

PRODUCTIVITY AND THE DENSITY OF HUMAN CAPITAL

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Keywords: Agglomeration, Productivity, Density, Knowledge Spillovers

JEL Classification: R12, J24, O40

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I. INTRODUCTION

Virtually all of the economic activity in the United States occurs in and around cities, with metropolitan areas now accounting for nearly 90 percent of U.S. gross domestic product (Panek, Baumgardner, and McCormick 2007). However, differences in productivity within the United States are strikingly large. Figure 1 shows the distribution of average output per worker 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 the twenty least productive metropolitan areas, and more than one-half larger than the median metropolitan area. Meanwhile, the twenty least productive metropolitan areas were about one-fourth less productive than the median. In general, the most highly productive metropolitan areas also tend to be among the most crowded and the richest in human capital.

Theories of agglomeration that focus on learning and knowledge spillovers in cities emphasize the role 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 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 (Stroper and Venables 2004).

We argue that the amount of human capital in a metropolitan area influences the quality of these interactions, suggesting that the productivity-enhancing effects of density increase with 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.

While a number of studies have analyzed the productivity-enhancing effects of density and human capital separately, very few have examined their joint effect. Rosenthal and Strange (2008) find that proximity to college-educated workers drives much of the urban wage premium that is typically attributed to the spatial concentration of employment. Knudsen, Florida, Stolarick, and Gates (2008) provide evidence that density and regional creativity separately and jointly affect the rate of innovation in U.S. metropolitan areas. Our study builds from the insights of this recent work, but considers the more general relationship between aggregate productivity and the density of human capital in U.S. metropolitan areas.

To provide a structural framework for our analysis, we develop a model of urban productivity in which the agglomeration effect of density is enhanced by a metropolitan area's stock of human capital. Consistent with the existing literature, our model yields a set of estimating equations showing that the productivity of a metropolitan area is primarily determined by combinations of density, its human capital stock, and other spatial fixed effects. To estimate the parameters of this model, we utilize newly available data on metropolitan area gross domestic product to construct measures of output per

worker along with two measures of density that account for different aspects of the spatial distribution of population within metropolitan areas. While federal government agencies have historically measured and reported GDP at the national and state levels, the U.S. Bureau of Economic Analysis recently released experimental measures of GDP by metropolitan area. These data represent the most comprehensive measure of economic activity currently available for U.S. metropolitan areas, ideal to examine the agglomeration effects of the density of human capital.

Empirical analysis based on a comprehensive sample of 363 U.S. metropolitan areas over the 2001 to 2005 period reveals that, on average, a doubling of density increases productivity by about 10 percent, while a doubling of what we refer to as urban density increases productivity by roughly 20 percent. Perhaps more importantly, consistent with theories of learning and knowledge spillovers in cities, we find 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 level realize half the average productivity gain, while doubling density in metropolitan areas with a human capital stock that is one standard deviation above the mean level yields productivity benefits that are about 1.5 times larger than average. Overall, this paper provides new evidence on the productivity enhancing effects of the density of human capital.

II. DENSITY, HUMAN CAPITAL, AND URBAN PRODUCTIVITY

Given the vast literature devoted to understanding the nature and sources of agglomeration economies, a complete review of this research is not possible. Instead, our purpose here is to provide context for our work by briefly describing the studies that

serve as a core foundation of our analysis and by highlighting recent research that is closely related to our study. Duranton and Puga (2004) and Rosenthal and Strange (2004) provide comprehensive reviews of the theoretical micro-foundations and 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.

While microeconomic theories of agglomeration based on sharing, matching, and learning among firms and individuals in cities emphasize the role of density in enhancing productivity, early empirical studies of urban productivity instead focused on city size. Findings from this literature suggest that productivity increases by 3 to 8 percent when population is doubled (Sveikauskas 1975; Segal 1976; Moomaw 1981). Importantly, these studies were among the first to use aggregate production functions to model the productivity of urban areas. As such, explanations for these findings focus on the static efficiencies permitted by specialization and the division of labor, although Sveikauskas (1975) provides some discussion of the role of cities in the generation of new ideas and exchange of information when describing potential dynamic efficiencies arising from urban agglomeration.

Our work is most closely related to research analyzing the link between aggregate regional productivity and the density of economic activity. Using models derived from aggregate production functions and data on value added for U.S. states and European regions, results from this literature suggest that productivity increases by 4.5 to 6 percent when employment density is doubled (Ciccone and Hall 1996; Ciccone 2002). Explanations for these findings appeal to theories of increasing returns arising from local

spatial externalities, reduced transport costs, and a greater diversity of local intermediate products and services. While knowledge spillovers can be viewed as a type of local spatial externality with the potential to boost productivity, these studies are more general and do not focus on specific types of spatial externalities. Moreover, while this research controls for differences in the quality of the local labor force by including measures of regional human capital stocks in the empirical analysis, the primary focus of this work is on establishing the role of density as a determinant of labor productivity.

Recent theoretical research has attempted to explain the distribution of population density observed in the United States by appealing to differences in productivity or consumption amenities across space (Rappaport 2008a, 2008b). The approach used in this literature is to develop and calibrate static general equilibrium models of “city crowdedness” using estimates of the productivity benefits or value of consumption amenities related to density, and then compare the simulation results from these models to empirical patterns of population density measured across U.S. metropolitan areas. With respect to productivity, Rappaport (2008a) calculates that the elasticity with respect to density required to sustain the observed distribution of crowdedness across U.S. metropolitan areas increases non-linearly from 5 percent to 12 percent as density increases from one-fourth the national density to four times the national density. Based on the results of his simulation, Rappaport concludes that the agglomeration effects required to sustain high levels of crowdedness considerably exceed the range established in the existing literature, particularly for the most crowded places. To explain this gap, he suggests that productivity differences unrelated to density and differences in consumption amenities across U.S. metropolitan areas may compensate for the shortfall in increasing

returns related to density. Our results showing that the agglomeration effects of density are enhanced by a region's stock of human capital also help explain the gap identified by this research.

