivity as it accelerates the adoption of new technology. The MAR theory implies that a local monopoly is more beneficial for city productivity since it allows innovators to internalize the benefits of developing new technologies, fostering innovation and growth. Similar to Glaeser et al. (1992), we define local competition at the city-level as

$$Competition_{c,t} = \frac{Establishments\ per\ Employee_{c,t}}{Establishments\ per\ Employee_{t}} \tag{8}$$

where *Establishments per Employee*$_{c,t}$ is the total number of establishments in city c at time t, scaled by the corresponding total number of employees. The denominator is *Establishments per Employee*$_t$, the total number of establishments nationwide at time t, scaled by the corresponding total number of employees.

The skill composition of the local workforce can lead to human capital externalities that facilitate city-level productivity. We measure human capital using the education level of the local workforce (see, e.g., Combes et al., 2008; Moretti, 2004). Specifically, we define education at the city-level as

$$Education_{c,t} = \frac{College\text{-}Educated\ Population_{c,t}}{Total\ Population\ Over\ 25_{c,t}} \tag{9}$$

where *College-Educated Population*$_{c,t}$ is the total number of persons in city c at time t who hold a bachelor's degree or higher level of educational attainment and *Total Population Over 25*$_{c,t}$ is the corresponding total population over 25 years of age. We note that *Education*$_{c,t}$ captures the composite effect of human capital externalities and the limited substitutability of high- and low-skilled workers in a city (see, e.g., Combes and Gobillon, 2015; Rossi-Hansberg et al., 2019).

2.2.2 Consumption Amenities

The non-productive characteristics that make some locations more attractive to workers, $X^w_{c,t}$, thus possibly influencing wages, are largely time-invariant. For example, weather, proximity to the ocean, and proximity to mountains do not vary over time.

We include natural amenity measures in our regressions to capture the geographical desirability of a location. Specifically, we include mean January and July temperatures, mean sunlight in January, mean July humidity, the share of the city that is water, and an indicator for whether the topography is mountainous.

2.2.3 Rent Determinants

As is the case for wages, many of the non-productive characteristics that create higher or lower rents in a city are fixed over time. For example, the presence of sloped terrain or bodies of water is fixed. However, many cities have increased man-made land use restrictions over time (Gyourko et al., 2021; Baum-Snow and Han, 2022). We include two point-in-time measures of the restrictiveness of land use regulation.

3 Data

The main empirical analyses in this study revolve around the estimation of Eq. (5). To proceed with that estimation, we need to construct a data set with a firm-city-year panel of employment and match it to a city-year panel of urban characteristics. In the following section, we outline the construction of that data set.

3.1 Employment Data

Our employment data set is based on information from Data Axle. Data Axle is a leading business data and analytics firm that provides annual establishment-level information based on the Infogroup Business Data historical files. The Data Axle database covers all public and private firms in the U.S. since 1997. From that database, we obtain annual data sets for the 1997–2021 period. Those annual data sets contain information on the unique identity of each establishment, its exact location, the firm and industry to which it belongs, and the total number of employees per establishment. In our analyses, we define an establishment's location by the Core-Based Statistical Area (CBSA) in which it is situated.

From the initial Data Axle sample, we focus on firms that have at least 500 employees in at least one year over the 1997–2021 period. Figure 1 presents a breakdown of the sample firms by industry based on the 2-digit NAICS classification of the firms' headquarters.

[Insert Figure 1 about here.]

3.2 Data on City Characteristics

We match the firm-CBSA-year panel of firms' employment data with information on key drivers of agglomeration economies at the CBSA-year level. The drivers of agglomeration economies that we include in our analyses are outlined in Section 2.2. Here, we provide details on the data used to construct the corresponding variables.

We obtain annual data on the number of square miles of each CBSA (*Total Area*) from the U.S. Census Bureau's County TIGER/Line Shapefiles. We calculate employment density by dividing total employment from the U.S. Census Bureau's County Business Patterns Data set by *Total Area*.

We construct *Specialization*, *Diversity*, and *Competition* directly from the DataAxle employment data. We take the data on educational attainment required to construct the variable *Education* from the U.S. Census Bureau's American Community Survey data sets. Data on natural amenities are from the U.S. Department of Agriculture. We obtain the data for the variable *Regulation* from the Wharton Residential Land Use

Regulatory Index (WRLURI).[4] The WRLURI data are available for 2006 and 2018. We linearly interpolate the data for the missing years and extrapolate for years prior to 2006 and after 2018.

