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Productivity and the Density of Human Capital

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Abstract

We estimate a model of urban productivity in which the agglomeration effect of density is enhanced by a metropolitan area's stock of human capital. Estimation accounts for potential biases due to the endogeneity of density and industrial composition effects. Using new information on output per worker for U.S. metropolitan areas along with a measure of density that accounts for the spatial distribution of population, we find that a doubling of density increases productivity by 2 to 4 percent. Consistent with theories of learning and knowledge spillovers in cities, we demonstrate that the elasticity of average labor productivity with respect to density increases with human capital. Metropolitan areas with a human capital stock one standard deviation below the mean realize no productivity gain, while doubling density in metropolitan areas with a human capital stock one standard deviation above the mean yields productivity benefits that are about twice the average. These patterns are particularly pronounced in industries where the exchange of information and sharing of ideas are important parts of the production process.

Key words: agglomeration, productivity, density, knowledge spillovers

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I. INTRODUCTION

Virtually all of the economic activity in the United States occurs in and around cities, with metropolitan areas accounting for nearly 90 percent of U.S. gross domestic product. However, while metropolitan areas as a whole are highly productive, differences in productivity across metropolitan areas are strikingly large. Figure 1 shows the distribution of average output per worker observed across U.S. metropolitan areas between 2001 and 2005. During this period, average output per worker in the twenty most-productive metropolitan areas was two times larger than in the twenty least-productive metropolitan areas, and more than one-half larger than the value for the median metropolitan area. Meanwhile, the twenty least-productive metropolitan areas were about one-fourth less productive than the median.

Modern empirical studies of urban agglomeration economies demonstrate that the density of economic activity explains much of the productivity differences observed across space. Using models derived from aggregate production functions and value-added data for U.S. states and European regions, results from these studies suggest that productivity increases by 4.5 to 6 percent when employment density is doubled (Ciccone and Hall, 1996; Ciccone, 2002).[1] Recent research examining patterns in wages and firm total factor productivity (TFP) argues that these aggregate studies overstate the magnitude of urban agglomeration economies because they do not account for potential biases introduced by sorting—that is, people (or firms) with more valuable skills and

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[1] Early empirical studies of urban productivity focused on city size rather than density. Findings from this literature suggest that productivity increases by 3 to 8 percent when population is doubled (Sveikauskas, 1975; Segal, 1976; Moomaw, 1981). Redding (2010) and Rosenthal and Strange (2004) provide comprehensive reviews of the empirical evidence of agglomeration economies, while Melo, Graham, and Noland (2009) provide a recent meta-analysis of study characteristics affecting the magnitudes of existing estimates of agglomeration effects.

output may locate in denser places. Employing a rich panel of individuals and firms in France, Combes et al. (2008, 2010) show that accounting for sorting reduces their estimated density elasticity by about 50 percent. Thus, depending on the measure of productivity used, their elasticity estimates suggest that productivity increases by 2 to 3.5 percent when employment density is doubled. While this literature has deepened our understanding about the magnitude of urban agglomeration economies, evidence on the source of such productivity effects remains scarce.

Theories of agglomeration focusing on learning and knowledge spillovers in cities emphasize the roles of density and human capital in boosting urban productivity (Marshall, 1890; Jacobs, 1969; Lucas, 1988; Glaeser, 1999). From a microeconomic perspective, one of the key benefits of density is that it lowers the costs of generating new ideas and exchanging information. In particular, the close physical proximity of firms and people in dense urban areas facilitates the flow of knowledge by increasing the amount of interaction and face-to-face contact that people experience. Such contact has been shown to enhance productivity when information is imperfect, rapidly changing, or not easily codified—key features of many of the most valuable economic activities today (Storper and Venables, 2004).

These explanations about the mechanisms by which density enhances urban economic activity suggest that not all types of interactions facilitated by a dense population are created equal. It is likely that bringing together people involved in idea generation and high-skilled activities provides a larger boost to productivity than assembling individuals who employ lower levels of human capital. More generally, we argue that the skills and knowledge possessed by individuals in a metropolitan area influence the quality of interpersonal interactions, suggesting that the productivity-enhancing effects of density are augmented by a metropolitan area's stock of human capital. Specifically, if learning and knowledge spillovers are important, increasing the interaction of highly-skilled people within a fixed geographic area is likely to result in more innovation and provide a greater boost to productivity than increasing the density of those with lower skills. We refer to this interaction of density and skill as the *density of human capital*.

There has been a recent resurgence of interest among urban economists and regional scientists in empirical analysis of the microfoundations of urban agglomeration economies (see, e.g., Baldwin, Brown, and Rigby, 2010; Fu and Hong, 2011; and Park and von Rabenau, 2011).[2] While a number of studies have analyzed the productivity-enhancing effects of density on its own, very few have examined the joint effect of density and human capital. In a recent article, Glaeser and Resseger (2010) found a stronger correlation between per-worker productivity and city size in places with higher levels of human capital, and interpret this complementarity as evidence in support of knowledge-based theories of agglomeration. Likewise, recent empirical research examining the attenuation of human capital spillovers among individuals suggests that the density of human capital may be an important determinant of aggregate urban productivity. Along these lines, Rosenthal and Strange (2008a) find that proximity to college-educated workers drives much of the urban wage premium that is typically attributed to the spatial concentration of employment. In addition, other research examining whether knowledge spillovers enhance innovation in cities has highlighted the

[2] Duranton and Puga (2004) review the microeconomic foundations of urban agglomeration economies, and classify them into three broad categories: sharing, matching, and learning.

role of density in the production of new ideas and exchange of information. Consistent with this view, Carlino, Chatterjee, and Hunt (2007) find that doubling the employment density in the most urbanized portion of a metropolitan area is associated with a 20 percent increase in patent intensity. Knudsen et al. (2008) extend this work and provide evidence that density and regional creativity—separately and jointly— affect the rate of innovation in U.S. metropolitan areas, indicating that the density of highly-skilled people is an important determinant of urban innovation. This study builds from the insights of this recent empirical work by considering the relationship between aggregate urban productivity and the density of human capital in U.S. metropolitan areas, extending the literature on the measurement and magnitude of urban agglomeration effects and providing information on their source.

The paper presents new estimates of the magnitude of agglomeration economies at work in U.S. metropolitan areas. To provide a structural framework for our regressions, we present a model of urban productivity that explicitly incorporates the complementarity between cities and skills. However, given the focus of modern empirical studies of urban agglomeration, this complementarity arises in our model because the agglomeration effect of density, rather than size as examined by Glaeser and Resseger (2010), is enhanced by a metropolitan area's stock of human capital due to the ease with which it facilitates interaction. Consistent with the existing literature, the model yields a set of estimating equations showing that the productivity of a metropolitan area is primarily determined by population density, the human capital stock, and other factors that vary by region.

Our empirical analysis emphasizes careful measurement and addresses complex identification problems. To estimate the parameters of this model, we utilize newly available data on metropolitan area gross domestic product (GDP) to construct measures of output per worker along with an improved measure of density that accounts for the spatial distribution of population within metropolitan areas. Importantly, our work also accounts for two distinct types of identification issues that may arise in empirical studies of agglomeration. As the existing literature makes clear, the use of aggregate output per worker data to measure urban productivity introduces a classic endogeneity problem—that is, population density and productivity may be simultaneously determined if people are attracted to more productive places or if there is an unobserved local variable that is correlated with both density and productivity. We address this fundamental identification problem by including spatial fixed effects in our empirical model and by using an instrumental variables approach to estimate the model's parameters, with instruments for population density based on historical measures of population and a region's climate, which is an increasingly important consumption amenity. Moreover, as recent research suggests, we also account for potential biases related to sorting by implementing a two-step estimation approach. This framework, similar to that proposed by Combes et al. (2008, 2010), allows us to condition out the portion of measured productivity due strictly to the industrial composition of a metropolitan area. Thus, our work allows for precise measurement of the magnitude of urban agglomeration economies related to population density.

Based on a comprehensive sample of 363 U.S. metropolitan areas over the 2001 to 2005 period, our empirical analysis reveals that a doubling of density increases productivity by an average of 2 to 4 percent, which falls below the range established by existing studies of aggregate productivity, but is in line with recent estimates based on individual wage and firm TFP data. Perhaps more importantly, consistent with theories of learning and knowledge spillovers in cities, we demonstrate that the elasticity of average labor productivity with respect to density increases with human capital. Metropolitan areas with a human capital stock that is one standard deviation below the mean realize no productivity gain, while doubling density in metropolitan areas with a human capital stock that is one standard deviation above the mean yields productivity benefits that are about two times larger than average. In fact, using plausible parameter values to calibrate our model of urban productivity, we find a negative net agglomeration effect in metropolitan areas with a human capital stock about one standard deviation below the mean, suggesting that the negative congestion effects of density swamp the positive spillover effects in unskilled places.

An extension to our aggregate productivity analysis provides insights into the underlying sources of these productivity effects, which has been an elusive task in the existing literature (Puga, 2010). To do so, we estimate our empirical model incorporating the density of human capital separately for a wide range of industry sectors. While a handful of studies have utilized the aggregate metro GDP data, we are the first to analyze the industry-level GDP data at the metropolitan area. We demonstrate that both the average effect of density and the density of human capital are highest among knowledge-based industries—such as Professional Services, Arts and Entertainment, Information, and Finance—where the exchange of information and sharing of ideas are important parts of the production process. Thus, not only does this paper provide new estimates on the magnitude of aggregate urban agglomeration economies, but it also addresses a gap in the existing literature by offering evidence consistent with the idea that learning and knowledge spillovers in cities are an important source of such productivity effects.

Finally, results from our analysis provide an enhanced understanding of the mechanisms by which agglomeration enhances output in the most productive U.S. metropolitan areas—important given that the 50 most productive metropolitan areas account for 60 percent of U.S. GDP. Relative to conventional models of urban agglomeration, we show that incorporating the density of human capital explains the highly non-linear distribution of productivity observed across the most productive metropolitan areas. Knowing the keys to productivity in these places helps us understand factors influencing the overall level of economic activity in the United States.