While the geographic concentration of human capital is widely thought to enhance urban productivity by facilitating knowledge spillovers, empirical work analyzing the existence and magnitude of such spillovers is mixed. Rauch (1993) finds that a one-year increase in the average education of a metropolitan area is associated with a 3 to 5 percent increase in wages, after controlling for individual characteristics and the private returns to education. Similarly, using an instrumental variables approach to address potential endogeneity issues related to a region's stock of college graduates, Moretti (2004) finds that a one-percentage point increase in the proportion of a metropolitan area's residents with a college degree increases average wages by 0.6 to 1.2 percent beyond the private returns to education. In contrast, Acemoglu and Angrist (2000) find little empirical support for the existence of knowledge spillovers using an instrumental variables approach that targets the lower portion of the educational attainment distribution (i.e., child labor and compulsory schooling laws). To the extent that knowledge spillovers boost urban productivity, the existing empirical research indicates that such spillovers 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., middle or high school). Moreover, while the idea that the close proximity created by dense urban areas is important in facilitating knowledge spillovers certainly underlies this research, early empirical studies attempting to establish the existence of knowledge spillovers do not explicitly consider the interaction of density and human capital.

Recent empirical research examining the attenuation of human capital spillovers at the micro level suggests that the density of human capital may be an important determinant of aggregate urban productivity. Rosenthal and Strange (2008) show that proximity to college-educated workers enhances the wages of both high-skill and low-skill workers, while proximity to workers with less than a college education does not. Moreover, they demonstrate that these effects attenuate sharply with distance: increasing the concentration of human capital within five miles of a given worker's place of employment results in significantly higher wage premiums than increasing the concentration of human capital by the same amount 5 to 25 miles away. Similarly, using detailed data for the Boston metropolitan area, Fu (2007) finds evidence of the effects of four types of human capital spillovers: depth of human capital stock, Marshallian labor market externalities, Jacobs labor market externalities, and the thickness of the labor market, and shows that different types of knowledge spillovers attenuate at different speeds over different distances.

Other research examining whether knowledge spillovers enhance innovation in cities has highlighted the 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. However, as with much of the existing literature, this research focuses on the separate effects of density and human capital. The exception to the existing literature is new research by Knudsen, Florida, Stolarick, and Gates (2008), who explicitly examine the interaction of a composite density index and an occupation-based measure human capital referred to as "creative

capital.” Importantly, this research shows that density and creativity positively affect the number of patents granted per capita in U.S. metropolitan areas both separately and jointly, indicating that the density of highly-skilled people is an important determinant of the rate of urban innovation. Our work builds directly from this important insight, but considers the more general relationship between productivity and the density of human capital in U.S. metropolitan areas.

III. A MODEL OF URBAN PRODUCTIVITY

To provide a structural framework for our empirical analysis, we develop 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 production at any given time in metropolitan area i contained within a larger region j is given by:¹

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

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 assumed to be homogeneous within and across metropolitan areas, so differences in knowledge and skills across metropolitan areas are captured in our 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 assume that $\alpha + \beta = 1$, which implies that there are constant returns to scale in the reproducible factors.

¹ Following Ciccone (2002), a larger region is defined as a fixed geographic area containing several metropolitan areas, such as a state.

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:

$$A_{ij} = \gamma_0 D_{ij}^{\gamma_1} \quad \gamma_1 > 0 \quad (2)$$

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. Although density is assumed to increase productivity in our model, spatial equilibrium requires that individual utility and firm profits be equalized across space. Thus, 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.

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:

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

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:

$$K_{ij} = \frac{\alpha Y_{ij}}{r_{kj}} \quad (4)$$

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:

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

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.

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

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

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

$$\gamma_{ij} = \eta_0 + \eta_1 \log \frac{H_{ij}}{L_{ij}} \quad \eta_0 > 0, \eta_1 > 0 \quad (7)$$

Substituting γ_{ij} from (7) for γ_i in (6) yields our second estimating equation:

$$\log \frac{Y_{ij}}{L_{ij}} = \log \phi_j + \frac{\eta_0}{1-\alpha} \log D_{ij} + \frac{\eta_1}{1-\alpha} (\log D_{ij}) (\log \frac{H_{ij}}{L_{ij}}) + \frac{\beta}{1-\alpha} \log \frac{H_{ij}}{L_{ij}} \quad (8)$$

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

IV. 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 regions within the same country, we minimize this source of unobserved 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. *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:

$$\log y_{ij} = \alpha_j + \beta_1 \log D_{ij} + \beta_2 \log h_{ij} + u_{ij} \quad (9)$$

where y_{ij} is output per worker, D_{ij} is a measure density, h_{ij} is a measure of the regional human capital stock, $\beta_1 = \frac{\gamma_1}{1-\alpha}$ is the elasticity of average labor productivity with respect to density, $\beta_2 = \frac{\beta}{1-\alpha}$ 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 exogenous total factor productivity in metropolitan area i and the larger region j in which it is contained. We estimate the constant term, α_j , by including state-level fixed effects that control for differences in exogenous total factor productivity, rental prices of capital, and resulting differences in physical capital intensity between U.S. states.