Table 1 presents descriptive statistics on selected characteristics of the top-10 largest CBSAs in the U.S. over the 1997–2021 period. The top-10 largest CBSAs are determined by their mean total employment over that period. The CBSAs are listed in rank order of their mean total employment (from largest to smallest). New York is the top-ranked CBSA by total mean employment, followed by Los Angeles and Chicago. Among the top-10 largest CBSAs, New York has the highest employment density, while Dallas covers the largest land area. The most specialized cities are Washington, D.C. (government and related services) and Houston (oil industry). Chicago and Atlanta have the most diverse industrial composition. All of the top-10 largest CBSAs house nearly 100 distinct industries. San Francisco and Los Angeles are the most competitive CBSAs, based on the local number of establishments per employee. Washington, D.C., San Francisco, and Boston have the most highly educated workforces. Boston, San Francisco, and Philadelphia exhibit the tightest land use regulations relative to the national average.

[Insert Table 1 about here.]

We construct the final data set for our main empirical analyses by matching the CBSA-year panel of city characteristics to the firm-CBSA-year panel of employment data by CBSA code and year.

[4]The Wharton Residential Land Use Regulatory Index (WRLURI) data are available from Joseph Gyourko's website at Wharton, see here.

3.3 Descriptive Statistics

Table 2 presents descriptive statistics on our firm-year panel data set. The statistics reported show that the average firm in the sample operates 16 establishments per year, across ten CBSAs. The average firm is active in the sample for approximately 14 years. During that time, annual firm-level employment averages approximately 2,500 workers. The annual mean growth rate in total employment (respectively, the total number of establishments) is 16% (4%). The average sample firm opens a new establishment in 60% of sample years and enters a new CBSA in 33% of sample years.

[Insert Table 2 about here.]

Table 3 presents descriptive statistics on our firm-CBSA-year panel data set. The statistics reported show that the average firm in the sample operates 1.5 establishments per CBSA each year, and operates those establishments for ten years on average. During that time, annual firm-level employment averages approximately 240 workers per CBSA. On average, the CBSA with the most employees hosts approximately 37% of the firms' total workforce. By contrast, the CBSA with the least employees on average hosts approximately 2% of the firms' total workforce. The annual mean growth rate in total CBSA-employment (respectively, the total number of establishments) for the sample firms is approximately 76% (4%).

[Insert Table 3 about here.]

In sum, the descriptive statistics discussed here suggest that U.S. manufacturing firms are highly geographically dispersed. They are also fairly dynamic, frequently opening new establishments and expanding their operations into new CBSAs.

Table 4 presents descriptive statistics on the firm-CBSA-year observations of employment in the sample matched to CBSA-year characteristics. Mean firm-CBSA-year employment is 294 employees. The average employment density across the CBSAs in the matched sample is 374 employees per square mile. The average total land area is 5,785 square miles. The mean level of specialization (diversity) across the CBSAs in the matched sample is approximately 726 (29). We note that specialization and diversity are not opposites—a city with a specialization in one main industry can, at the same time, have a broad base of other industries (Duranton and Puga, 2000). The average CBSA in the sample houses approximately 97 active industries and has a level of competition consistent with the U.S. as a whole, with a mean value of 1.0. On average, 34% of the CBSA-level population hold a bachelor's degree or higher. The mean value of land use regulation is 0.14, slightly higher than the overall U.S. average (the WRLURI data are standardized across the CBSAs in the U.S. to have a mean of zero, such that a positive value indicates an above-average level of land use regulation).

[Insert Table 4 about here.]

3.4 Nontradability Index

The location choice for firms that produce output not easily consumed in a location different from the one in which it is produced depends on local consumption rather than how the city affects productive capacity. Further, there is a direct relationship between employment growth in a city and the growth of non-tradable output that does not depend on the agglomeration economies that we are interested in. For example, we would trivially find that McDonald's has operations in nearly every American city. We would also find that employment in the construction industry is growing in successful cities for reasons unrelated to agglomeration economies.

To focus on the drivers of employment growth for firms that have a choice of where to produce because of productivity factors, rather than simply overall population growth that creates demand for the product, we create a measure of the nontradability of a firm's output. Specifically, we divide the total number of cities a firm has employment in by total firm employment to create an index of nontradability. Intuitively, large firms that produce in only a handful of locations must be producing tradable output since their output is likely consumed across many cities, given they are large firms, but only produced in a few. Our measure would assign a score very close to 0 for these firms. In contrast, firms that produce in a large number of cities must be producing output consumed locally such that these firms will have higher scores on our nontradability score. We then standardize the score by subtracting off its mean across our firm-years and dividing by the standard deviation.