II. A MODEL OF URBAN PRODUCTIVITY

To provide a structural framework for our empirical analysis, we present a general model of urban productivity that builds on previous work (Mankiw, Romer, and Weil, 1992; Ciccone and Hall, 1996; Hall and Jones, 1999; Ciccone, 2002). Specifically, we assume production occurs according to a human-capital augmented Cobb-Douglas production function, so output (Y) at any given time in metropolitan area i contained within a larger region j is given by:[3]

$$Y_{ij} = A_{ij} K_{ij}^{\alpha} H_{ij}^{\beta} L_{ij}^{1-\alpha-\beta} \tag{1}$$

where A_{ij} is a Hicks-neutral technology parameter, K_{ij} is physical capital, H_{ij} is human capital, and L_{ij} is the amount of labor available at the metropolitan area level. Labor (L) is

[3] Following Ciccone (2002), a larger region is defined as a fixed geographic area containing several metropolitan areas, such as a state.

assumed to be homogeneous within and across metropolitan areas, so differences in knowledge and skills across metropolitan areas are captured in the measure of human capital (H). The parameters α, β, and $1-\alpha-\beta$ represent the elasticity of output with respect to physical capital, human capital, and labor. We invoke the standard assumption that there are constant returns to scale in the reproducible factors, i.e., $\alpha + \beta = 1$.

Consistent with the literature analyzing urban productivity (see, e.g., Sveikauskas, 1975; Carlino and Voith, 1992), we assume that the agglomeration effects of density (D) operate through the Hicks-neutral technology parameter (A) as follows:

$$A_{ij} = \gamma_0 D_{ij}^{\gamma_1} \tag{2}$$

where γ_1 represents the elasticity of output with respect to density and γ_0 denotes other factors of the technology parameter that are independent of density. Importantly, the parameter γ_1 measures the net agglomeration effect of density, which incorporates both the (positive) spillovers and (negative) congestion effects arising from density. Thus, the sign of this parameter will depend on the relative strength of each opposing force.

It is well known that data measuring the regional stock of physical capital are not available at the required level of geography, and, because of the durability of physical capital, attempts to construct such measures are likely to introduce measurement bias in cross-sectional studies of urban productivity (Moomaw, 1981). We address this problem by assuming that the rental price of capital (r_k) is the same everywhere within a larger region j containing several metropolitan areas, and then use the capital-demand function to substitute the factor price for the factor quantity. That is, solving (1) for the marginal product of capital in region j and equating it to the rental price of capital gives:

$$r_{kj} = A_{ij}\alpha K_{ij}^{\alpha-1} H_{ij}^{\beta} L_{ij}^{1-\alpha-\beta} \tag{3}$$

The capital-demand function for metropolitan areas in this larger region can be derived by substituting (1) into (3) and solving for K_{ij}, which yields:

$$K_{ij} = \frac{\alpha Y_{ij}}{r_{kj}} \tag{4}$$

This capital-demand function can then be used to substitute for the amount of physical capital in (1). Doing so, substituting (2), and solving for average labor productivity gives:

$$\frac{Y_{ij}}{L_{ij}} = \phi_j D_{ij}^{\frac{\gamma_1}{1-\alpha}} \left(\frac{H_{ij}}{L_{ij}}\right)^{\frac{\beta}{1-\alpha}} \tag{5}$$

where ϕ_j is a constant that depends on the rental price of capital in the larger region j, and thus may vary across larger regions.[4]

Taking the logarithmic transformation of (5) yields the first equation we will estimate:

$$\log\frac{Y_{ij}}{L_{ij}} = \log\phi_j + \frac{\gamma_1}{1-\alpha}\log D_{ij} + \frac{\beta}{1-\alpha}\log\frac{H_{ij}}{L_{ij}} \tag{6}$$

Consistent with the estimating equations relied upon in the existing literature (Ciccone and Hall, 1996; Ciccone, 2002), equation (6) relates urban productivity to density and regional stocks of human capital, but does not allow for the interaction of

4 Spatial equilibrium requires that individual utility and firm profits be equalized across space. Thus, the idea that productivity will be higher in denser metropolitan areas when $\gamma_1 > 0$ raises the question of why some people or firms choose to locate in low-density metropolitan areas. While not explicitly part of our theoretical framework, differences in preferences and the price of land or housing can explain why people and firms continue to locate in less-dense areas despite the productivity advantages of physical proximity.

density and human capital. While density can enhance labor productivity by increasing the frequency of physical interactions and face-to-face contact, the amount of human capital in a region is likely to influence the quality of these interactions. Thus, if learning and knowledge spillovers are important, increasing the interaction of highly skilled people within a fixed geographic area is likely to result in more innovation and provide a greater boost to productivity than increasing the density of those with lower skills. To account for this possibility, our model departs from those established in the existing literature in that we allow the agglomeration effect of density to increase with higher stocks of metropolitan area human capital. Formally, we assume the elasticity of output with respect to density varies with human capital as follows:

$$\gamma_{1ij} = \delta_0 + \delta_1 \log \frac{H_{ij}}{L_{ij}} \qquad \delta_1 > 0 \tag{7}$$

where δ_1 represents the contribution of human capital to the net agglomeration effect of density and δ_0 denotes other factors of this parameter that are independent of human capital. The assumption that $\delta_1 > 0$ implies that the density and human capital are complements in production. Substituting γ_{1ij} from (7) for γ_1 in (6) yields our second estimating equation:

$$\log\frac{Y_{ij}}{L_{ij}} = \log\phi_j + \frac{\delta_0}{1-\alpha}\log D_{ij} + \frac{\delta_1}{1-\alpha}(\log D_{ij})(\log\frac{H_{ij}}{L_{ij}}) + \frac{\beta}{1-\alpha}\log\frac{H_{ij}}{L_{ij}} \tag{8}$$

Estimation of equations (6) and (8) requires detailed data on density, regional stocks of human capital, and output per worker measured at the metropolitan area level, which until recently were not available.

III. EMPIRICAL ANALYSIS OF URBAN PRODUCTIVITY

Our empirical analysis relates measures of density and human capital to output per worker at the metropolitan area level. Cross-country studies that employ a similar empirical framework have been criticized for failing to account for differences in legal and political institutions, cultural attitudes, and social norms. Hall and Jones (1999) present compelling evidence that differences in social infrastructure explain a large amount of the differences in capital accumulation, productivity, and output observed across countries. By focusing our analysis on metropolitan areas within the same country, we minimize this source of heterogeneity. Another advantage of using the metropolitan area as the unit of analysis is that it more closely reflects the local labor markets where knowledge spillovers and related synergies that boost productivity are most likely to occur. Moreover, metropolitan areas represent a more meaningful economic unit of observation than countries since there are far fewer arbitrary or institutional limitations on labor and capital mobility.

A. *Data, Variables, and Descriptive Statistics*

Table 1 presents descriptive statistics for the main variables used in the study. Because GDP data are now available at the metropolitan area level, we are able to use these geographic areas as the unit of observation for our analysis.[5] As such, we are able to construct a comprehensive dataset incorporating all 363 metropolitan areas in the United States by collecting data at the county level and then aggregating to the metropolitan area. Thus, our study is more comprehensive and at a finer level of geography than the most comparable previous research focusing on agglomeration in the United States.

[5] Metropolitan area definitions, based on county aggregates, correspond to those issued by the Office of Management and Budget, and were last revised in December 2006.

Our measure of urban productivity is average output per worker between 2001 and 2005.[6] This variable is constructed using data on metropolitan area GDP and total employment published by the U.S. Bureau of Economic Analysis (BEA). We use average output per worker over this five-year time interval in an effort to account for fluctuations in the business cycle, as the time period for which metropolitan area GDP data are available includes a recession year (2001) and the expansion that followed (2002 through 2005). On average, output per worker averaged nearly $56,000 in U.S. metropolitan areas during this period.

Table 2 presents a ranking of the top and bottom 20 U.S. metropolitan areas based on average output per worker between 2001 and 2005. With an average output per worker of nearly $115,000, the Bridgeport-Stamford-Norwalk, CT metropolitan area ranks highest among metropolitan areas based on this metric. Also among the top 20 metropolitan areas are a number of familiar places (e.g., San Jose and San Francisco, CA; New York City; Washington, DC; Boston, MA) and a few unexpected locations (e.g., Casper, WY; Lake Charles, LA). The lowest ranking U.S. metropolitan area based on output per worker is Logan, UT, which has an average output per worker of just under $36,000—one-third of that observed in the highest-ranked metropolitan area.

Because theories of learning and knowledge spillovers emphasize physical interaction as the mechanism through which information and ideas are spread, we utilize a measure of density that captures the proximity of people within metropolitan areas. We also focus on a population-based measure of density, rather than employment-based

[6] While this information is updated as more recent figures become available, we focus our attention on the 2001 to 2005 time period as the data for these years are final estimates, and therefore represent the most accurate information currently available. See U.S. Bureau of Economic Analysis (2009) and Panek, Baumgardner, and McCormick (2007) for more information.

measures, as the exchange of information and ideas need not be confined to places of employment. Data on population and land area are drawn from the 2000 Census. Our measure of population density is calculated as the population-weighted average of county-subdivision densities, which represents the crowdedness experienced by the typical person in a metropolitan area (Glaeser and Kahn, 2004; Rappaport, 2008). By contrast, un-weighted population density measures provide the density experienced by the average unit of land. Population density, as experienced by the typical person in U.S. metropolitan areas, averaged 1,240 people per square mile in 2000, compared to 265 people per square mile using an un-weighted measure.[7]

As shown in Figure 2, which highlights the Boston, Denver, Atlanta, and Indianapolis metropolitan areas, population tends to be distributed quite unevenly within U.S. metropolitan areas, although to varying degrees. For example, Boston's measured population density increases from 1,252 to 4,978 people per square mile when weighted by county-subdivision, an increase in rank from 9th to 6th overall. Perhaps more strikingly, Denver's measured population density increases from 258 to 2,691 people per square mile, an increase in rank from 121st to 27th overall. Of course, some metropolitan areas, such as Atlanta and Indianapolis, tend to fall in the rankings even though their measured population density increases when using a weighted measure. Thus, simple measures of density tend to understate the actual crowdedness experienced by most of the people living and working in metropolitan areas. Our measure adjusts for this problem by using county-subdivision densities to account for the spatial distribution of population within metropolitan areas. In addition, as the Denver example illustrates, the use of a

[7] The correlation between the raw and weighted population density measures is 0.80, while the Spearman rank correlation is 0.60.

weighted density measure mitigates the problem caused by the presence of large, but sparsely populated counties as the relatively small weights assigned to the county-subdivisions that comprise these places reduce their influence.

