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Jaison R. Abel
Todd M. Gabe

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Abstract

We examine the relationship between human capital and economic activity in U.S. metropolitan areas, extending the literature in two ways. First, we utilize new data on metropolitan area GDP to measure economic activity. Results show that a one-percentage-point increase in the proportion of residents with a college degree is associated with about a 2 percent increase in metropolitan area GDP per capita. Second, we develop measures of human capital that reflect the types of knowledge within U.S. metropolitan areas. Regional knowledge stocks related to the provision of producer services and information technology are important determinants of economic vitality.

Key words: human capital, knowledge, new economy, productivity

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I. INTRODUCTION

Human capital refers to the knowledge and skills embodied in people. Like physical capital, it has the potential to create value as a source of output and income. Regional economic studies have linked higher levels of human capital to increases in employment and population growth, wages, and housing prices (Moretti 2004; Simon 1998; Glaeser, Scheinkman and Shleifer 1995; Rauch 1993). In addition, larger stocks of human capital have been shown to lead to more rapid reinvention and increases in long-run economic vitality (Glaeser 2005; Glaeser and Saiz 2004). These empirical findings are explained by the fact that human capital increases individual-level productivity and idea generation (Becker 1964). Thus, by extension, a higher level of human capital within a region raises regional productivity. In addition, the geographic concentration of human capital facilitates knowledge spillovers, which further enhance regional productivity, fuel innovation, and promote growth (Moretti 2004; Rauch 1993; Romer 1990; Lucas 1988; Jacobs 1969; Marshall 1890).

This paper explores how different types of human capital, represented by educational attainment and measures of regional stocks of knowledge, influence the level of economic activity in urban America. Hall and Jones (1999) argue that focusing on levels, rather than growth rates, provides an analysis of differences in long-run economic performance most directly relevant to economic welfare. They note, “long-run differences in levels are the interesting thing to explain” (Hall and Jones 1999, p. 85). By studying the relationship between the amounts of different types of human capital and the level of economic activity, we view our work as attempting to explain the long-run variation in economic performance across U.S. metropolitan areas.

Our research extends the existing literature in two ways. First, to represent economic activity, we utilize newly available data from the U.S. Bureau of Economic Analysis (BEA) on metropolitan area gross domestic product (GDP). These data represent the most comprehensive measure of urban economic activity available. Second, we move beyond the conventional proxy for human capital—i.e., educational attainment—and develop new measures that reflect the types of knowledge that exist within U.S. metropolitan areas. It is widely recognized that some types of human capital are obtained through experience or interactions with others, rather than formal education. As such, we use occupation-level data to construct new measures of the types of knowledge within a large sample of places. In this sense, our work also contributes to the growing literature emphasizing occupation-based regional analysis (Gabe 2009; Florida, Mellander, and Stolarick 2008; Markusen 2004; Feser 2003).

Using educational attainment as an indicator of human capital, we find a strong positive relationship between the proportion of residents with a college degree and the level of economic activity across U.S. metropolitan areas. Moreover, we show that it is not only the amount of formal education that matters, but that the type of knowledge possessed by workers in a region also plays a key role in determining the level of economic activity.

II. ECONOMIC ACTIVITY IN URBAN AMERICA

Gross domestic product captures the market value of all final goods and services produced within a geographic area in a given time period. While federal government agencies have historically measured GDP at the national and state levels, the U.S. BEA recently released experimental measures of GDP by metropolitan area. These new data are available for the years 2001 to 2005, and cover 363 metropolitan areas in the United States.[1]

Virtually all of the economic activity in the United States occurs in and around cities. Metropolitan areas housed more than 80 percent of the U.S. population and produced nearly 90 percent of U.S. GDP during the 2001 to 2005 period. However, considerable variation exists in the level of economic activity among U.S. metropolitan areas. In 2005, for example, the metropolitan area with the largest GDP—New York—produced over $1 trillion in final goods and services, while the smallest metropolitan area—Lewiston, ID—produced only $1.5 billion in final goods and services; a more than 600-fold difference in the size of each metropolitan area's economy.