We can aggregate firms by 4-digit NAICS codes to assess how nontradable an industry's output is. Table 5 compares our nontradability index to the classification by Mian and Sufi (2014). Reassuringly, the average score is highest for industries that Mian and Sufi (2014) classify as nontradable and lowest for industries that Mian and Sufi (2014) classify as tradable. However, our measure reveals that many industries classified as tradable based on the classification in Mian and Sufi (2014) are in fact populated by firms that produce in many cities suggesting limitations of the measure based solely on where an industry produces. One possible reason for the discrepancy is that the competitive structure of certain industries lends itself to more or less concentration. Our within-firm measure instead directly measures how dispersed firms' production structure is.

[Insert Table 5 about here.]

4 What Determines Where Firms Employ People?

We now turn to the analyses of the city characteristics that may spur firms' local employment. In this section, we first describe the regression model that we specify to implement the empirical strategy outlined in Section 2.1. Then, we discuss the estimation results on the determinants of firms' employment choices across cities.

4.1 Econometric Specification

We implement our empirical strategy for identifying the drivers of firms' employment choices across cities over time by estimating unbalanced panel regressions of the form

$$\begin{aligned} \textit{Employment}_{i,c,t} &= \beta_1 \textit{Density}_{c,t-1} + \beta_2 \textit{Total Area}_{c,t-1} + \beta_3 \textit{Specialization}_{c,t-1} \\ &+ \beta_4 \textit{Diversity}_{c,t-1} + \beta_5 \textit{\# Industries}_{c,t-1} + \beta_6 \textit{Competition}_{c,t-1} + \beta_7 \textit{Education}_{c,t-1} + \\ &\beta_8 \textit{Amenities}_c + \beta_9 \textit{Regulation}_{c,t-1} + \beta_{10} \textit{Employment}_{i,c,t-1} + \gamma_{i,t} + \epsilon_{i,c,t} \end{aligned} \quad (10)$$

where $\textit{Employment}_{i,c,t}$ is total employment of firm i in CBSA c and year t. The explanatory variables are defined as in Section 2.2.[5] The time-varying predictors are lagged by one year with respect to the observation of the dependent variable. We account for the lag of employment, $\textit{Employment}_{i,c,t-1}$, to capture adjustment costs. To ease the interpretation of the coefficient estimates, we transform all explanatory variables, except *Amenities* and *Regulation*, into their natural logarithms.[6] $\gamma_{i,t}$ are firm-by-year fixed effects to account for unobserved, time-varying firm characteristics that may affect firms' location choices and employment dynamics, such as firm size, profitability,

[5] Appendix Table A.1 presents pairwise correlation coefficients for the variables in Eq. (10). The statistics reported indicate no serious concerns about multicollinearity between the regression variables.

[6] The WRLURI data behind our *Regulation* variable are standardized to have a mean of zero and a standard deviation of one, such that we cannot take logs without losing a significant amount of data.

and management efficiency. $\epsilon_{i,c,t}$ is the residual. We estimate Eq. (10) using OLS, with standard errors clustered at the CBSAs level.

4.2 What Types of Agglomeration Economies Matter?

Table 6 presents the results from estimating Eq. (10). The results presented in column 1 refer to a baseline estimation without firm-by-year fixed effects and without the lagged value of the dependent variable as a predictor of firm-CBSA-year employment. In column 2, we add firm-by-year fixed effects to account for time-varying factors that drive employment choices across firms. Column 3 represents our preferred specification in which we account for firm-by-year fixed effects and lagged employment.

[Insert Table 6 about here.]

Across the different columns of Table 6, the coefficient estimates reported suggest that higher levels of density in a city are associated with higher employment. In our preferred specification (tabulated in column 6), the coefficient estimate for density is approximately 0.05. This coefficient estimate is numerically consistent with benchmark studies assessing the effects of density on productivity in the U.S., such as the estimates reported in Ciccone and Hall (1996), Rosenthal and Strange (2008), Combes et al. (2010), and Davis et al. (2014). We note that the inclusion of firm-by-year fixed effects and of lagged employment significantly affect the magnitude of the coefficient estimate of density, suggesting that both firms' sorting across locations and adjustment costs can confound estimation results.

The results reported in Table 6 indicate that firms have significantly higher employment in cities with a larger total area. This finding is consistent with the results presented in Combes et al. (2012) who document, using French data, that firms are more productive in larger cities. In combination with our finding on density, those results suggest that cities experience productivity gains from growth in their density and, simultaneously, from growth in their spatial scale.

Prior work has focused on estimating the effects of local market size on industry-level employment growth in different countries, with mixed results. Combes (2000) documents a positive (negative) impact of market size on local industrial employment growth in manufacturing (service) industries in France. Viladecans-Marsal (2004) shows that, in Spain, market size is insignificant in explaining industrial employment growth across six different industries and has a non-linear effect in three others. We provide firm-level evidence consistent with prior works that identify a positive association between the size of the local economy and industry-level employment growth.