Finally, to measure the human capital stock in U.S. metropolitan areas, we scale the number of people in each metropolitan area with a college degree by the working age population using data from the U.S. Census for 2000. While this education-based measure of human capital likely fails to capture the full array of knowledge and skills within a metropolitan area, it is a conventional measure of human capital that has been linked to a number of measures of regional vitality (see, e.g., Glaeser, Scheinkman, and Shleifer, 1995; Glaeser and Saiz, 2004; and Rosenthal and Strange, 2008a; and Bauer, Schweitzer, and Shane, 2011).[8] We focus on this dimension of educational attainment because, to the extent that knowledge spillovers boost urban productivity, the existing empirical research indicates that human capital-based externalities are likely to be more important at the higher end of the educational attainment spectrum, i.e., college graduates, than at the lower end, i.e., those completing only high school or less formal education (Rauch, 1993; Acemoglu and Angrist, 2000; Moretti, 2004).

Before turning to a more formal empirical analysis that allows us to estimate the parameters of our model, it is informative to examine productivity differences across U.S. metropolitan areas at different levels of density and human capital. Table 3 shows the average output per worker for metropolitan areas classified as either high or low density and high or low human capital using the mean values of each measure as the cutoff

8 While beyond the scope of this paper focusing on productivity enhancing effects of density, alternative measures of regional human capital have been developed using occupation clusters or by measuring the knowledge and skills required to perform a job. Recent examples include Florida, Mellander, and Stolarick (2008); Bacolod, Blum, and Strange (2009, 2010); and Abel and Gabe (2011).

between groupings. For metropolitan areas classified as "Low Human Capital," moving from "Low Density" to "High Density" is associated with a $3,363 increase in productivity. By comparison, this difference in productivity increases to $8,342 for metropolitan areas classified as "High Human Capital"—a difference of nearly $5,000. Thus, even at the most basic level, these descriptive statistics are consistent with the idea that the density of human capital is an important determinant of productivity in U.S. metropolitan areas.

B. Estimation Approach

We exploit the cross-sectional variation in output per worker that exists across U.S. metropolitan areas to estimate equations (6) and (8). The stochastic specification of our first estimating equation is:

$$\log y_{ij} = \theta \log D_{ij} + \eta \log h_{ij} + \sigma_j + u_{ij} \tag{9}$$

where y_{ij} is output per worker, D_{ij} is a measure of density, h_{ij} is a measure of the regional human capital stock, $\theta = \frac{\gamma_1}{1-\alpha}$ is the elasticity of average labor productivity with respect to density, $\eta = \frac{\beta}{1-\alpha}$ is the elasticity of average labor productivity with respect to the regional human capital stock, and u_{ij} is an error term that captures differences between total factor productivity in metropolitan area i and the larger region j in which it is contained. State-level spatial fixed effects, σ_j, are included in the model to control for differences in total factor productivity, rental prices of capital, and any resulting differences in physical capital intensity between U.S. states.[9]

[9] When a metropolitan area crosses state boundaries, we assign it to the state in which the largest city within the metropolitan area is located.

Similarly, the stochastic specification of our second estimating equation is expressed as follows:

$$\log y_{ij} = \theta_0 \log D_{ij} + \theta_1 (\log D_{ij})(\log h_{ij}) + \psi \log h_{ij} + \sigma_j + \varepsilon_{ij} \qquad (10)$$

where $\theta_0 = \frac{\delta_0}{1-\alpha}$, $\theta_1 = \frac{\delta_1}{1-\alpha}$, and $\psi = \frac{\beta}{1-\alpha}$, and ε_{ij} is an error term as before. Given this specification, the elasticity of average labor productivity with respect to density is derived using the mean human capital stock, i.e., $\theta = \theta_0 + \theta_1 \log \overline{h}$, as this parameter will vary with the interaction term.

Our model of urban productivity assumes that output is homogenous across metropolitan areas. However, inspection of Tables 1 and 2 indicates that considerable variation exists in what metropolitan areas make and suggests that such differences are likely to influence measured productivity, which would bias our results if denser places also tend to specialize in the production of high value-added goods and services. For example, metropolitan areas with a large share of their output in finance (e.g., Bridgeport-Stamford-Norwalk, CT; Charlotte, NC; New York City), information technology (e.g., San Jose, CA; Seattle, WA; Boston, MA), and natural-resource intensive activities (e.g., Houston, TX; Lake Charles, LA; and Casper, WY) are among the most productive metropolitan areas in the United States. People with unobserved skill differences are likely to sort into these metropolitan areas based, in part, on where they earn the highest return.

To address this potential identification problem, we implement a two-step estimation approach, similar to that proposed by Combes et al. (2008, 2010), to account for potential sorting effects by individuals and firms. However, because we do not have value-added data at the individual or firm level, we must make our adjustment using more aggregate metropolitan area-level data. In the first step of our estimation, we regress our measure of average labor productivity, log y_{ij}, on the share of employment in ten major industry sectors, and obtain the portion of average labor productivity that is unexplained by the industry structure of a metropolitan area, log y_{ij}'.[10] Doing so allows us to condition out any sectoral effects, including those associated with sorting, that may exist in the original productivity data. Then, in the second step, we use this adjusted measure to represent the amount of homogeneous output (i.e., accounting for industrial composition) per worker.

We begin our analysis by estimating equations (9) and (10) using ordinary least squares (OLS) for each measure of urban productivity, and then later re-estimate these equations with our sector-adjusted measure of urban productivity using an instrumental variables approach to investigate the direction and magnitude of potential bias arising from the endogeneity of density. Given our econometric specification, coefficient estimates can be readily interpreted as elasticities, which allows for direct comparison to prior work. Finally, because the metropolitan area GDP figures we rely on to construct our measures of output per worker are derived by the U.S. BEA, in part, using state-level GDP data, error terms between metropolitan areas in the same state may be correlated. As such, we compute and report robust standard errors that are clustered at the state level.

[10] Industry employment shares were constructed using data on private, government, and total employment by metropolitan area in 2000 provided by the Regional Economic Information System of the U.S. Bureau of Economic Analysis. Due to data limitations largely related to confidentiality considerations, the "Agricultural Services, Forestry, and Fishing" and "Mining" categories were combined into a single category we label "Agricultural and Mining" and estimation was required to compute a complete set of industry shares for some metropolitan areas. Thus, the sectors included in our analysis are: Agricultural and Mining; Construction; Farm (i.e., value of production, which is distinct from agricultural services); Finance, Insurance, and Real Estate; Government; Manufacturing; Retail Trade; Services; Transportation and Public Utilities; and Wholesale Trade. Descriptive statistics are reported in Table 1.

Clustering at the state level tends to increase the coefficient standard errors, which reduces their associated level of significance, but does not affect the coefficient estimates.

C. Aggregate Productivity Results

Table 4 presents the results of our regression analysis related to the productivity enhancing effects of density. Columns (1) and (2) shows OLS results using the unadjusted measure of urban productivity, log y_{ij}, as our dependent variable, first when the effects of density and human capital are estimated separately, i.e., equation (9), and then when the interaction of density and human capital is included, i.e., equation (10). Overall, our baseline empirical models perform quite well, explaining more than half of the variation in the natural logarithm of output per worker across U.S. metropolitan areas. In addition, the expected relationships hold at conventionally accepted levels for all of the variables included in our models. Importantly, we find a positive and statistically significant effect from the interaction of density and human capital, consistent with theories emphasizing the importance of learning and knowledge spillovers in cities. Interpreting the initial results shown in Table 4, we find that a doubling of density is associated with a 9.7 percent increase in productivity.

Assessing the average effect of density when an interaction term is present requires calculating the coefficient at the mean level of human capital. When this is done, we again find that a doubling of density is associated with a 9.7 percent increase in productivity. However, the magnitude of this relationship varies by 8.7 percentage points (i.e., 13.4 percent relative to 4.8 percent) when comparing a metropolitan area with a human capital stock that is one standard deviation above the mean to one with a human capital stock that is one standard deviation below the mean. The magnitude of this change in θ—what we label the density of human capital—can be interpreted as a measure of the strength of the complementarity between density and skill.

Our baseline results are similar to those reported by Glaeser and Resseger (2010), who find that a doubling of population size is associated with a 9.8 increase in productivity when population size and human capital are treated as independent variables and an 8.0 percent increase in productivity when these variables are interacted. Building from these baseline results, we extend our analysis to account for potential biases arising from differences in the industrial composition of metropolitan areas. Columns (3) and (4) show corresponding OLS results when our sector-adjusted measure of urban productivity, log y_{ij}', is used as the dependent variable.[11] As before, our empirical models continue to perform quite well, with R-squared values exceeding 0.30 and the expected relationships holding at conventional levels for the variables in our models. However, after adjusting for differences in what is made in metropolitan areas, the estimated effect of density on urban productivity falls to 1.9 percent, on average, in both models—one-fifth of our baseline estimates. Thus, failing to account for industry composition effects appears to overstate the magnitude of urban agglomeration economies.

Consistent with the idea that the agglomeration effect of density is enhanced by a metropolitan area's human capital stock, we continue to find that the interaction of population density and human capital has a positive and statistically significant effect on urban productivity. Panel (a) of Figure 3 plots the productivity effect from doubling population density at different human capital stock levels based on estimates from Column (4) in Table 4, and shows that metropolitan areas with a human capital stock that

[11] The correlation between the raw and sector-adjusted measures of urban productivity is 0.73, while the Spearman rank correlation is 0.70.

is one standard deviation below the mean realize no productivity gain (i.e., -0.5 percent compared to 1.9 percent), while doubling density in metropolitan areas with a human capital stock that is one standard deviation above the mean yields productivity benefits that are nearly two times larger than average (i.e., 3.6 percent compared to 1.9 percent).[12]

Our OLS estimation assumes that population density and the productivity of metropolitan areas are exogenous when state-level spatial fixed effects capturing differences in total factor productivity and physical capital intensity at the state level are included in the estimation. However, if these spatial fixed effects do not capture fully differences in metropolitan area productivity, our OLS estimates may be biased. Specifically, because of the availability of higher wages, the most productive metropolitan areas might be able to attract more people, which subsequently increases density. To assess the effects of this potential concern, we re-estimate our regression models using an instrumental variables approach and perform Wu-Hausman tests for endogeneity bias.