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

$$\log y_{ij} = \alpha_j + \beta_1 \log D_{ij} + \beta_2 (\log D_{ij})(\log h_{ij}) + \beta_3 \log h_{ij} + \varepsilon_{ij} \quad (10)$$

where $\beta_1 = \frac{\eta_0}{1-\alpha}$, $\beta_2 = \frac{\eta_1}{1-\alpha}$, and $\beta_3 = \frac{\beta}{1-\alpha}$, and ε_{ij} is an error term as before. Given this

specification, the elasticity of productivity with respect to density or human capital will vary with the interaction term.

We begin by estimating equations (9) and (10) using ordinary least squares (OLS), and then later re-estimate these equations using two-stage least squares (2SLS) to investigate the direction and magnitudes of potential biases arising from the endogeneity of our measures 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, 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. 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.

B. Data and Variables

Table 1 presents the descriptive statistics for the variables used in our study. Because GDP data are now available at the metropolitan area level, we use these geographic areas as the unit of observation for our analysis.² 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 complete and at a finer level of geography than previous research.

² 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 dependent variable is average output per worker during the 2001 to 2005 period. This variable is constructed using data on metropolitan area GDP and total employment published by the U.S. Bureau of Economic Analysis. 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 (2002-2005).³ 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.

We utilize two measures of density in our analysis, with each capturing different aspects of the proximity of people in metropolitan areas. As such, we focus on population-based measures of density, rather than employment-based measures, as the

³ While data on metropolitan area GDP are currently available for the 2001 to 2006 period, we focus our attention on the shorter 2001 to 2005 period as the data for these years reflect revised estimates, and therefore represent the most accurate information currently available. See U.S. Bureau of Economic Analysis (2007, 2008) and Panek, Baumgardner, and McCormick (2007) for more information.

exchange of ideas and information need not be confined to places of employment. Data on population and land area are drawn from the 2000 Census.

Our first 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 2008a). In 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.

Most of the interactions that take place in U.S. metropolitan areas occur on only a small fraction of the land area, which we refer to as urban areas. The U.S. Census Bureau classifies as “urban” all land, population, and housing located within an urbanized area (UA) or urban cluster (UC), which are the most densely settled portions of metropolitan areas. Across all U.S. metropolitan areas, more than 85 percent of the population lives on less than nine percent of the land located in metropolitan areas. We utilize data on urban areas to calculate our second measure of population density, which we refer to as urban density. As with our first measure, this variable is calculated as the population-weighted average of the urban portion of county-subdivision densities, which represents the crowdedness experienced by the typical person in the urban area of a metropolitan area. Urban density, as experienced by the typical person in U.S. metropolitan areas, averaged 2,471 people per square mile in 2000.

Figure 2 provides an example of our density measures relative to their un-weighted counterparts using the Buffalo-Niagara metropolitan area to illustrate. With nearly 1.2 million people and total land area of just under 1,600 square miles, population

density in Buffalo averages around 750 people per square mile. As is clear from Figure 2, however, the population is unevenly distributed within the metropolitan area, with 90 percent of the population living in or nearby the urban area. Thus, this simple measure of density greatly understates the actual crowdedness experienced by most of the people living and working in the metropolitan area. Our measure adjusts for this problem by using county-subdivision densities to account for the spatial distribution of population within metropolitan areas. The weighted population density in Buffalo is 3,275 people per square mile, more than four times the un-weighted measure. By comparison, urban density in Buffalo is 4,034 people per square mile.

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 working age population in 2000 using data from the U.S. Census. While this 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; Glaser and Saiz 2004; Moretti 2004; and Rosenthal and Strange 2008, among others).

C. Empirical Results

Tables 3 and 4 present the results of our regression analysis related to the productivity enhancing effects of density and urban density, respectively. Column (1) of each table shows OLS results corresponding to models in which the effects of density and human capital are estimated separately (i.e., equation (9)), while Column (2) of each table shows OLS results that correspond to models that include the interaction of density of human capital (i.e., equation (10)). Overall, our 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 holds 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 results shown in Table 3, where density is the primary variable of interest, 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. Thus, our estimates of the productivity enhancing effects of density in U.S. metropolitan areas are larger than the 4.5 to 6 percent range established in the existing literature based on data from U.S. States and European regions during the late 1980s (Ciccone and Hall 1996; Ciccone 2002). That our estimates exceed those established in the existing literature may be due to our ability to capture more fully the intensity of physical interaction, both in terms of the geography we analyze and our measurement of density, in our study. Alternatively, our findings may simple reflect an increase in the importance of density, as knowledge-based activities have become a larger part of the U.S. economy. Indeed, our results are generally in line with recent estimates of the level of productivity required to sustain high levels of crowdedness in U.S. metropolitan areas (Rappaport 2008a). In addition, we find that doubling a metropolitan area's human capital stock increases urban productivity by roughly 20 percent in both specifications.

Consistent with the idea that the agglomeration effect of density is enhanced by a region's stock of human capital, we find that the interaction of population density and human capital has a positive and statistically significant effect on urban productivity. Figure 3 plots the productivity effect from doubling population density at different human capital stock levels, and shows that metropolitan areas with a human capital stock that is one standard deviation below the mean level realize about half of the average productivity gain (i.e., 4.8 percent compared to 9.7 percent), while doubling density in metropolitan areas with a human capital stock that is one standard deviation above the mean level yields productivity benefits that are about 1.5 times larger than average (i.e., 13.5 percent compared to 9.7 percent).

Turning to the interpretation of the results shown in Table 4, where urban density is the primary variable of interest, we find that a doubling of urban density is associated with a 22.5 percent increase in productivity. Evaluated at the mean level of human capital, our estimate of the productivity enhancing effect of doubling urban density falls slightly to 20.6 percent. Thus, the elasticity of labor productivity with respect to urban density is about two times larger than that estimated with respect to population density. This pattern of results is consistent with recent research showing that the effects of knowledge spillovers attenuate sharply with distance (Fu 2007; Rosenthal and Strange 2008). As before, we continue to find that doubling a metropolitan area's human capital stock increases urban productivity by about 20 percent in both specifications. Figure 4 plots the productivity enhancing effect of doubling urban density at different human capital stock levels, and shows a pattern similar to that described previously, although the slope of the relationship is not as steep when compared to that established for our first

measure of density. These findings provide additional insight into the productivity enhancing effects of the density of human capital.