The estimates shown in Table 6 indicate that higher degrees of industrial specialization in cities have an insignificant influence on firms' employment in those locations. Henderson et al. (1995) document that MAR economies are associated with higher industrial growth at the industry level in eight manufacturing industries. In contrast, Glaeser et al. (1992) show that industry-level employment grows more slowly in cities where that industry accounts for a large share of total local employment. Combes (2000) also present evidence that, in France, high industrial specialization is associated with lower employment growth within that industry. Instead of looking at the industry-level, we are able to study employment within firms. Our granular firm-CBSA-level data suggest that cities do not benefit from greater specialization. Of course, our sample focuses only on manufacturing firms. Henderson (2003) and Combes et al. (2008) both find larger effects of specialization in service industries, where firms could experience greater technological spillover effects.

Our estimates further indicate that a city's industrial diversity is a significant determinant of employment once we control for firms' sorting and adjustment costs (columns 2 and 3). Previous work suggests that the effect of diversity is not robust (Combes and Gobillon, 2015). Our results based on granular establishment-level employment data reveal evidence that is consistent with the intuition of Jacobs (1969).

The MAR theory implies that higher levels of local competition hinder growth, as a local monopoly allows firms to internalize the benefits of developing innovations. On the other hand, Jacobs (1969) and Porter (1990) posit that local competition is beneficial for growth as it spurs the adoption of new technologies. Our estimates concur with the former rationale, as the coefficient estimates reported in columns 2 and 3 of Table 6 indicate significantly negative effects of competition on employment for tradable firms.

Our results indicate that the skill level of the local workforce is an insignificant driver of firms' employment choices. This finding is inconsistent with prior research in the U.S. (see, e.g., Simon, 2004).However, the education level of the local workforce captures the composite effect of human capital externalities and the limited substitutability of high- and low-skilled labor. A further decomposition of those effects could reveal more nuanced insights.

The results tabulated in Table 6 further suggest that tighter land use regulations, proxied by the WRLURI data, are do not affect the employment choices of local firms. However, we note that the WRLURI data are only available for 2006 and 2018. A more complete time series of local land use regulations may produce different estimates.

Lastly, the estimates in Table 6 indicate that natural amenities influence employment. Specifically, our results suggest that higher January (July) temperatures are associated with lower (higher) employment. Our results further suggest that humidity and a mountainous topography are also associated with higher employment.

5 Conclusions

We corroborate the importance of employment density, city size, and industrial diversity in productivity. Further, we show that productivity declines as competition within a city increases. We do not find that industrial specialization increases city productivity, nor do we find robust evidence that the education levels of the local workforce or local land use regulations strongly influence city productivity.

A limitation of our analysis is that the city-level determinants of firm births may differ from those of growth within existing firms. Suggestive of such a result, Combes et al. (2004) find different determinants of growth within a plant versus growth in the number of plants in France. Furthermore, we do not identify the city-level productivity factors that influence large firms' choices of whether and when to enter a new city. Nevertheless, for the large firms we study here, that many cities try to court, our analysis suggests that cities can increase employment by taking steps to allow for additional density, a larger spatial scale, and greater industrial diversity.

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Figure 1. Breakdown of Industries

This figure depicts the breakdown of the firm-CBSA-year observations in our final sample by industry by 2-digit NAICS codes. The data used to produce this figure are from Data Axle.