Clearly, population size explains much of the differential observed among metropolitan area economies. Thus, GDP per capita provides a more meaningful measure to compare the level of economic activity across metropolitan areas. Figure 1 shows the distribution of economic activity in U.S. metropolitan areas based on average GDP per capita between 2001 and 2005. At nearly $75,000, the Bridgeport-Stamford-Norwalk, CT metropolitan area ranks highest among metropolitan areas. Also among the top metropolitan areas are a number of familiar places (e.g., San Jose, CA; Washington, DC; Boston, MA) and a few unexpected locations (e.g., Casper, WY; Sioux Falls, SD). The lowest ranking metropolitan area based on this metric is McAllen, TX, which has an average GDP per capita of just under $15,000—one-fifth of that observed in the highest-ranked metropolitan area. While adjusting for size of place reduces the variation in the

1 See Panek, Baumgardner and McCormick (2007) for more information.

level of economic activity across metropolitan areas, a more than five-fold difference in GDP per capita remains unexplained.

III. EDUCATION AND URBAN ECONOMIC ACTIVITY

Our empirical analysis relates measures of human capital to GDP per capita at the metropolitan area level. Thus, our work is most directly related to studies of the determinants of economic activity that utilize the city or region as the unit of observation (e.g., Florida, Mellander and Stolarick 2008; McGranahan and Wojan 2007; Glaeser and Saiz 2004; Ciccone and Hall 1996; and Glaeser, Scheinkman and Shleifer 1995), rather than the individual (e.g., Moretti 2004; Rauch 1993). As such, we cannot separately identify the private and social benefits arising from human capital accumulation. Rather, our work focuses only on its aggregate contribution to economic activity.

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 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 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 and Description of Variables*

Our dependent variable, GDPPC, is average GDP per capita during the 2001 to 2005 period. This variable is constructed using data on metropolitan area GDP from the U.S. BEA and U.S. Census data on metropolitan area population. We use average GDP per capita over this five-year time interval 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).[2]

As our measure of the amount of human capital within U.S. metropolitan areas, we use 2000 Census data to calculate the proportion of each metropolitan area's working-age population with a college degree. This explanatory variable, COLLEGE, is the primary variable of interest in our initial analysis. While this measure of human capital, based on formal education, likely fails to capture the full array of knowledge and skills within a metropolitan area, educational attainment is a conventional indicator of human capital that is widely used in the regional science literature.[3] In the next section of the paper, we extend our analysis to include additional human capital measures that reflect the types of knowledge within metropolitan areas.

As control variables, we construct two measures of physical capital investment by metropolitan area using information from the U.S. BEA.[4] The first control variable, CAPEQUIP, is the estimated annual investment in capital equipment and software; the

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2 Our results are not sensitive to choice of year within this period or method of averaging when constructing the dependent variable.

3 Years of schooling, sometimes used in the labor economics literature to analyze an individual's private return to education, is an alternative measure of educational attainment. The correlation between the proportion of residents with a college degree and average years of schooling in a metropolitan area is 0.73. Standardized regression results using this alternative measure of educational attainment (available from the authors upon request) are nearly identical to results reported in the paper.

4 See Meade, Rzeznik and Robinson-Smith (2003) for more information.

second control variable, CAPSTRUCT, is the estimated annual investment in capital structures. Investment in equipment and software includes items such as computers, software, automobiles, and other machinery, whereas investment in structures includes items such as buildings, telecommunications, and electric light and power. We use national-level data by industry to estimate the amount of physical capital investment per worker, and then allocate these measures to each metropolitan area based on the composition of industry employment that existed in 2000.[5] Along with accounting for differences in capital investment across regions, these measures also capture the industrial composition of U.S. metropolitan areas, which may contribute to differences in economic activity. Our final control variable, DENS, is the 2000 population density for each metropolitan area, included to account for the effects of urban agglomeration on productivity (Ciccone 2002; Ciccone and Hall 1996).[6]

We use data covering 290 U.S. metropolitan areas for our empirical analysis.[7] The sample captures 95 percent of metropolitan area GDP and 94 percent of metropolitan area population. Further, the 290 metropolitan areas in our sample represent 85 percent of

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5 Economic growth models typically relate the long-run level of output to the steady-state stock of physical capital, rather than the investment rate. However, because data on the stock of physical capital are not available, we use flow measures to control for differences in physical capital across U.S. metropolitan areas. Constructing these variables required the assumption that industry-level investment per worker is similar across U.S. metropolitan areas as information that would allow us to vary the investment rate by metropolitan area is not available. Further, it is possible that the actual amount of investment per worker is related to the amount of human capital in the region, which would bias our results. To assess the robustness of the relationship between human capital and metropolitan area GDP per capita, we also report results with these measures of physical capital omitted from the model.