Implementing instrumental variables estimation requires that we identify variables that are correlated with density (i.e., relevant) but unrelated to modern differences in productivity across metropolitan areas (i.e., exogenous). We consider a set of two such variables to instrument for population density: population size in 1900 and a climate index based on temperature and precipitation.[13] The logic of our first instrumental

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[12] As a robustness check, we re-estimated our regression models using employment density in place of weighted population density, which are highly correlated ($r = 0.79$) measures of density. When the employment-based measure is used in the regression analysis, the average estimated productivity effect of doubling density ranged from 11 percent (compared to 10 percent) in the baseline models to 3 percent (compared to 2 percent) in the models that account for industry composition effects, with similar patterns of variation around the average effect arising from the complementarity between density and skill.

[13] Historical population figures are derived using county-level data published by the U.S. Census. The data for our climate index are drawn from the *2007 County and City Data Book* published by the U.S.

variable, which has been used extensively in the existing literature, rests on the assumption that historical sources of agglomeration in the United States have remaining influences only on the preferences of where people live, rather than through modern differences in productivity. Similarly, the logic of our second instrumental variable is that climate, a valuable consumption amenity, also primarily influences the preferences of where people choose to live. Indeed, recent research has shown that U.S. residents migrated to places with nice weather throughout most of the 20th century, and that much of this movement was driven by an increased valuation of climate as a consumption amenity (Rappaport, 2007). In addition, because population density is part of the interaction term in our key estimation equation, we must also identify additional instruments to examine the endogeneity of the interaction term itself. A natural set of instrumental variables for the interaction term is the interaction of our existing instruments, population in 1900 and climate, with the remaining component of the interaction term, the human capital stock (Wooldridge, 2002).

Columns (5) and (6) of Table 4 report the results of our instrumental variables regression analysis.[14] First-stage regression results (not reported) show that the population density of a metropolitan area is positively related to its size in 1900 and negatively related to our climate index, indicating that warm, dry places tend to be more

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Census, and correspond to the central city within each metropolitan area. We use the annual number of heating degree days and annual amount of precipitation, averaged over the period 1971-2000, to construct our climate index. To develop relative measures of temperature and precipitation, we first scale each variable by the average value and then normalize each variable so the maximum value equals 100. Our climate index is an evenly weighted sum of these two measures, renormalized to a 100-scale. Higher values of the index indicate a relatively cold and wet climate, while lower values of the index indicate a relatively warm and dry climate. Descriptive statistics are provided in Table 1.

[14] We employ LIML for our instrumental variables regression analysis as Stock and Yogo (2005) demonstrate that it is superior to 2SLS in the presence of weak instruments. However, results using conventional 2SLS are nearly identical to those obtained with LIML.

densely populated. Thus, consistent with expectations, historical measures of population and climate both appear to be strong predictors of a metropolitan area's population density in 2000. However, a key advantage of using multiple instrumental variables is that it allows us to test formally their validity. As the bottom panel of Table 4 shows, the first stage Cragg-Donald Wald *F*-statistic for the excluded instruments is 49.11 when density is treated as endogenous and 14.71 when both density and the interaction term are treated as endogenous. Therefore, we can reject the null hypothesis of weak instruments based on the Stock and Yogo (2005) test.[15] Moreover, with *p*-values of 0.779 and 0.297, respectively, Sargan tests of over-identifying restrictions indicate that our instruments are also uncorrelated with the error term.[16] As our instruments meet both the relevance and exogeneity conditions, we conclude that they are valid.

Turning now to our parameter estimates, the general pattern of results from the second-stage regressions are consistent with those obtained using OLS estimation. On average, a doubling of density increases urban productivity by about 4.0 percent in models without the interaction term, reported in Columns (5), and by 2.6 percent in models with the interaction term, reported in Columns (6). Further, the interaction of density and human capital remains positive and significant when treating both density and the interaction term as endogenous.

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[15] Stock and Yogo (2005) develop a weak instrument test that compares the Cragg-Donald Wald *F*-statistic from the two-stage regression model to a critical value that depends on the number of endogenous variables, number of instruments, and the tolerance for the "size distortion" of a test ($\alpha =$ 0.05) of the null hypothesis that the instruments are weak. The size distortion tolerance (e.g., 10 percent) accounts for the idea that using the weakest combination of instruments might lead to a conclusion of biased second-stage estimates (from a Wald test), whereas using the entire group of instruments does not.

[16] This test of overidentifying restrictions is computed as N x R^2, where N is the number of observations and R^2 is computed from a regression of the residuals from the second stage regression on all exogenous variables and the instruments. The test statistic is distributed χ^2 with degrees of freedom equal to the number of overidentifying restrictions, in our case one or two depending on the model specification.

Panel (b) of Figure 3 plots the productivity enhancing effect of doubling density at different human capital stock levels based on these IV estimates, and shows a pattern similar to that described previously, although the slope of the relationship is a bit steeper when compared to analogous OLS estimates. Again, metropolitan areas with a human capital stock that is one standard deviation below the mean realize no productivity gain (i.e., -1.0 percent compared to 2.6 percent), while doubling density in metropolitan areas with a human capital stock that is one standard deviation above the mean yields productivity benefits that are two times larger than average (i.e., 5.3 percent compared to 2.6 percent).

The fact that the point estimates we obtain using instrumental variables are slightly larger than our OLS estimates is consistent with the presence of a small amount of measurement error. However, across both model specifications, Wu-Hausman tests indicate that our instrumental variables estimates do not systematically differ from our OLS estimates. These findings are consistent with those set forth in the existing literature, where accounting for the potential endogeneity of density typically does not yield noticeable changes in the size of urban agglomeration estimates (Melo, Graham, and Noland, 2009).[17]

[17] As an additional robustness check of our results pertaining to the effects of density on urban productivity, we also considered the possibility that, along with population density, a metropolitan area's human capital stock may be endogenously determined. Similar to Moretti (2004) and Wheeler (2004), we expanded the instrument set to include variables related to the presence of a land grant university and lagged age structure of metropolitan areas. In general, the expanded instrument sets we considered continued to pass the Stock and Yogo weak instrument test and Sargan over-identification test, confirming the validity of such instruments. In addition, the resulting second-stage point estimates were consistent with those obtained using OLS estimation and quite similar to the IV estimates reported in Table 4. However, as is common with instrumental variables analysis of this nature, expanding the number of endogenous variables increased the standard errors of our estimates by a factor of two to four. Wu-Hausman tests confirmed that these IV estimates, accounting for the potential endogeneity of human capital, did not systematically differ from the OLS estimates.

D. Magnitude of Net Agglomeration Effect

Our model of urban productivity allows us to estimate the net agglomeration effect of density, γ_1, by combining the estimates of θ presented above with an estimate of the income share of physical capital, α, which is widely believed to be around 0.3 (Mankiw, Romer, and Weil, 1992; Ciccone, 2002). Based on the OLS estimates, we find an average net agglomeration effect of density of 1.3 percent. Consistent with the existing literature, this result indicates that, on average, the (positive) spillover effects of density are more important than any (negative) congestion effects. However, because the spillover effects of density are enhanced by a metropolitan area's human capital stock due to the quality of interactions, the net agglomeration effect of density will also vary. According to our estimates, the congestion effect of density offsets any positive spillover effect for metropolitan areas with a human capital stock about one standard deviation below the mean (i.e., -0.3 percent compared to 1.3 percent). By contrast, metropolitan areas with a human capital stock one standard deviation above the mean realize twice the net agglomeration effect of density (i.e., 2.5 percent compared to 1.3 percent). Thus, our analysis indicates that density helps boost economic activity in metropolitan areas with a high concentration of highly-skilled people.

E. Source of Productivity Effect

Our empirical results provide evidence that density and human capital work in combination to shape the aggregate productivity of metropolitan areas. However, it is likely that these forces have differential effects depending on the type of output produced. If so, examining the relationship between the productivity of different industry sectors and the density of a region's human capital stock may provide a window into the underlying source of these urban agglomeration economies, which is an important unresolved issue.

To undertake such an analysis, we utilize industry-level metropolitan area GDP and employment data published by the U.S. BEA to calculate average output per worker between 2001 and 2005 for 17 industry sectors, and then use these variables to estimate equation (10) separately for each industry sector. Our intent here is to provide a first look at the relative effects of density—and its interaction with human capital—on productivity across the industry sectors, with less attention paid to some of the measurement and endogeneity issues examined in the analysis of aggregate urban productivity. A more detailed analysis of industry-level productivity, beyond the scope of the current paper, is hindered by the limited availability of data in some metropolitan areas and issues related to identifying valid instrument sets for each of the industry sectors.[18]

Thus, given the limitations described above and the exploratory nature of this analysis, we restrict our attention to OLS models of industry productivity. Table 5 shows the regression results for this industry-specific analysis. As with our aggregate analysis, the model continues to perform well, in some cases explaining well over one-half of the variation in an industrial sector's productivity. Moreover, tests of joint significance show that density is a significant determinant of urban productivity for all of the industry sectors considered except Agricultural and Mining, and Transportation and Utilities.

Figure 4 provides a summary of our industry-specific findings relative to the aggregate results discussed previously, focusing on the 15 industry sectors for which density was found to be an important determinant of urban productivity. Along the

[18] Due to data disclosure limitations, GDP data are not reported in all available years for most sectors at the metropolitan area level, significantly limiting the number of observations available.

horizontal axis, we plot the average elasticity of labor productivity with respect to density for each industry sector. The vertical line at 9.7 percent corresponds to our baseline aggregate urban productivity OLS estimates (see column 2 of Table 4). Density provides a relatively large boost to the productivity of workers in those industry sectors with higher values of this measure. Along the vertical axis, we measure the density of human capital—that is, the change in the elasticity of labor productivity with respect to density for a metropolitan area with a human capital stock one standard deviation above the mean compared to a metropolitan area with a human capital stock that is one standard deviation below the mean—for each industry sector. Again, the horizontal line at 8.7 percentage points, calculated using OLS estimates reported in column 2 of Table 4, corresponds to our baseline aggregate urban productivity estimates. Higher values of this measure identify those industry sectors where the complementarity between density and skill is strongest.