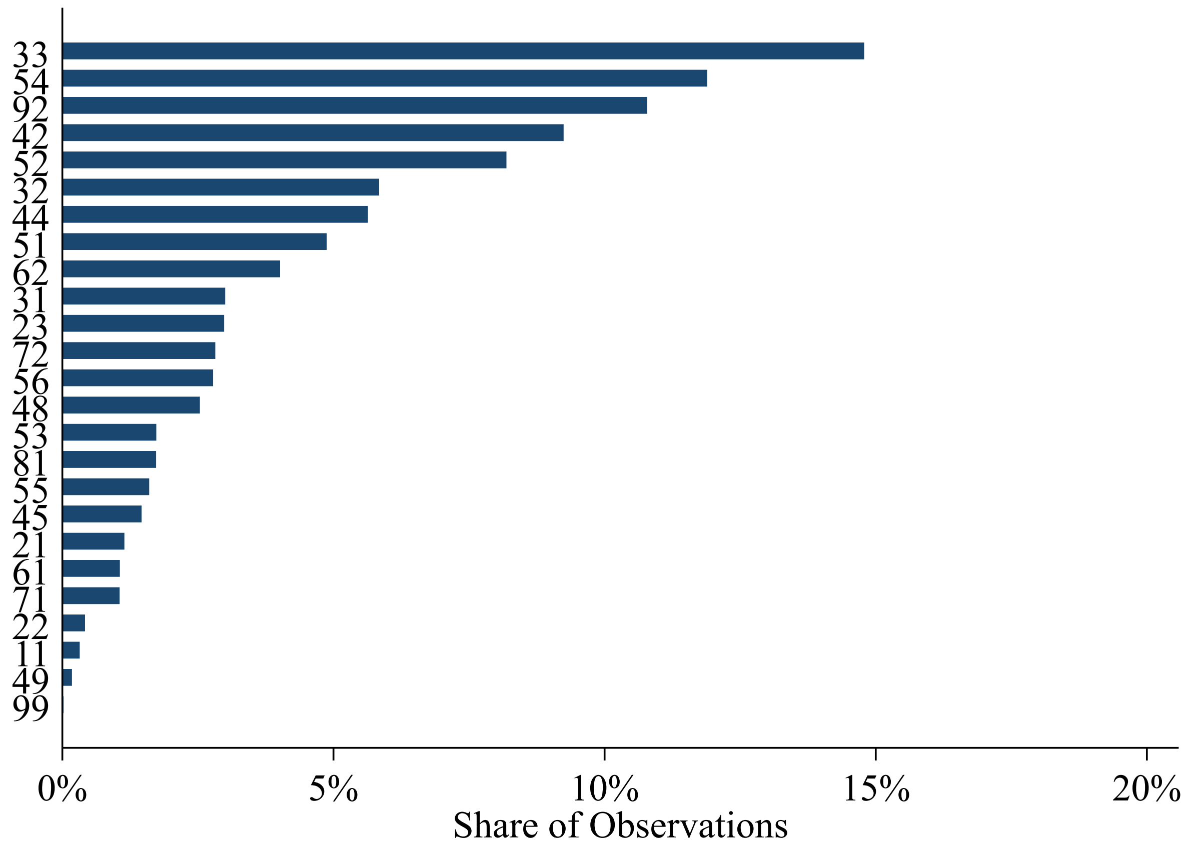

Table 1. Top-10 Cities by Key Characteristics

This table presents descriptive statistics on the top-10 largest CBSAs in the U.S., observed over the 1997–2021 period. The top-10 largest CBSAs are determined by their man total employment over the 1997–2021 period. The CBSAs are listed in rank order of their mean total employment (from largest to smallest). The columns show the means of city characteristics over the 1997–2021 period. *Density* is total employment in a CBSA, scaled by that CBSA's land area (in square miles). *Total Area* is the total land area of a CBSA (in square miles). *Specialization* is the maximum of the employment share of a given industry (defined by 3-digit NAICS code) in a city, scaled by the corresponding share of that industry's employment nationwide. *Diversity* is the inverse of the sum across all industries active in a CBSA of the squared differences between a given industry's employment share in a given CBSA-year and the corresponding employment share of that industry nationwide. # *Industries* is the number of active industries (those with non-zero employment) in a given CBSA-year. *Competition* is the number of establishments per employee in a given CBSA-year, scaled by the corresponding number of establishments per employee nationwide. *Education* is the share of the total population over 25 years of age with a bachelor's degree or higher level of educational attainment in a given CBSA-year. *Regulation* is the CBSA's assigned value of the Wharton Residential Land Use Regulatory Index (WRLURI).

	CBSA		Density	Total Area	Specialization	Diversity	# Industries	Competition	Education	Regulation
1	35620	New York	1104	7072	302	27.9	99	1.08	0.36	0.27
2	31080	Los Angeles	1083	4849	514	29.6	97	1.12	0.30	0.32
3	16980	Chicago	566	7196	242	30.4	98	0.91	0.34	0.04
4	19100	Dallas	303	8982	626	29.7	98	0.97	0.31	-0.30
5	37980	Philadelphia	552	4602	459	28.5	98	0.98	0.33	0.68
6	14460	Boston	675	3487	351	27.0	98	0.97	0.43	1.15
7	47900	Washington	392	5870	2158	22.9	99	0.92	0.47	0.02
8	26420	Houston	264	8625	1810	28.7	98	0.98	0.29	0.11
9	12060	Atlanta	256	8463	757	30.1	97	0.99	0.35	-0.23
10	41860	San Francisco	799	2472	676	27.2	98	1.13	0.44	0.60

Table 2. Descriptive Statistics on Firm-Year Panel

This table presents descriptive statistics on the firms in the final sample, observed over the 1997–2021 period. # *Establishments* is the number of establishments a firm operates in a given sample year. # *CBSAs* is the number of CBSAs in which a firm operates active establishments in a given sample year. # *Years* is the number of years during which we observe a firm in the sample. *Employment* is the total number of employees that a firm has in a given sample year. *Employment Growth* is the annual growth rate in the number of employees that a firm experiences during the sample period. *Establishment Growth* is the annual growth rate in the number of active establishments that a firm experiences during the sample period. *New Establishment* is an indicator that takes the value of one if a firm opens a new establishment in a given sample year. *New CBSA* is an indicator that takes the value of one if a firm enters a new CBSA, in which it does not previously operate any active establishments, in a given sample year.