6 Early empirical studies of urban agglomeration focused on city size rather than density (Segal 1976; Sveikauskas 1975). Our results (available from the authors upon request) remain unchanged if population size—rather than density—is used to control for urban agglomeration economies.

7 Our reliance on a subset of the 363 metropolitan areas included in the U.S. BEA metropolitan GDP data is due to differences in metropolitan area definitions between the U.S. BEA and U.S. Census. Our dataset is constructed using metropolitan area definitions utilized by the U.S. BEA, which correspond to those issued by the Office of Management and Budget (OMB) in December 2006. We then make appropriate adjustments to the U.S. Census data to match, as closely as possible, the OMB metropolitan area definitions.

total U.S. GDP and nearly 80 percent of the population. Table 1 presents descriptive statistics for the variables used in our base empirical analysis.

B. Estimation Approach and Discussion of Regression Results

Using the data discussed above and multiple regression analysis, we estimate the following reduced-form equation exploiting the cross-sectional variation in economic activity that exists across U.S. metropolitan areas:

$$ln\ (\mathrm{GDPPC}_i) = \alpha + \beta_1\mathrm{COLLEGE}_i + \beta_2\mathrm{CAPEQUIP}_i + \beta_3\mathrm{CAPSTRUCT}_i + \beta_4\mathrm{DENS}_i + \sigma_i + \varepsilon_i \quad (1)$$

where $i \equiv$ MSA, $\sigma_i \equiv$ state-level fixed effect, and $\varepsilon_i \equiv$ i.i.d. disturbance term. To mitigate any bias induced by potential endogeneity issues, we employ lagged independent variables measured at the beginning of the study period. Moreover, the inclusion of state fixed effects in our empirical specification minimizes the influence of any unobserved variables that may be correlated with both the dependent variable and the disturbance term. Nonetheless, to assess the magnitudes of any endogeneity bias, we estimate equation (1) using ordinary least squares (OLS) and two-stage least squares (2SLS) treating college share as endogenous and find little difference in our main results.

Column (1) of Table 2 presents the results of our OLS regression analysis. Overall, the empirical model performs quite well, explaining more than 60 percent of the variation in the natural logarithm of metropolitan area GDP per capita. In addition, the expected relationship holds for all of the variables in our model, and three of the four variables are significant at conventionally accepted levels. Notably, we find that a one-percentage point increase in the proportion of a metropolitan area's working-age population with a college degree is associated with a more than two percent increase in GDP per capita. Our results with respect to physical capital depend on the type of investment; increasing spending on capital equipment by $1,000 per worker results in a more than 18 percent increase in GDP per capita, while increasing investment in capital structures does not have a statistically significant effect on economic activity. Finally, increasing the population density of a metropolitan area by one-hundred people per square mile results in a 1.8 percent increase in GDP per capita. This finding is consistent with research that has demonstrated the presence of urban production externalities related to the density of economic activity (Ciccone 2002; Ciccone and Hall 1996).[8]

To compare results across independent variables, we also examine the change in GDP per capita given a one-standard deviation increase in each variable. We find that such a change in educational attainment, capital equipment, capital structure, and population density results in an approximately 17 percent, 10 percent, 1 percent, and 6 percent, increase in GDP per capita, respectively. Thus, the amount of human capital in a metropolitan area appears to play a leading role in explaining observed differences in the level of economic activity.

Column (2) of Table 2 presents the results of our analysis when the physical capital measures are omitted from the base empirical model (see footnote 5). Doing so reduces the explanatory power of the model as well as the estimated effect of education on urban economic activity, but does not substantially alter our key conclusions related to the relationship between human capital and metropolitan area GDP per capita.[9] Human

8 Evaluated at mean values, our results imply that a doubling of population density is associated with a 5.3 percent increase in economic activity, which is within the 4.5 to 6 percent range established by Ciccone and Hall (1996) and Ciccone (2002) for U.S. states and European regions, respectively.

9 We also estimated a version of the model omitting the capital structure variable, which does not have a significant effect on GDP per capita. The estimated coefficients corresponding to the other explanatory variables are nearly identical to those reported in Column (1) of Table 2.

capital, as measured by the educational attainment of a metropolitan area, remains a strong predictor of urban economic activity.

The endogeneity of a metropolitan area's college-educated workforce is another concern that might arise in cross-sectional analysis of this nature. That is, the proportion of college graduates in a metropolitan area may be driven by the amount of economic activity in that metropolitan area, which would bias our OLS regression results. This issue is of particular concern given research indicating that a divergence in human capital levels has occurred across cities over the past several decades (Berry and Glaeser 2005). To investigate this issue, we re-estimate our regression model using 2SLS and perform Hausman specification tests for endogeneity bias.