D. Endogeneity of Density and Urban Density

Our OLS estimation assume that our measures of density and the productivity of metropolitan areas are exogenous when 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, highly productive metropolitan areas are able to attract more people, which subsequently increases density. To assess the effects of this potential concern, we re-estimate our regression models using 2SLS.

The presence of an interaction term in our key estimation equations poses an econometric challenge, as the literature has not reached a consensus on the most appropriate way to address the potential endogeneity of the interaction term itself. One approach is to regress the interaction term on a set of instruments in a first stage regression, and then use this predicted value in a second-stage regression. However, recent theoretical research has demonstrated that such a method can produce biased estimates of the interaction term, particularly when additional regressors correlated with the actual endogenous variable are included in the first stage regression (Harrison 2008). Because this type of correlation occurs frequently in applied research, Harrison proposes an alternative method to minimize such bias where the predicted value from a first stage regression of the actual endogenous variable is used to construct a new interaction term. We follow this new method to implement our 2SLS analysis. Specifically, the predicted

values from the first stage regressions of density and urban density are multiplied by our human capital stock variable to construct new interaction terms, and then these predicted values are used in the second stage regressions.

Implementing 2SLS estimation requires that we identify variables that are unrelated to modern differences in productivity across metropolitan areas but correlated with density and urban density. We use a set of two such variables to instrument for our measures of density: population in 1900 and the presence of a professional sports franchise in 1970. The logic of our first instrumental variable, which has been used extensively in the existing literature, assumes 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.⁴ The logic of our second instrumental variable, which we introduce here, is that the relationship between density and the presence of a professional sports franchise in a metropolitan area operate through consumption amenities, rather than through differences in modern productivity.

To determine whether a metropolitan area hosted a professional sports franchise in 1970, we limited our attention to the four most popular major sports leagues in the United States: Major League Baseball (MLB), the National Football League (NFL), the National Basketball Association (NBA), and the National Hockey League (NHL).⁵ Because operating a franchise in any of these major sports leagues requires large fixed investments to build stadiums or arenas, agglomeration influences the location decisions of such franchises. Indeed, a leading explanation for the existence of cities is the

⁴ Metropolitan area population figures for 1900 are derived using county-level data published by the U.S. Census.

⁵ Metropolitan area professional sports franchise data were collected from baseball-reference.com, nfl.com, nba.com, and nhl.com using information on historical standings for the 1970 season.

existence of indivisibilities in the provision of shared facilities such as these. Consistent with this idea, Rappaport and Wilkerson (2001, Appendix 1) show that a large number of the professional sports franchises in the United States are located in the largest and most crowded metropolitan areas. We selected the year 1970 because it is the earliest year available that allows us to include franchises that were added during the significant expansions of the NBA and NHL during the 1960s, as well as the franchises that joined the NFL as part of the AFL-NFL merger in 1970.

Another advantage of focusing on these four major sports leagues is that they target a national audience. As such, it is in the interest of each sports league to coordinate the location decisions of individual franchises in an effort to promote a broad geographic coverage across the United States. In 1970, for example, metropolitan areas as geographically diverse as Atlanta, GA; Boston, MA; Buffalo, NY; Dallas, TX; Detroit, MI; Green Bay, WI; Kansas City, MO; Portland, OR; and San Diego, CA each hosted a professional sports franchise—cities whose economic fortunes varied considerably at the beginning of the 21st century. Moreover, a number of highly productive metropolitan areas today, such as Austin, TX; Charlotte, NC; Lake Charles, LA; Orlando, FL; and San Jose, CA did not host a professional sports franchise in 1970.

The results of our two-stage analysis are provided in the last two columns of Tables 3 and 4, treating density and urban density along with the corresponding interaction term as endogenous, respectively. The top panel in each table reports the R-squared and coefficient estimates for our instrumental variables from our first stage regressions. More than 60 percent of the variation in density and urban density observed across U.S. metropolitan areas is explained by our first stage regressions, and both

instruments are positive and statistically significant predictors of each measure of density. In addition, the first-stage F -statistic for the excluded instruments is 20.42 when density is the variable of interest and 15.68 when urban density is the variable of interest; both of which exceed the critical value of 7.03 (nominal 5 percent Wald test that the maximum size is no more than 10 percent) provided by Stock and Yogo (2005), suggesting that our instruments are strong.⁶

The bottom panel of Tables 3 and 4 report the results from our second stage regressions. In general, the pattern of results from the second-stage regressions is consistent with those obtained using OLS estimation. Most importantly, as shown in Column (4) of each table, the interaction of density and human capital remains positive and significant. However, the magnitudes of the effects of density and human capital differ relative to our base case analysis. In general, we find that the relative importance of density as a determinant of urban productivity increases when compared to a region's stock of human capital. Specifically, the average effect of doubling density increases from nearly 10 percent to more than 20 percent, while the average effect of doubling a region's human capital stock falls from around 20 percent to less than 10 percent. We find a similar pattern with respect to urban density: the average effect of doubling urban density increases from roughly 20 percent to more than 45 percent, while the average effect from doubling a region's human capital stock falls from about 20 percent to between 11 and 13 percent. These findings differ from those set forth in the existing

⁶ Stock and Yogo (2005) develop critical values for weak instrument tests when standard errors are i.i.d. based on the performance of the Wald test for the coefficient of the endogenous regressors. Their test is based on the rejection rate the researcher is willing to tolerate (e.g., 10 percent) when the true rejection rate is the standard 5 percent rate. Importantly, no such critical values are available in the literature for the case of clustered robust standard errors. However, relative to the critical values established by Stock and Yogo, our restricted instrument set appears to pass this weak instrument test.

literature, where accounting for the potential endogeneity of agglomeration typically does not yield noticeable changes in the size of urban agglomeration estimates (Melo, Graham, and Noland 2009).