	N	Mean	Median	Std. Dev.	Min.	Max.
# Establishments	269,988	143	21	880.0	1	69,701
# CBSAs	269,988	35	10	85.2	1	934
# Years	269,988	18	18	7.3	1	25
Employment	269,988	4343	941	21143.3	0	1,617,586
Employment Growth	245,616	0.70	0	63.9	-1	23,624
Establishment Growth	245,616	0.20	0	5.4	-1	1,821
New Establishment	270,013	0.73	1	0.4	0	1
New CBSA	270,013	0.33	0	0.5	0	1

Table 3. Descriptive Statistics on Firm-CBSA-Year Panel

This table presents descriptive statistics on the firm-CBSA-year observations in the final sample over the 1997–2021 period. *# Establishments* is the number of establishments a firm operates in a given CBSA and given sample year. *# Years* is the number of years during which we observe a firm in a given CBSA in the sample. *Employment* is the total number of employees that a firm has in a given CBSA and given sample year. *Max. Employment Share* is the share of total employment that a firm has in the CBSA with the most employees in a given year. *Min. Employment Share* is the share of total employment that a firm has in the CBSA with the least employees in a given year. *Employment Growth* is the annual growth rate in the number of employees that a firm experiences in a given CBSA during the sample period. *Establishment Growth* is the annual growth rate in the number of active establishments that a firm experiences in a given CBSA during the sample period.

	N	Mean	Median	Std. Dev.	Min.	Max.
# Establishments	9,388,523	3.85	1	14.55	1	2,843.00
# Years	9,388,523	14.7	14	7.61	1	25
Employment	9,388,523	120.3	16	699	0	174,251
Max. Employment Share	9,388,523	0.22	0.15	0.21	0	1
Min. Employment Share	9,388,523	0.01	0	0.06	0	1
Employment Growth	7,937,886	0.32	0	17.65	-1	20,999
Establishment Growth	7,937,886	0.06	0	0.91	-1	569

Table 4. Descriptive Statistics on Matched Sample

This table presents descriptive statistics on the firm-CBSA-year observations of employment in the sample matched to CBSA-year characteristics over the 1997–2021 period. *Employment* is the total number of employees in a given firm-CBSA-year. The CBSA-year characteristics are defined as follows. *Density* is total employment in a CBSA, scaled by that CBSA's land area in square miles. *Total Area* is the total land area of a CBSA in square miles. *Specialization* is the maximum of the employment share of a given industry (defined by 3-digit NAICS code) in a city, scaled by the corresponding share of that industry's employment nationwide. *Diversity* is the inverse of the sum across all industries active in a CBSA of the squared differences between a given industry's employment share in a given CBSA-year and the corresponding employment share of that industry nationwide. *# Industries* is the number of active industries (those with non-zero employment) in a given CBSA-year. *Competition* is the number of establishments per employee in a given CBSA-year, scaled by the corresponding number of establishments per employee nationwide. *Education* is the share of the total population over 25 years of age with a bachelor's degree or higher level of educational attainment in a given CBSA-year. *Regulation* is the CBSA's assigned value of the Wharton Residential Land Use Regulatory Index (WRLURI). *MeanJanTemp* and *MeanJulyTemp* are the average January and July temperatures in Fahrenheit. *MeanJanSun* is the mean total number of hours of sun in the month of January. *MeanJulyHumid* is the average percent humidity in July. *PctWater* is the percent of the city's primary county that is water. *Mountainous* is an indicator variable if the U.S. geographic survey indicates that the topography is mountainous.