With this framework in place, it is possible to classify each of the industry sectors into quadrants based on the relative importance of density to sector productivity and the relative strength of the complementarity that exists between density and skill. The industry sectors in the upper right quadrant of Figure 4—Professional Services, Arts and Entertainment, Information, and Finance—receive a relatively large boost in productivity from density and exhibit the strongest complementarities between density and skill. These sectors are some of the most innovative, highly creative, and valuable in the U.S. economy. By contrast, those sectors in which density remains an important determinant of urban productivity, but where the density of human capital is less robust—Real Estate, Management, and Wholesale Trade—are contained in the lower right quadrant.

Interestingly, our estimates indicate that density has the largest productivity effect in the Real Estate sector, presumably through its impact on land values, while the complementarity between density and skill in this sector is not significant.

Not surprisingly, we find no industry sectors for which density provides a relatively small boost to productivity with strong complementarities between density and skill. Therefore, the remaining industry sectors fall into the lower left quadrant, where the productivity enhancing effect of density and the complementarity between density and skill is relatively weak. Examples of such sectors include Construction, Manufacturing, Retail Trade, and Education and Health. In addition, Accommodation and Food Services is also part of this quadrant, but like the Management and Real Estate sectors, the complementarity between density and skill is not statistically significant for this sector.

Taken together, this pattern of results is consistent with the knowledge spillover theory of urban agglomeration. That is, the sectors that appear to benefit most from the density of human capital are creative, knowledge-based industries where the exchange of information and sharing of ideas are important parts of the production process. This finding suggests that an important source of the aggregate productivity effect we measure arises from the benefits that physical proximity provides in the transmission of knowledge and ideas among people.

F. Evaluation of Model Performance

Consistent with theories of learning and knowledge spillovers in cities, our empirical results demonstrate that the density of human capital plays an important role in determining the aggregate productivity of a metropolitan area. This insight helps explain the large differences in productivity observed across U.S. metropolitan areas, particularly for the most productive metropolitan areas. Indeed, this finding is consistent with recent theoretical research demonstrating that a non-linear relationship between density and productivity is required to sustain the observed distribution of crowdedness across U.S. metropolitan areas, particularly among the most crowded places (Rappaport, 2008). In our model, such a non-linearity arises because there are larger productivity gains from increasing the physical interaction of highly-skilled people than those with lower skills.

As such, our model of urban productivity, which allows the agglomeration effect of density to increase with a metropolitan area's human capital stock, tends to outperform the empirical specification that does not take this important interaction into account. For example, Boston's average output per worker during the 2001 to 2005 period was just over \$80,000. By comparison, the baseline model predicts Boston's output per worker to be about \$74,000, while the model that includes an interaction term predicts a value of more than \$78,000—a \$4,000 difference that is much closer to the actual value.

To illustrate more generally, Figure 5 provides a comparison of the actual output per worker to a non-linear trend line fit through the predicted values from each of our models for the 50 most productive metropolitan areas in the United States. The trend lines for each model's predicted values are actually quite close for metropolitan areas with output per worker of \$65,000 or less, i.e., those outside the top 50. However, as is clear from the figure, our model incorporating the productivity enhancing effects of the density of human capital does a better job of predicting the large differences in output per worker observed among the most productive metropolitan areas than the baseline model. Importantly, these seemingly small differences in average labor productivity have significant implications for aggregate output as the 50 most productive metropolitan areas produce nearly 60 percent of U.S. gross domestic product. Thus, our findings help contribute to a deeper understanding of the connection between urban productivity and the level of economic activity in the United States more generally.

IV. CONCLUSIONS

As the U.S. economy continues to move away from manufacturing and goods distribution to the production of new ideas, it is important to gain a better understanding of the factors that drive modern productivity. This paper provides new evidence on the productivity enhancing effects of the density of human capital. Specifically, we use recently available information on output per worker at the metropolitan area level along with a measure of density that accounts for the spatial distribution of population within metropolitan areas to estimate a model of aggregate urban productivity in which the agglomeration effect of density is enhanced by a metropolitan area's stock of human capital.

On average, we find that a doubling of density increases metropolitan area productivity by 2 to 4 percent. Thus, our estimates are smaller than the most comparable estimates of 4.5 to 6 percent established in the existing literature, which rely on value-added data from U.S. States and European regions during the late 1980s (Ciccone and Hall, 1996; Ciccone, 2002), but are generally in line with more recent estimates of 2 to 3.5 percent that account for the endogeneity of the quantity and quality of labor using French wage and firm TFP data (Combes et al., 2008, 2010). Consistent with this recent research, we find that potential biases resulting from differences in the industrial composition of metropolitan areas, such as those due to sorting, are qualitatively more important than potential biases related to the joint determination of density and urban productivity. Thus, the finer level of geography used in the analysis along with our ability to account for industrial composition effects yields more precise estimates of the magnitude of aggregate urban agglomeration economies in the U.S. than was previously available.

Further, we demonstrate that the elasticity of average labor productivity with respect to density increases with a metropolitan area's stock of human capital. Consistent with theories of learning and knowledge spillovers in cities, metropolitan areas with a human capital stock one standard deviation below the mean realize no productivity gain, while doubling density in metropolitan areas with a human capital stock one standard deviation above the mean yields productivity benefits that are about twice the average. Moreover, these patterns are particularly pronounced in knowledge-based industries—such as Professional Services, Arts and Entertainment, Information, and Finance—where the exchange of information and sharing of ideas are important parts of the production process. These findings, based on analysis of aggregate metropolitan area productivity, also corresponds to the conclusions set forth by Rosenthal and Strange (2008a, p. 387), based on micro-analysis of wages, who remark that "the positive effect of agglomeration is really due to the presence of human capital." Thus, this research also provides new evidence that learning and knowledge spillovers are an important source of aggregate urban agglomeration economies.

A potential limitation of our analysis, shared by all existing studies of aggregate urban productivity, is that we may not account fully for potential unobserved heterogeneity in skills arising from the spatial sorting of firms and individuals. This issue may be of particular concern as recent empirical research has demonstrated that highly educated professionals in dense cities work longer hours than their counterparts in less crowded places and those without a college degree (Rosenthal and Strange, 2008b). Combes et al. (2008, 2010) argue that existing estimates of agglomeration economies derived from aggregate production functions are upward biased by as much as 50 percent because they fail to account for individual attributes. In contrast, using U.S. data, Glaeser and Mare (2001) find little evidence that sorting biases the urban wage premium. While our research does account for potential biases related to industrial composition effects, further research on the effects of spatial sorting is clearly warranted.

Finally, while our findings are most directly connected to theories of agglomeration emphasizing the role of learning and knowledge spillovers in cities, other mechanisms through which the density of human capital influences productivity may also contribute to our results. In particular, recent empirical research has confirmed that thicker labor markets yield significant productivity benefits by improving the quality of matches between workers and jobs (Andersson, Burgess, and Lane, 2007). Therefore, while our research has established an important connection between aggregate urban productivity and the density of human capital, additional research is required to develop a more complete understanding of the productivity effect we have identified.

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Table 1: Descriptive Statistics

Variable	Mean	Std Dev	Minimum	Maximum
Main Variables				
Output Per Worker	$55,866	$10,535	$35,867	$114,798
Population Density	1,240.0	1,340.7	11.2	18,551.5
Human Capital Stock	21.5%	6.4%	9.0%	48.9%
Industrial Composition				
Agricultural and Mining	2.0%	2.3%	0.1%	20.0%
Construction	5.9%	1.4%	2.2%	11.4%
Farm	2.1%	2.2%	0.0%	15.1%
Finance, Insurance, and Real Estate	6.7%	2.1%	2.9%	21.4%
Government	15.8%	7.1%	5.4%	63.7%
Manufacturing	12.3%	6.8%	1.6%	46.9%
Retail Trade	17.6%	2.1%	10.3%	27.4%
Services	29.3%	5.2%	12.8%	55.1%
Transportation and Public Utilities	4.4%	1.6%	1.7%	16.8%
Wholesale Trade	3.9%	1.3%	0.5%	7.7%
Instrumental Variables				
Population in 1900	128,415	354,299	381	5,231,448
Climate	63.0	16.6	7.3	100.0

Notes: Output Per Worker is 2001-2005 average. Population Density is calculated using the weighted average of county sub-divisions in each metropolitan area, and is expressed as people per square mile in 2000. Human Capital Stock is calculated as the number of people (25+) with a four-year college degree scaled by working-age population in each metropolitan area in 2000. Industry shares are estimated using employment information for each sector relative to total employment in each metropolitan area in 2000. Population in 1900 is based on county-level Census data aggregated according to current metropolitan area definitions. Climate is represented as an index constructed using information on heating degree days and precipitation for each metropolitan area for the period 1971-2000. Based on 363 observations.

Sources: Current Dollar Gross Domestic Product by Metropolitan Statistical Area, U.S. Bureau of Economic Analysis; Total Employment by Industry (SA25), U.S. Bureau of Economic Analysis; *2007 County and City Data Book*, U.S. Bureau of Census; United States Census (2000), U.S. Bureau of Census.