While Hausman specification tests detect some evidence of the endogeneity of both density and urban density, it is important to note that the standard errors generally increase with our 2SLS estimation, often substantially. Therefore, it remains possible that the OLS and 2SLS coefficient estimates are realizations of the same parameter distribution. This concern is particularly warranted when considering the results from models that include an interaction term, as the OLS coefficient estimates are generally within one standard deviation of the 2SLS coefficient estimates. Nonetheless, to the extent that the endogeneity of density biases our OLS estimates, it appears we have underestimated the productivity effects resulting from the density of human capital.

V. 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 new measures of output per worker at the metropolitan area level along with two measures of density that account for different aspects of 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 about 10 percent—twice as large as the most comparable estimates in the existing literature that rely on data from U.S. States and European regions during the late 1980s (Ciccone and Hall 1996; Ciccone 2002), but generally in line with recent theoretical research analyzing the level of productivity required to sustain high levels of crowdedness in U.S. metropolitan areas (Rappaport 2008a). Moreover, our estimate of the productivity enhancing effects of density increases to 20 percent when we use an alternative measure of urban density that focuses on the land areas in which most of the interaction occurs within metropolitan areas. This pattern of results is consistent with recent research showing that the effects of knowledge spillovers attenuate sharply with distance (Fu 2007; Rosenthal and Strange 2008).

New to the literature, we demonstrate that the elasticity of average productivity with respect to both density and urban density increases with a region's stock of human capital, consistent with theories of learning and knowledge spillovers in cities. Metropolitan areas with a human capital stock that is one standard deviation below the mean level realize half of the average productivity gain, while doubling density in metropolitan areas with a human capital stock that is one standard deviation above the mean level yields productivity benefits that are about 1.5 times larger than average. A similar pattern holds when urban density is used to measure the crowdedness of U.S. metropolitan areas. These findings, based on analysis of aggregate metropolitan area productivity, correspond to the conclusions set forth by Rosenthal and Strange, based on micro-analysis of wages, who remark that “the positive effect of agglomeration is really due to the presence of human capital” (Rosenthal and Strange 2008, p. 387).

A limitation of our current analysis, shared by all existing studies of aggregate urban productivity, is that we do not account fully for potential unobserved heterogeneity in skills arising from spatial sorting. This issue is of particular concern given recent research indicating that a divergence in human capital levels has occurred across cities over the past several decades (Berry and Glaeser 2005). Based on an analysis of individual-level wage data from France, Combes, Duranton, and Gobillon (2008) argue that 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. Further research on the effects of spatial sorting is clearly warranted.

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). In addition, our results are also broadly consistent with recent empirical research showing 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 2003). 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 sources of this productivity effect.

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Table 1: Descriptive Statistics

Variable	Mean	Std Dev	Minimum	Maximum
Output Per Worker	\$55,884	\$10,558	\$35,778	\$114,840
Density	1,240.0	1,340.7	11.2	18,551.5
Urban Density	2,471.0	1,321.5	698.8	19,346.1
Human Capital Stock	21.5%	6.4%	9.0%	48.9%
<i>Natural Logarithm of:</i>				
Output Per Worker	10.92	0.17	10.49	11.65
Density	6.76	0.92	2.42	9.83
Urban Density	7.73	0.39	6.55	9.87
Human Capital Stock	-1.58	0.30	-2.41	-0.72

Notes: Output Per Worker is 2001-2005 average; all other variables are from 2000. Density and Urban Density are calculated using the weighted average of county sub-divisions in each metropolitan area, and are expressed as people per square mile. 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. Based on 363 observations.

Sources: Current Dollar Gross Domestic Product by Metropolitan Statistical Area, U.S. Bureau of Economic Analysis; Total Employment by Industry (CA25), U.S. Bureau of Economic Analysis; 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	\$114,840
2	San Jose-Sunnyvale-Santa Clara, CA	\$101,440
3	Charlotte-Gastonia-Concord, NC-SC	\$95,560
4	New York-Northern New Jersey-Long Island, NY-NJ-PA	\$92,462
5	San Francisco-Oakland-Fremont, CA	\$90,248
6	Houston-Sugar Land-Baytown, TX	\$88,381
7	Anchorage, AK	\$84,117
8	Washington-Arlington-Alexandria, DC-VA-MD-WV	\$83,954
9	Casper, WY	\$81,038
10	Seattle-Tacoma-Bellevue, WA	\$81,015
11	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	\$80,410
12	Dallas-Fort Worth-Arlington, TX	\$80,163
13	Boston-Cambridge-Quincy, MA-NH	\$80,118
14	Lake Charles, LA	\$78,217
15	Hartford-West Hartford-East Hartford, CT	\$77,836
16	Chicago-Naperville-Joliet, IL-IN-WI	\$77,343
17	Atlanta-Sandy Springs-Marietta, GA	\$76,820
18	Farmington, NM	\$76,718
19	Detroit-Warren-Livonia, MI	\$76,599
20	Denver-Aurora, CO	\$76,440
344	Kingston, NY	\$42,909
345	Johnstown, PA	\$42,880
346	Florence-Muscle Shoals, AL	\$42,859
347	Lawrence, KS	\$42,835
348	Abilene, TX	\$42,618
349	Flagstaff, AZ	\$42,528
350	Grand Forks, ND-MN	\$42,470
351	Lake Havasu City-Kingman, AZ	\$42,411
352	Grand Junction, CO	\$42,403
353	Lewiston, ID-WA	\$42,364
354	Pocatello, ID	\$42,193
355	College Station-Bryan, TX	\$42,064
356	Hot Springs, AR	\$41,804
357	State College, PA	\$41,410
358	Cumberland, MD-WV	\$41,357
359	St. George, UT	\$40,423
360	Prescott, AZ	\$40,334
361	McAllen-Edinburg-Mission, TX	\$38,085
362	Brownsville-Harlingen, TX	\$36,782
363	Logan, UT-ID	\$35,778