	N	Mean	Median	Std. Dev.	Min.	Max.
Employment	5,634,836	161	22	855	0	174,251
Density	5,634,836	205	124	234	1	1301
Total Area	5,634,836	3874	2847	3485	224	27277
Specialization	5,634,836	1067	637	2046	167	75570
Diversity	5,634,836	27.3	28.0	4.4	2.3	37.8
# Industries	5,634,836	94.2	96.0	4.7	63.0	99.0
Competition	5,634,836	1.00	0.98	0.14	0.26	2.32
Education	5,634,836	0.29	0.28	0.08	0.05	0.65
Regulation	5,634,836	0.02	0.03	0.77	-3.52	5.82
MeanJanTemp	5,634,836	36.4	35.6	12.4	5.9	66.8
MeanJanSun	5,634,836	154.4	151.0	39.4	48.0	260.0
MeanJulyTemp	5,634,836	75.8	75.5	5.5	56.5	91.1
MeanJulyHumid	5,634,836	57.6	61.0	14.9	19.0	79.0
PctWater	5,634,836	8.06	2.68	12.80	0.01	75.00
Mountainous	5,634,836	0.27	0.00	0.45	0.00	1.00

Table 5. Nontradability Index at 4-digit NAICS Level and Mian and Sufi (2014) Industry Classification

This table summarizes the nontradability index at the 4-digit NAICS industry level and computes scores by the Mian and Sufi (2014) categories.

Mian and Sufi (2014) Category	p25	Median	p75	Mean	Std. Dev.	Min.	Max.
other	-0.059	-0.042	0.004	-0.001	0.140	-0.070	4.979
tradable	-0.062	-0.053	-0.035	-0.036	0.063	-0.070	0.728
non-tradable	-0.056	-0.039	0.008	0.007	0.131	-0.070	0.886
construction	-0.058	-0.038	-0.002	-0.007	0.100	-0.070	0.919
Total	-0.060	-0.045	-0.009	-0.011	0.120	-0.070	4.979

Table 6. Determinants of Firm-CBSA-Year Employment

This table presents output from Eq. (10), estimated over the 1997–2021 period. The dependent variable is the natural logarithm of *Employment*, defined as the total number of employees in a given firm-CBSA-year. See Table 4 for independent variable definitions. All variables, except *Regulation* and the physical geography variables, are transformed to their natural logarithms. All time-varying explanatory variables are lagged by one year relative to the observation of the dependent variable. Firm-by-year fixed effects are included as indicated. t-statistics, based on clustered standard errors (by CBSA), are shown in parentheses. Tradable firms are those with a nontradable index score below the 25th percentile. Nontradable firms are those with a nontradable index score above the 75th percentile. Significance is indicated as follows: *** p<0.001, ** p<0.05, * p<0.1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
lag_emp			0.91***			0.91***			0.89***
			(0.0014)			(0.0018)			(0.0015)
lag_density	0.38***	0.51***	0.048***	0.27***	0.52***	0.046***	0.38***	0.46***	0.049***
	(0.0079)	(0.010)	(0.0012)	(0.013)	(0.014)	(0.0015)	(0.012)	(0.012)	(0.0014)
lag_area	0.37***	0.52***	0.051***	0.24***	0.50***	0.046***	0.41***	0.49***	0.055***
	(0.0070)	(0.011)	(0.0013)	(0.012)	(0.014)	(0.0017)	(0.0096)	(0.011)	(0.0015)
lag_specialization	0.0081**	-0.0059	-0.00083	-0.0093	-0.0077	-0.0010	0.0031	-0.0034	-0.00030
	(0.0040)	(0.0039)	(0.00065)	(0.010)	(0.0086)	(0.00096)	(0.0076)	(0.0076)	(0.0012)
lag_diversity	-0.058***	0.015	-0.00087	0.025	0.10***	0.0056	-0.091***	-0.10***	-0.013***
	(0.021)	(0.021)	(0.0028)	(0.040)	(0.036)	(0.0043)	(0.026)	(0.027)	(0.0040)
lag_no_ind	-0.82***	-0.0079	0.00070	0.97***	0.83***	0.087***	-1.61***	-0.94***	-0.081***
	(0.14)	(0.17)	(0.020)	(0.18)	(0.21)	(0.026)	(0.19)	(0.20)	(0.027)
lag_competition	0.034	-0.056	-0.00017	-0.33***	-0.41***	-0.032***	0.24***	0.26***	0.026***
	(0.040)	(0.036)	(0.0045)	(0.079)	(0.065)	(0.0072)	(0.046)	(0.047)	(0.0067)
lag_education	-0.12***	-0.015	0.00020	-0.19***	-0.062*	-0.0033	-0.068**	-0.012	-0.00028
	(0.018)	(0.017)	(0.0025)	(0.034)	(0.034)	(0.0039)	(0.027)	(0.025)	(0.0033)
regulation	0.0036	0.0082	0.0014*	0.0084	0.013	0.0036***	-0.0054	0.0029	-0.00031
	(0.0055)	(0.0055)	(0.00077)	(0.0070)	(0.0077)	(0.0010)	(0.0073)	(0.0073)	(0.0011)
meanjantemp	-0.0026***	-0.00059	-0.000062	-0.0015	-0.000055	-0.000049	-0.0026***	-0.0020***	-0.00020*
	(0.00066)	(0.00055)	(0.000071)	(0.0012)	(0.0011)	(0.00012)	(0.00075)	(0.00078)	(0.000100)
meanjansun	-0.00011	0.000035	4.8e-06	0.00048***	0.00036**	0.000034	-0.00039**	-0.00010	-1.8e-06
	(0.00014)	(0.000092)	(0.000014)	(0.00018)	(0.00017)	(0.000023)	(0.00018)	(0.00014)	(0.000021)
meanjulytemp	0.0026*	0.0021**	0.00038**	0.0014	0.00034	0.00031	0.0061***	0.0036**	0.00045**
	(0.0013)	(0.0011)	(0.00015)	(0.0022)	(0.0021)	(0.00025)	(0.0019)	(0.0018)	(0.00022)
meanjulyhumid	0.0015***	0.0010***	0.000097*	0.0019***	0.0018***	0.00015*	0.0019***	0.0011**	0.00015**
	(0.00041)	(0.00035)	(0.000049)	(0.00064)	(0.00057)	(0.000077)	(0.00051)	(0.00051)	(0.000066)
pctwater	0.00033	0.00043*	0.000051	0.00044	0.00056	0.000033	-0.000062	0.00031	0.000047
	(0.00027)	(0.00025)	(0.000037)	(0.00048)	(0.00045)	(0.000054)	(0.00049)	(0.00045)	(0.000064)
Mountainous	0.036**	0.021*	0.00033	0.057**	0.061***	0.0037	-0.011	-0.0051	-0.0012
	(0.014)	(0.012)	(0.0016)	(0.023)	(0.020)	(0.0024)	(0.018)	(0.017)	(0.0021)
Constant	2.25***	-3.28***	-0.33***	-3.49***	-6.21***	-0.61***	4.35***	0.59	-0.045
	(0.58)	(0.66)	(0.079)	(0.75)	(0.84)	(0.11)	(0.78)	(0.81)	(0.11)
Observations	3,819,839	3,819,839	3,819,839	984,799	984,799	984,799	928,819	928,819	928,819
R^2	0.090	0.514	0.919	0.058	0.357	0.898	0.169	0.429	0.889
Year FEs	Yes	No	No	Yes	No	No	Yes	Yes	Yes
Firm×Year FEs	No	Yes	Yes	No	Yes	Yes	No	No	No
Firm Types	All	All	All	Tradable	Tradable	Tradable	Nontradable	Nontradable	Nontradable