Table 2: Average Output Per Worker for Top and Bottom 20 U.S. Metropolitan Areas, 2001-2005

Rank	MSA	Average Output Per Worker
1	Bridgeport-Stamford-Norwalk, CT	$114,798
2	San Jose-Sunnyvale-Santa Clara, CA	$101,306
3	Charlotte-Gastonia-Concord, NC-SC	$95,161
4	New York-Northern New Jersey-Long Island, NY-NJ-PA	$92,560
5	San Francisco-Oakland-Fremont, CA	$90,143
6	Houston-Sugar Land-Baytown, TX	$88,327
7	Anchorage, AK	$84,302
8	Washington-Arlington-Alexandria, DC-VA-MD-WV	$83,887
9	Seattle-Tacoma-Bellevue, WA	$80,945
10	Casper, WY	$80,851
11	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	$80,400
12	Dallas-Fort Worth-Arlington, TX	$80,335
13	Boston-Cambridge-Quincy, MA-NH	$80,079
14	Chicago-Naperville-Joliet, IL-IN-WI	$77,303
15	Hartford-West Hartford-East Hartford, CT	$77,281
16	Lake Charles, LA	$77,235
17	Atlanta-Sandy Springs-Marietta, GA	$76,772
18	Detroit-Warren-Livonia, MI	$76,575
19	Farmington, NM	$76,475
20	Denver-Aurora, CO	$76,385
344	Florence-Muscle Shoals, AL	$42,911
345	Johnstown, PA	$42,877
346	Lawrence, KS	$42,790
347	Abilene, TX	$42,519
348	Lewiston, ID-WA	$42,507
349	Pocatello, ID	$42,452
350	Flagstaff, AZ	$42,450
351	Grand Forks, ND-MN	$42,375
352	Grand Junction, CO	$42,368
353	Lake Havasu City-Kingman, AZ	$42,322
354	Idaho Falls, ID	$42,229
355	College Station-Bryan, TX	$42,113
356	Hot Springs, AR	$41,819
357	Cumberland, MD-WV	$41,452
358	State College, PA	$41,414
359	St. George, UT	$40,426
360	Prescott, AZ	$40,212
361	McAllen-Edinburg-Mission, TX	$38,044
362	Brownsville-Harlingen, TX	$36,833
363	Logan, UT-ID	$35,867

Sources: Current Dollar Gross Domestic Product by Metropolitan Statistical Area, U.S. Bureau of Economic Analysis; Total Employment by Industry (SA25), U.S. Bureau of Economic Analysis.

Table 3: Average Output Per Worker According to Density and Human Capital Classifications

	Low Density	High Density	Difference
Low Human Capital	$51,014	$54,376	$3,363 **
High Human Capital	$56,293	$64,634	$8,342 **
		Difference-in-Difference:	$4,979 **

Notes: Metropolitan areas with population density or human capital stock greater than or equal to the mean are classified as "High Density" or "High Human Capital," respectively, while all others are classified as "Low Density" or "Low Human Capital." ** indicates difference is statistically significant at the .05 level. Based on 363 metropolitan areas.

Sources: Current Dollar Gross Domestic Product by Metropolitan Statistical Area, U.S. Bureau of Economic Analysis; Total Employment by Industry (SA25), U.S. Bureau of Economic Analysis; United States Census (2000), U.S. Bureau of Census.

Table 4: Density and Aggregate Productivity Estimation Results

	OLS				IV	
	(1)	(2)	(3)	(4)	(5)	(6)
	log *y*		log *y* '			
Population Density	0.097 ***	0.329 ***	0.019 **	0.128 ***	0.041 *	0.196 ***
	(0.012)	(0.059)	(0.009)	(0.036)	(0.021)	(0.046)
Interaction Term	--	0.151 ***	--	0.071 ***	--	0.110 ***
		(0.037)		(0.022)		(0.032)
Human Capital Stock	0.202 ***	-0.791 ***	0.086 ***	-0.382 **	0.062 **	-0.650 ***
	(0.036)	(0.250)	(0.024)	(0.145)	(0.028)	(0.208)
Adjusted-R^2	0.478	0.536	0.315	0.337	--	--
Average Elasticity of Labor Productivity wrt Density (θ)	9.7%	9.7%	1.9%	1.9%	4.1%	2.6%
Average Net Agglomeration Effect (γ_1)	6.8%	6.8%	1.3%	1.3%	2.8%	1.8%
Endogenous	--	--	--	--	Density	Density, Interaction
Instrument Set	--	--	--	--	P1900, Climate	P1900, Climate, P1900xHC, ClimatexHC
Cragg-Donald Wald *F*-statistic for Weak Instrument Test	--	--	--	--	49.11 +	14.71 +
Stock and Yogo 10% Maximal LIML Size Threshold					8.68	4.72
Sargan χ^2 Statistic for Overidentification Test	--	--	--	--	0.08	2.43
(*p*-value)					0.779	0.297
Wu-Hausman χ^2 Statistic for Endogeneity Test	--	--	--	--	1.88	2.87
(*p*-value)					0.171	0.238

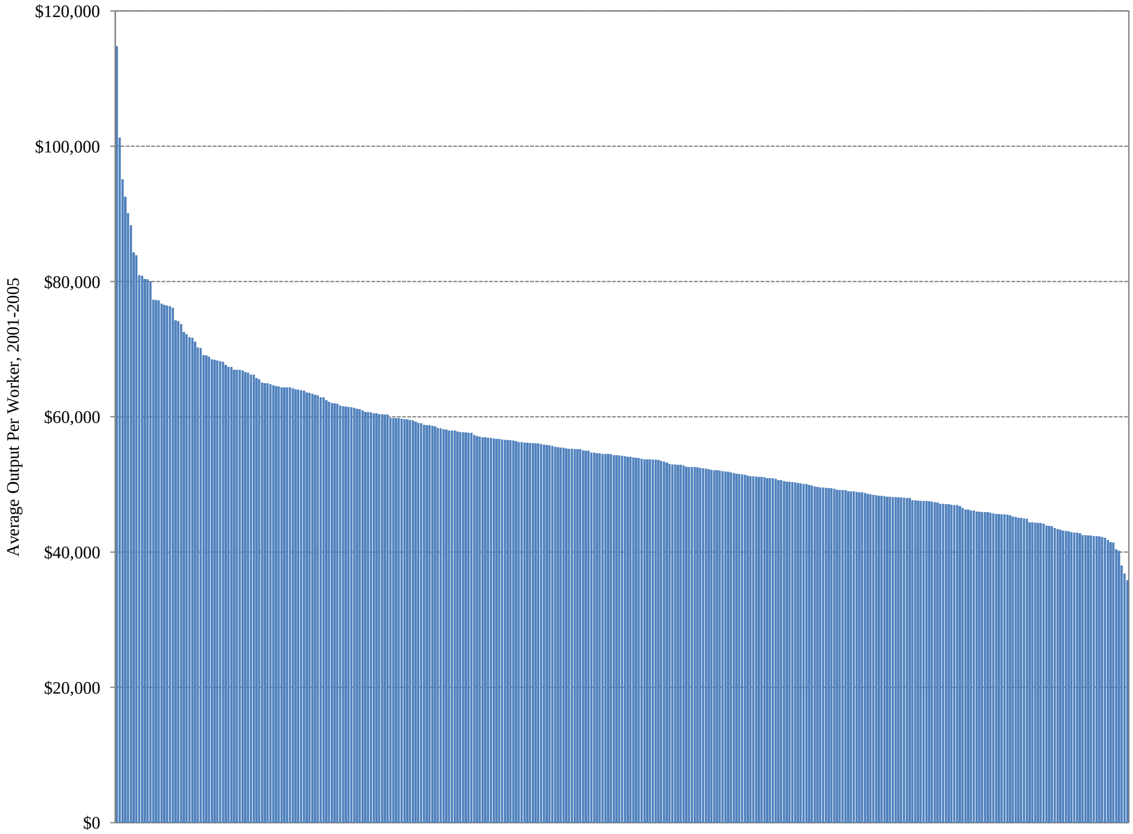
Notes: Robust standard errors clustered at the state level are reported in parentheses. ***, **, and * denote significance at the .01, .05, and .10 levels, respectively. All continuous variables, except climate, are included in log form in regressions. State-level spatial fixed effects are included in all models; these coefficients and the full results from the first stage regressions are omitted for brevity. IV estimates obtained using limited information maximum likelihood (LIML) estimator. + denotes that we can reject the null hypothesis of weak instruments based on the Stock and Yogo (2005) test (α = 0.05) using the 10% maximal LIML size threshold. Based on 363 observations.

Table 5: Density and Industry Sector Productivity Estimation Results

Industry Sector	Population Density	Interaction	Human Capital	Adjusted-R^2	N
Accomodation and Food Services	0.081 *	0.027	0.114	0.598	285
	(0.046)	(0.026)	(0.178)		
Administrative	0.257 ***	0.108 ***	-0.465 ***	0.430	248
	(0.042)	(0.026)	(0.176)		
Agricultural and Mining	0.358	0.190	-1.126	0.222	110
	(0.260)	(0.170)	(1.065)		
Arts and Entertainment	0.389 ***	0.163 **	-1.015 **	0.304	285
	(0.108)	(0.064)	(0.422)		
Construction	0.228 ***	0.092 ***	-0.430 ***	0.541	327
	(0.039)	(0.025)	(0.167)		
Education and Health	0.084 **	0.043 *	-0.166	0.459	224
	(0.837)	(0.024)	(0.164)		
Finance	0.411 ***	0.192 ***	-0.998 ***	0.657	324
	(0.058)	(0.036)	(0.236)		
Government	0.121 ***	0.043 **	-0.204	0.428	363
	(0.031)	(0.020)	(0.140)		
Information	0.506 ***	0.249 ***	-1.315 ***	0.391	300
	(0.075)	(0.046)	(0.302)		
Management	0.264 **	0.078	-0.224	0.388	202
	(0.264)	(0.062)	(0.409)		
Manufacturing	0.202 ***	0.084 *	-0.345	0.328	338
	(0.070)	(0.050)	(0.323)		
Other Services	0.190 ***	0.098 ***	-0.508 ***	0.677	345
	(0.035)	(0.023)	(0.153)		
Professional Services	0.392 ***	0.154 ***	-0.764 ***	0.453	249
	(0.049)	(0.030)	(0.201)		
Real Estate	0.221 **	0.036	0.301	0.503	324
	(0.110)	(0.065)	(0.438)		
Retail Trade	0.174 ***	0.084 ***	-0.422 ***	0.627	358
	(0.029)	(0.018)	(0.121)		
Transportation and Utilities	0.253 **	0.161 **	-0.943 *	0.336	162
	(0.128)	(0.074)	(0.517)		
Wholesale Trade	0.282 ***	0.115 ***	-0.485 *	0.482	255
	(0.067)	(0.042)	(0.282)		

Notes: Robust standard errors are reported in parentheses. ***, **, and * denote significance at the .01, .05, and .10 levels, respectively. All continuous variables are included in log form in regressions. State-level spatial fixed effects are included in all models; these coefficients are omitted for brevity.