Sources: Current Dollar Gross Domestic Product by Metropolitan Statistical Area, U.S. Bureau of Economic Analysis; Total Employment by Industry (CA25), U.S. Bureau of Economic Analysis.

Table 3: Density and Productivity Estimation Results

	OLS		2SLS	
	(1)	(2)	(3)	(4)
First Stage: Dependent Variable Log of Density				
Population 1900	--	--	0.193 *** (0.066)	0.193 *** (0.066)
Pro Sports 1970	--	--	0.724 *** (0.193)	0.724 *** (0.193)
R ²	--	--	0.661	0.661
N			363	363
Second Stage: Dependent Variable is Log of Average Output Per Worker				
Intercept	10.426 *** (0.121)	8.897 *** (0.482)	9.241 *** (0.322)	8.212 *** (0.387)
Density	0.097 *** (0.012)	0.330 *** (0.059)	0.228 *** (0.036)	0.390 *** (0.058)
Human Capital Stock	0.201 *** (0.036)	-0.795 *** (0.250)	0.057 (0.051)	-0.710 ** (0.274)
Interaction	--	0.151 *** (0.037)	--	0.120 *** (0.043)
R ²	0.552	0.603	--	--
N	363	363	363	363

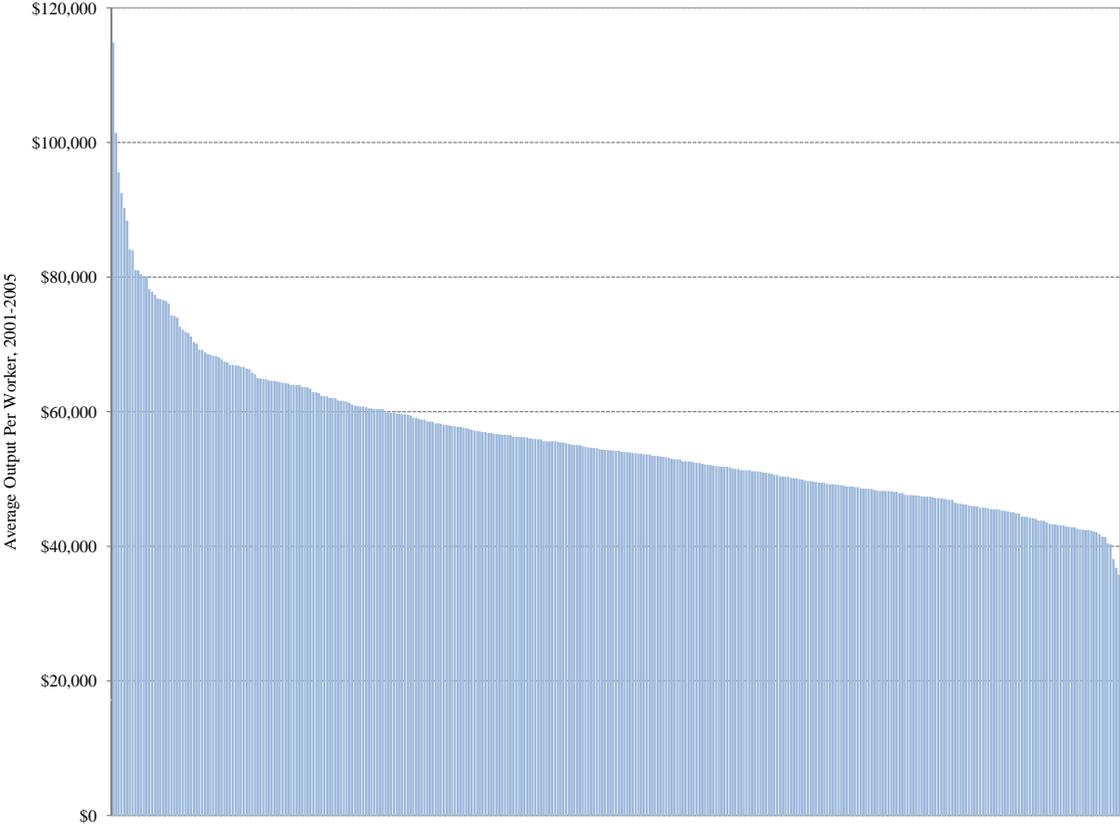
Notes: Robust standard errors clustered at the state level are reported in parentheses. All continuous variables are included in log form in regressions. State fixed effects are included in all models; these coefficients and the full results from the first stage regressions are omitted for brevity. ***, **, and * denote significance at the .01, .05, and .10 levels, respectively. Based on 363 observations.