The challenge with performing such analysis is the identification of good instruments for the potentially endogenous explanatory variable. For an instrumental variable to be valid, it must be relevant (i.e., correlated with the potentially endogenous explanatory variable) and exogenous (i.e., uncorrelated with the disturbance term). We consider two instrumental variables: the presence of a land-grant university within a metropolitan and a climate index based on temperature and precipitation.

Moretti (2004) shows that the presence of a land-grant university is a good predictor of cross-sectional variation in college share, and demonstrates that metropolitan areas with land-grant universities generally appear to be similar to those without one along a wide array of demographic characteristics. An added advantage of this instrument relative to the presence of any university or college is that it is likely to be more random since land-grant universities were established in the nineteenth century following the land-grant movement, and thus are unlikely to be influenced by current levels of economic activity.[10] Other research has established a link between climate and human capital within the United States (Rappaport 2007; Glaeser and Saiz 2004). Thus, as a second instrumental variable, we develop a climate index that measures the relative temperature and precipitation of the metropolitan areas in our sample.[11] The climate of a metropolitan area can be considered exogenous, as it is not influenced by current levels of economic activity.

The results of this two-stage analysis are provided in Columns (3) and (4) of Table 2. Consistent with Moretti (2004), first-stage regression results indicate that the presence of a land-grant university increases a metropolitan area's proportion of residents with a college degree by over five percentage points. This is a sizeable effect since, on average, the places in our sample have a college share of about 23 percent. In addition, the first-stage regression results reported in Column (4) confirm that climate is a significant predictor of educational attainment. The first-stage *F*-statistic of 22.3 for the excluded instrument set exceeds the rule of thumb for strong instruments (i.e., *F*-statistic of at least 10) proposed by Staiger and Stock (1997). Further, we can reject the null hypothesis of weak instruments based on the Stock and Yogo (2005) test, indicating that

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[10] The Morrill Acts of 1862 and 1890 are credited for establishing the major land-grant universities that exist in the United States (Appleby 2007). There were 73 land-grant universities created before 1890, located in places ranging from Boston, MA and Orono, ME to Columbus, OH and Corvallis, OR. The 1994 Land-Grant Act added a number of tribal institutions to the list of land-grant universities, which are not included in our analysis.

[11] The data for our climate index are drawn from the 2007 *County and City Data Book* published by the U.S. 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 the 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 and climate, while lower values of the index indicate a relatively warm and dry climate.

our instruments are strong.[12] Moreover, with a *p*-value of 0.385, the Sargan test of overidentifying restrictions indicates that our instruments are also uncorrelated with the disturbance term.[13] As our instruments meet the instrument relevance and exogeneity conditions, we conclude that they are valid.

The top panel of Table 2 shows that our second-stage results are similar in sign and magnitude to those estimated using OLS.[14] Furthermore, results from Hausman specification tests for endogeneity bias do not identify any systematic differences between the OLS and 2SLS coefficients. As shown in the bottom panel of Table 2, the coefficients associated with the first stage residual are not significantly different from zero in any of the regression models (Hausman 1983). Therefore, any endogeneity of a metropolitan area's college share does not appreciably affect our OLS estimates.

IV. KNOWLEDGE AND URBAN ECONOMIC ACTIVITY

A limitation of our initial regression analyses is that human capital is measured simply as the presence or absence of a college degree. This approach emphasizes the amount of formal schooling (i.e., "vertical differentiation" of human capital) but says nothing about the specific subjects in which people possess knowledge and skills (i.e., "horizontal differentiation" of human capital) (Bacolod, Blum and Strange 2009).

[12] Stock and Yogo (2005) suggest a weak instrument test that compares an *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.

[13] 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 this case one.

[14] Because limited information maximum likelihood estimation (LIML) is more robust to the presence of weak instruments, we also estimated our model using this estimator and obtained identical results to those presented in the paper using 2SLS.

Previous studies have suggested that formal education provides an incomplete picture of human capital (Florida, Mellander and Stolarick 2008; Ingram and Neumann 2006; Goldin and Katz 1996; Lucas 1977). Such thinking is summarized nicely by Ingram and Neumann (2006, p. 38), who remark that "Years of education … is a coarse measure of skill: all degrees are not equivalent in terms of the skills they encompass, and all students – even those that graduate from the same institution with the same degree – do not achieve the same level of preparedness upon graduation." This idea suggests that the actual types of knowledge and skills possessed by a regional workforce may be associated with a metropolitan area's GDP per capita.