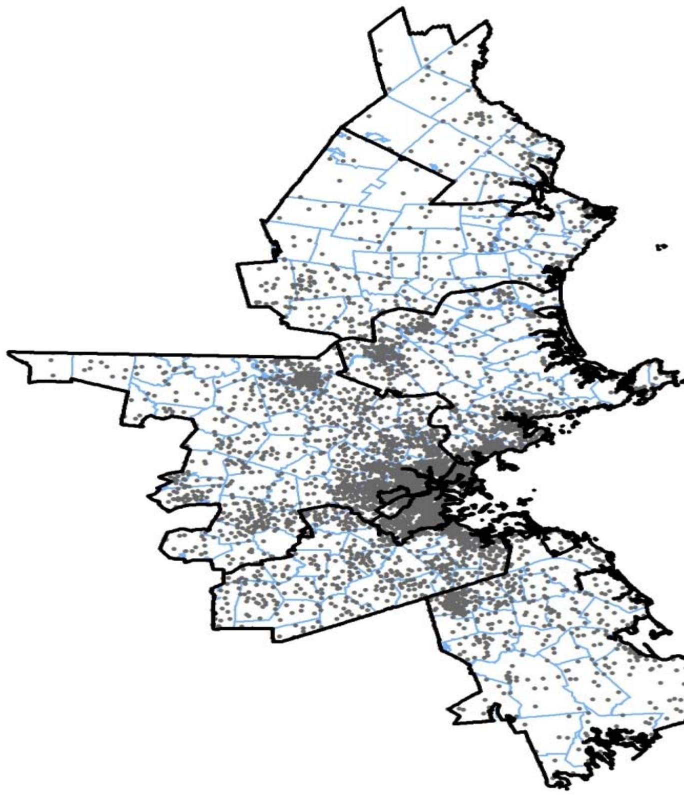
Figure 1: Distribution of Average Output Per Worker in U.S. Metropolitan Areas, 2001-2005



Sources: Current Dollar Gross Domestic Product by Metropolitan Statistical Area, U.S. Bureau of Economic Analysis; Total Employment by Industry (SA25), U.S. Bureau of Economic Analysis.

Figure 2: Distribution of Population Within Selected Metropolitan Areas, 2000

(a) Boston: Raw Density: 1,252 (#9), Weighted Density: 4,978 (#6)



(b) Denver: Raw Density: 258 (#121), Weighted Density: 2,691 (#27)

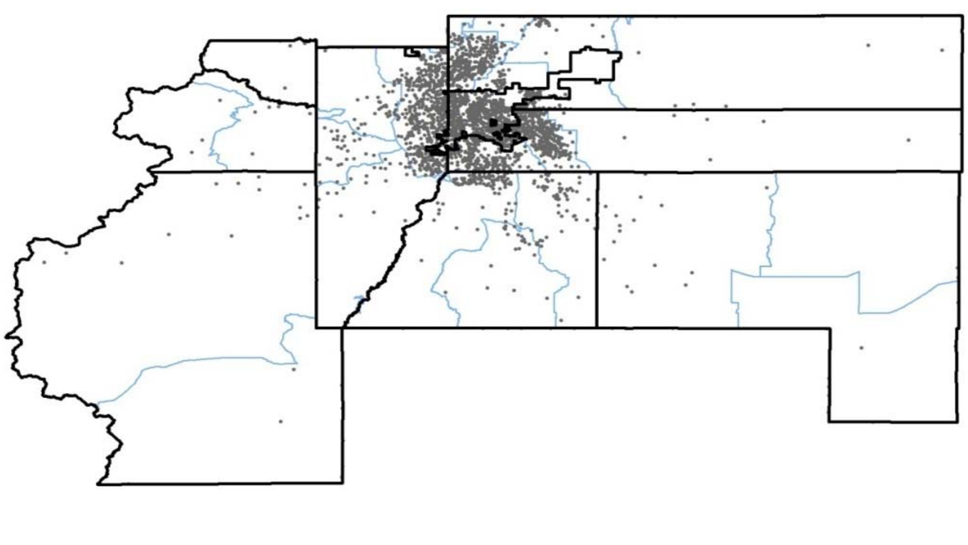
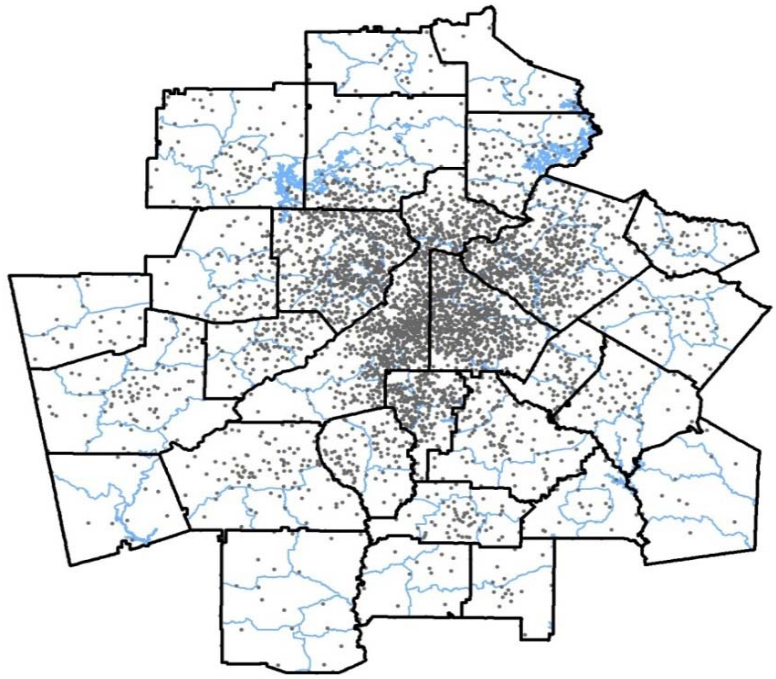
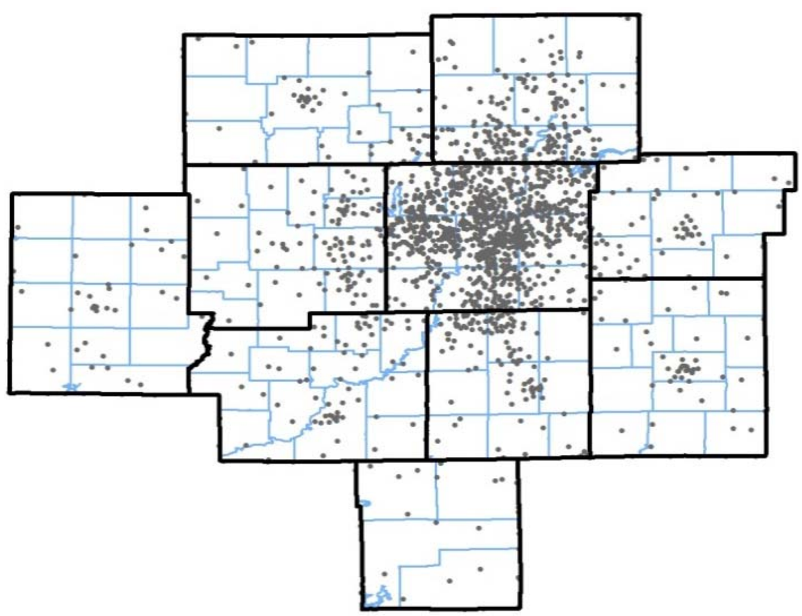


Figure 2 (Cont.): Distribution of Population Within Selected Metropolitan Areas, 2000

(c) Atlanta: Raw Density: 507 (#36), Weighted Density: 1,559 (#98)



(d) Indianapolis: Raw Density: 395 (#63), Weighted Density: 1,695 (#84)

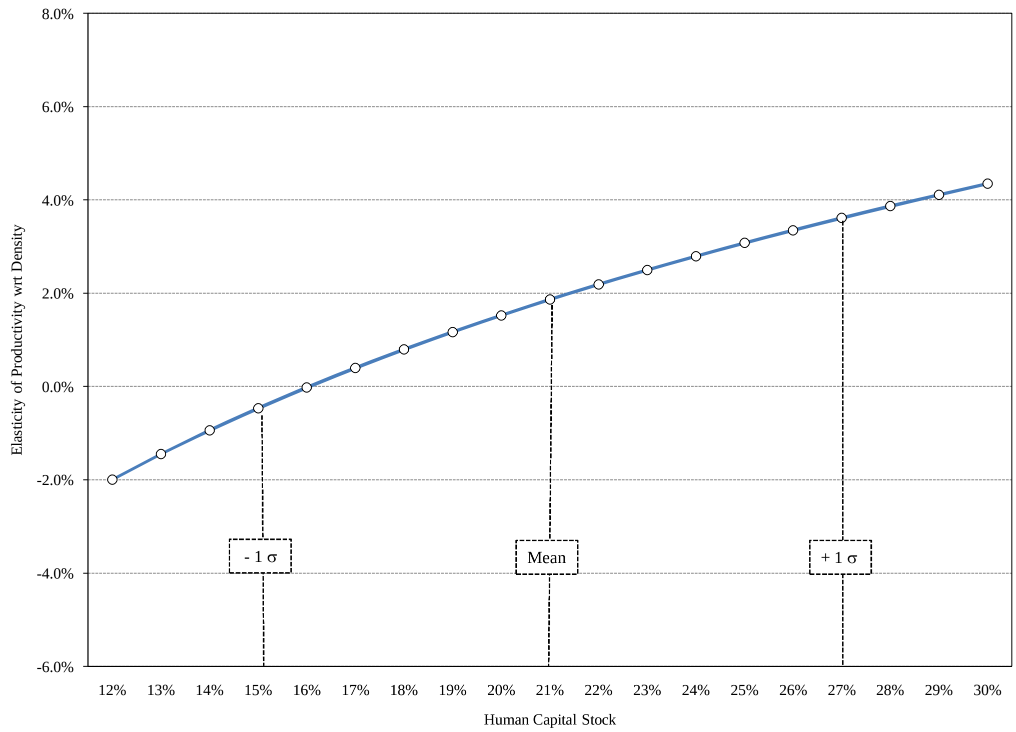


Notes: Black lines represent county/MSA boundaries. Blue lines represent county subdivision boundaries. Each dot represents 1,000 people. Density is expressed in people per square mile, with rank reported in parentheses.