Table 4: Urban Density and Productivity Estimation Results

	OLS		2SLS	
	(1)	(2)	(3)	(4)
First Stage: Dependent Variable Log of Urban Density				
Population 1900	--	--	0.075 ** (0.031)	0.075 ** (0.031)
Pro Sports 1970	--	--	0.366 *** (0.087)	0.366 *** (0.087)
R ²	--	--	0.675	0.675
N			363	363
Second Stage: Dependent Variable is Log of Average Output Per Worker				
Intercept	9.363 *** (0.218)	6.625 *** (0.909)	6.866 *** (0.816)	4.711 *** (1.104)
Urban Density	0.225 *** (0.025)	0.520 *** (0.096)	0.515 *** (0.096)	0.798 *** (0.141)
Human Capital Stock	0.223 *** (0.033)	-1.354 ** (0.520)	0.113 ** (0.051)	-1.536 ** (0.763)
Interaction	--	0.204 *** (0.066)	--	0.216 ** (0.098)
R ²	0.548	0.567	--	--
N	363	363	363	363

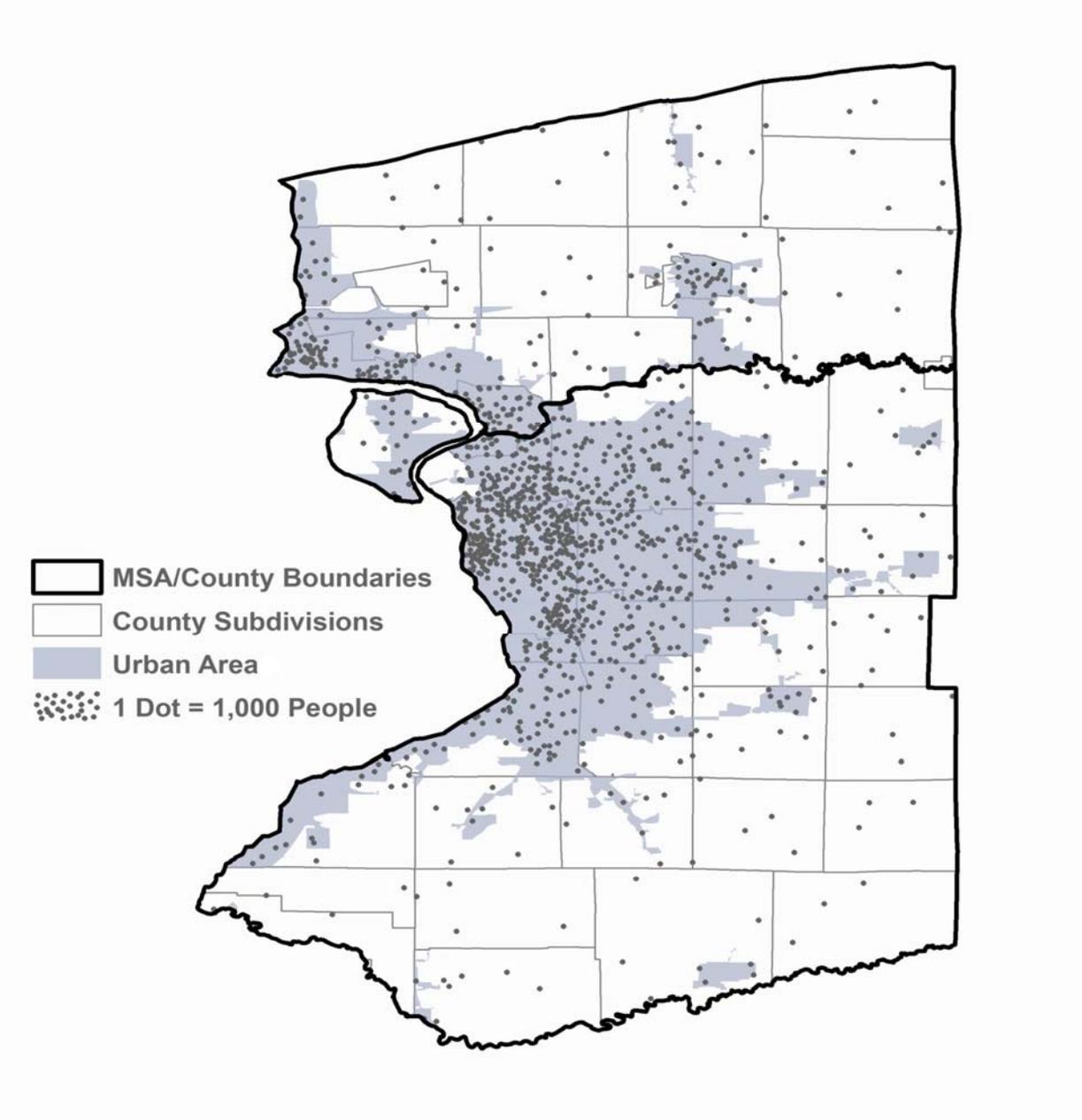
Notes: Robust standard errors clustered at the state level are reported in parentheses. All continuous variables are included in log form in regressions. State fixed effects are included in all models; these coefficients and the full results from the first stage regressions are omitted for brevity. ***, **, and * denote significance at the .01, .05, and .10 levels, respectively. Based on 363 observations.

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 (CA25), U.S. Bureau of Economic Analysis.