APPENDIX

Table A.1. Pairwise Correlation Coefficients in Matched Sample

This table presents pairwise correlation coefficients between the variables included in the matched sample over the 1997–2021 period. See Table 4 for variable definitions.

	Emp	*Dens.*	*Area*	*Spec.*	*Div.*	*# Ind.*	*Comp.*	*Edu.*	*Reg.*	*Jan○*	*JanSun*	*Jul○*	*JulHum*	*%H2O*	*Mountain*
Emp	1.00														
Dens.	0.24	1.00													
Area	0.19	0.15	1.00												
Spec.	-0.12	-0.40	-0.23	1.00											
Div.	0.08	0.24	0.30	-0.19	1.00										
# Ind.	0.22	0.67	0.57	-0.38	0.40	1.00									
Comp.	-0.06	-0.24	-0.06	0.08	0.13	-0.21	1.00								
Edu.	0.16	0.53	0.28	-0.30	-0.04	0.50	-0.14	1.00							
Reg.	0.05	0.20	0.10	-0.06	0.04	0.21	0.15	0.29	1.00						
Jan○	0.03	0.06	0.19	0.09	0.00	0.14	0.35	-0.13	0.07	1.00					
JanSun	0.02	-0.04	0.22	-0.06	0.00	0.07	0.21	0.02	0.16	0.50	1.00				
Jul○	0.01	-0.08	0.22	-0.03	-0.03	0.07	-0.06	-0.21	-0.16	0.54	0.45	1.00			
JulHum	0.04	0.36	-0.27	-0.04	0.01	0.10	-0.05	0.09	-0.11	0.14	-0.07	-0.09	1.00		
%H2O	0.05	0.32	-0.15	-0.07	0.03	0.11	0.11	0.15	0.09	0.09	0.00	-0.13	0.24	1.00	
Mountain	-0.01	-0.17	0.17	0.05	0.04	0.03	0.28	0.05	0.30	0.16	0.21	-0.30	-0.43	-0.12	1.00