Source: TIGER/Line files®; Census (2000), U.S. Census Bureau.

Figure 3: Productivity Effect of Doubling Population Density at Different Human Capital Stock Levels

(a) Based on OLS estimates reported in Column (4) of Table 4



(b) Based on IV estimates reported in Column (6) of Table 4

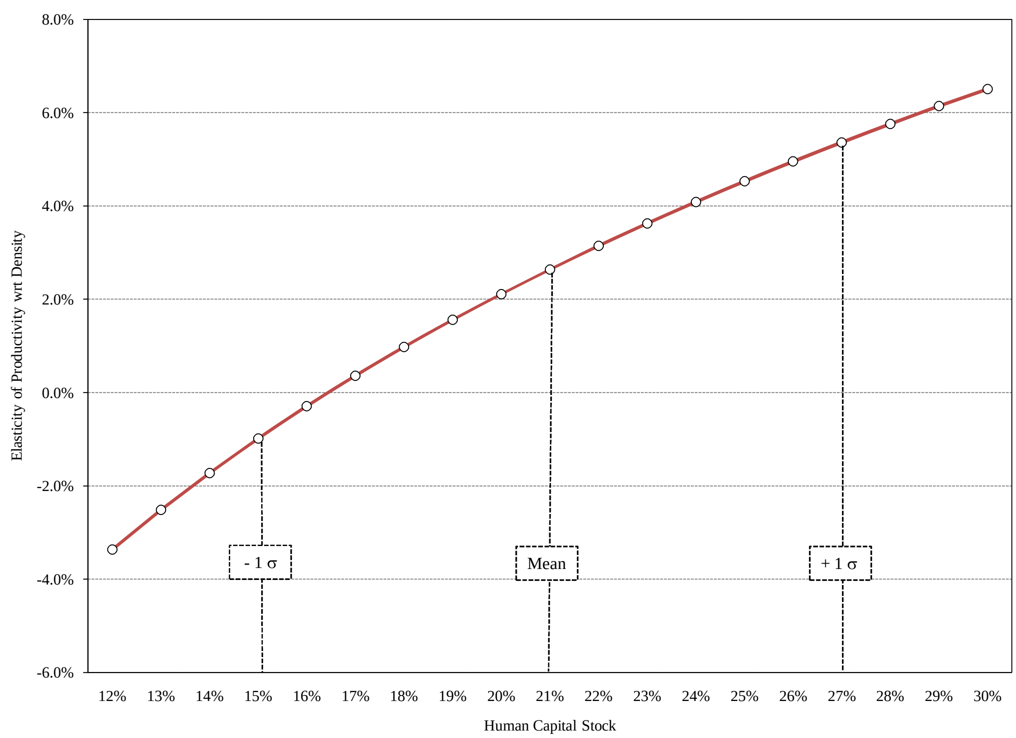
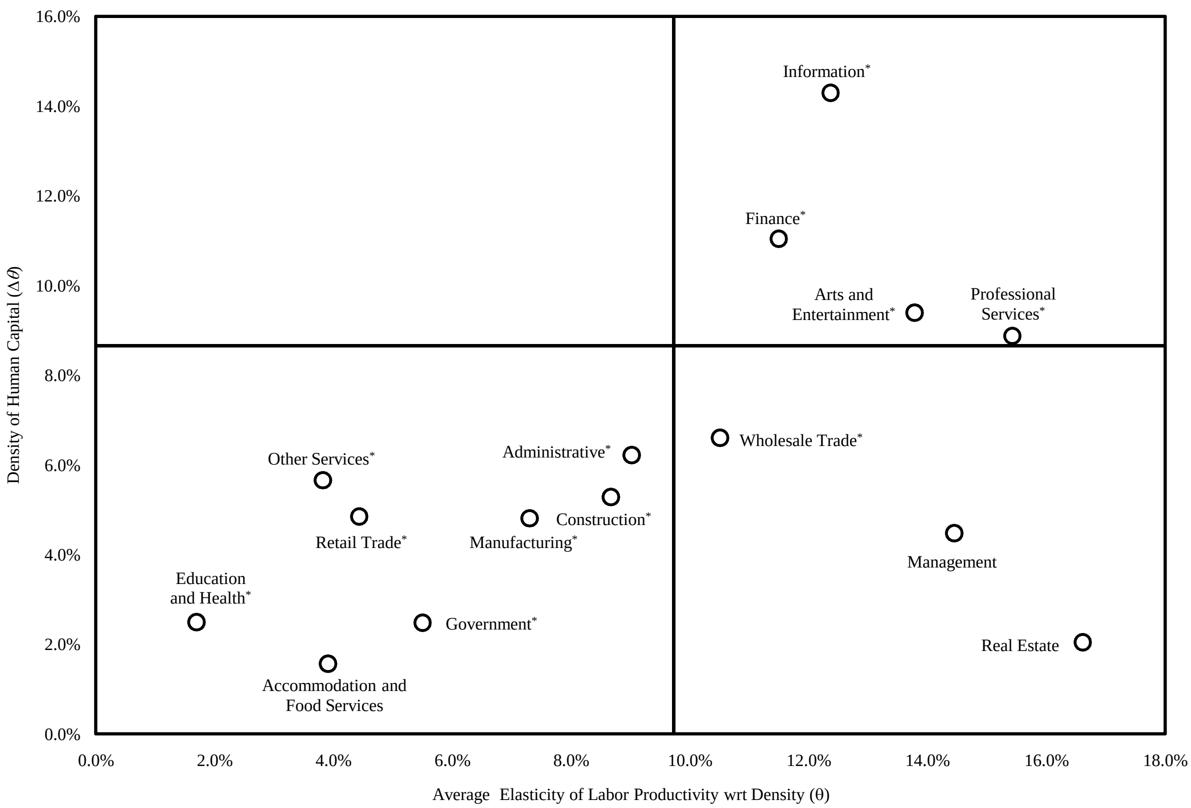
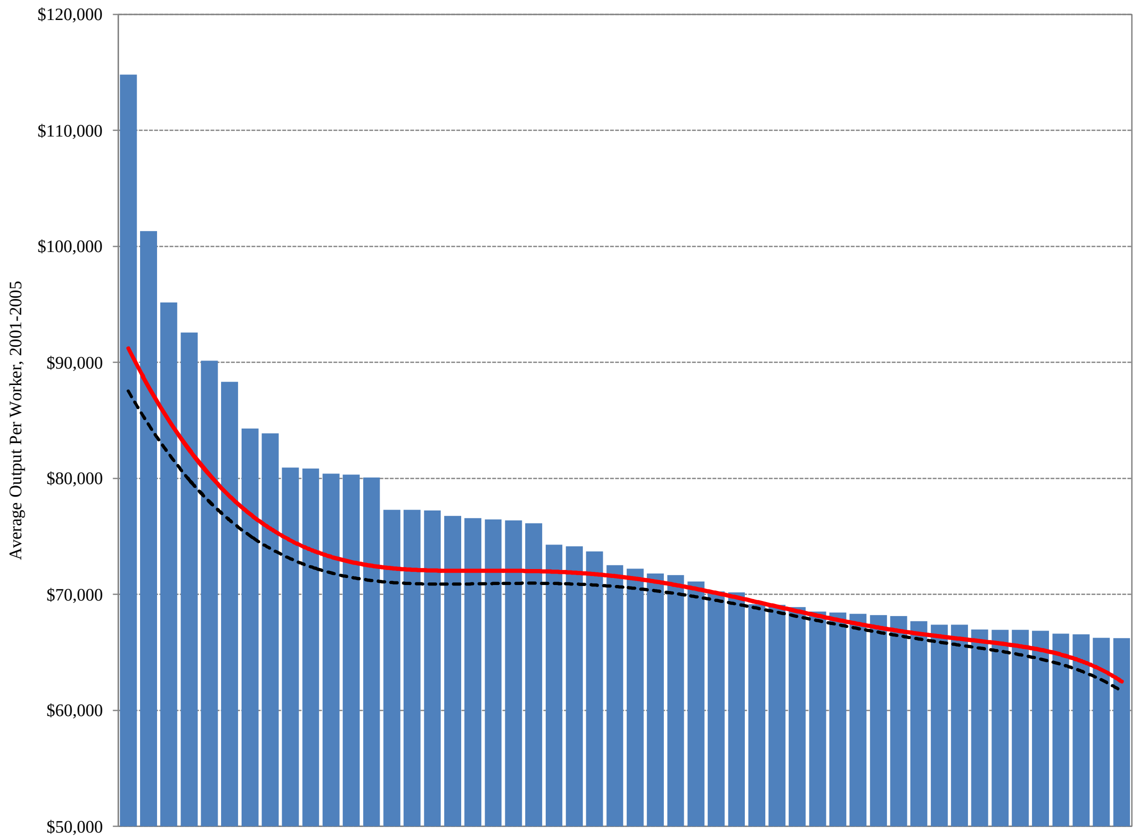


Figure 4: Classification of Industry Sector by Average and Change in Productivity Effect



Notes: The density of human capital ($\Delta\theta$) is expressed as the change in θ for a metropolitan area with a human capital stock one standard deviation above the mean compared to a metropolitan area with a human capital stock one standard deviation below the mean. * indicates that the estimated density of human capital effect ($\Delta\theta$) is statistically significant. Gridlines of 9.7% and 8.7% correspond to aggregate productivity estimates reported in Column (2) of Table 4. Industry sector results based on OLS estimates reported in Table 5.

Figure 5: Comparison of Actual and Predicted Values of Average Output Per Worker, Top 50 Metros, 2001-2005



Notes: Bars are actual values; solid and dotted lines represent non-linear trend lines fit through the predicted values of a model with and without an interaction term capturing the density of human capital, respectively, based on OLS estimates reported in Columns (3) and (4) of Table 4.

Sources: Current Dollar Gross Domestic Product by Metropolitan Statistical Area, U.S. Bureau of Economic Analysis; Total Employment by Industry (SA25), U.S. Bureau of Economic Analysis.