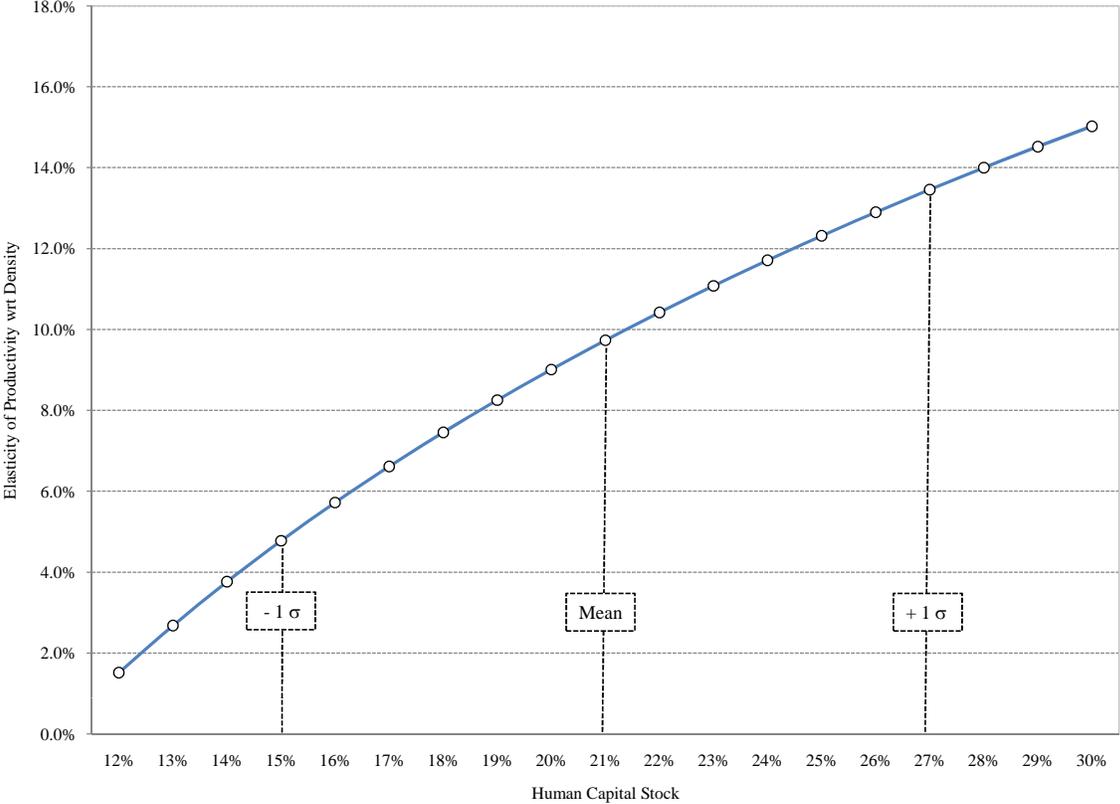
Figure 2: Distribution of Population within Buffalo-Niagara Metropolitan Statistical Area, 2000



Notes: The Buffalo-Niagara metropolitan statistical area includes Erie and Niagara county, which together contain 47 county subdivisions.

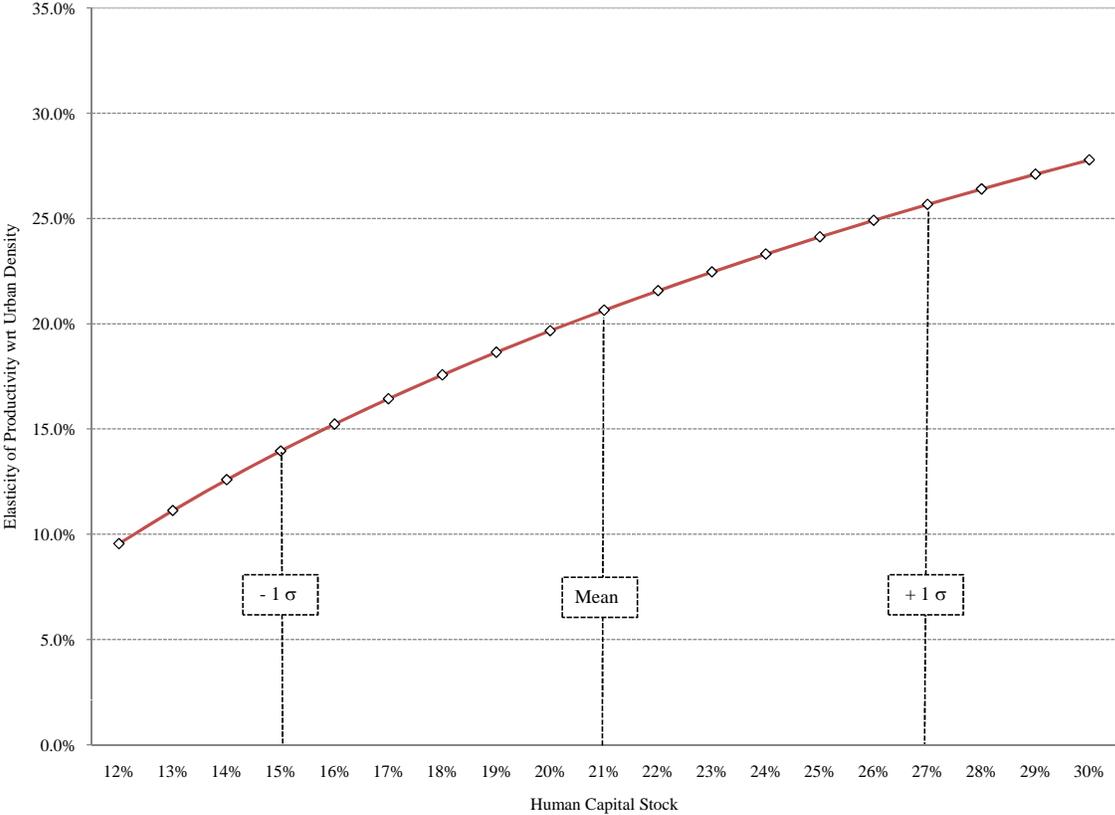
Source: TIGER/Line® files; Census (2000), U.S. Census Bureau.

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



Notes: Estimates are from Model 2 reported in Table 3. Based on 363 metropolitan areas.

Figure 4: Productivity Effect of Doubling Urban Density at Different Human Capital Stock Levels



Notes: Estimates are from Model 2 reported in Table 4. Based on 363 metropolitan areas.