Measuring the types of knowledge in U.S. metropolitan areas presents a number of challenges to empirical researchers since, unlike the attainment of a college degree, such information is not directly observable. Similar to Feser (2003), our approach allows us to infer the types of knowledge present in metropolitan areas using data on the knowledge requirements of occupations and the occupational structure of each metropolitan area. Florida, Mellander and Stolarick (2008, p. 618) suggest that unlike educational attainment, which is a measure of "potential talent or skill," occupations provide a strong indication of "utilized skill" as it is "absorbed by and used by the economy."

Information on the knowledge requirements of occupations is from the U.S. Department of Labor's Occupational Information Network (O*NET).[15] Table 3 shows the 33 knowledge areas for which this information is available, which includes a wide range of topics such as engineering and technology, public safety and security, and sales

[15] The O*NET database is described in detail by Peterson et al. (2001) and Feser (2003).

and marketing. The scale used in the O*NET surveys to rate the importance of knowledge ranges from 1 to 5, where a score of 1 is "not important" and a score of 5 is "extremely important." If a knowledge area is viewed as at least "somewhat important" (a score of 2 or higher), the respondent is asked to rate the level of knowledge required to perform the job. This scale ranges from 1 to 7, and different anchors are provided for each knowledge area.

Constructing the knowledge variables for our analysis involved matching occupational categories between the O*NET system and 2000 U.S. Census. In many cases, we combined multiple O*NET occupations into a single Census category. With this information available for 470 Census occupations, we calculated a knowledge index as the product of the knowledge importance and level. Feser (2003) used the same approach, noting that it places a greater emphasis on high knowledge that is relevant to a given occupation. We then use this information to develop knowledge indices for each metropolitan area. These variables are averages of the knowledge indices for the occupations considered in the analysis, weighted by the proportion of a metropolitan area's workforce in each occupation. With the knowledge profiles for each metropolitan area compiled, we construct a new knowledge-based measure of human capital by combining the individual knowledge area indexes and then examine the partial effects of each knowledge area on urban economic activity.

A. Aggregate Analysis of Knowledge

We begin our analysis of the relationship between knowledge and urban economic activity by re-estimating equation (1) using an aggregate knowledge-based measure of human capital, KNOWLEDGE, in place of the conventional education-based measure. To facilitate comparisons with our initial results, we calculate this new measure of regional human capital as the sum of each metropolitan area's 33 knowledge area indexes "standardized" by the number of standard deviations that a metropolitan area is above or below the average aggregate knowledge index score.[16] As such, the regression coefficient on this variable is interpreted as the percentage change in GDP per capita due to a one-standard deviation change in a region's aggregate stock of knowledge.

For comparison purposes, Table 4 shows a parallel set of regression results focusing on the relationship between knowledge and urban economic activity. Again, the empirical model performs well, explaining 50 percent of the variation in economic activity across U.S. metropolitan areas with the expected relationship holding for all of the variables in the model. OLS results reported in column (1) indicate that a one-standard deviation increase in a region's knowledge stock is associated with a 13.6 percent increase in economic activity, and columns (2)-(4) of Table 4 show that these results are robust to the omission of the physical capital variables and to treating a region's stock of knowledge as endogenous. While smaller than the 17 percent increase in economic activity associated with a one standard deviation change in educational attainment (see p. 8)—the conventional measure of human capital—these results confirm that human capital is an important driver of a region's economic vitality. However, the difference in results between the conventional and our new knowledge-based measure of human capital suggests that the contribution to urban economic activity is likely to differ depending on the type of knowledge involved, which we investigate in detail below.

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[16] The correlation between the share of residents with a college degree in a metropolitan area and our aggregate knowledge-based measure of human capital is 0.83.

B. Partial Analysis of Knowledge Areas

To analyze the relationship between individual knowledge types and urban economic activity, we disaggregate the knowledge index and conduct a partial analysis of the effects of each of the 33 knowledge areas. As above, the knowledge variables are standardized to facilitate comparisons across the subjects. These models also include, as additional controls not shown in the table, the explanatory variables from Table 2. Because of the difficulties associated with obtaining valid instruments for each of the 33 knowledge variables, we limit our analysis here to OLS regression models. As such, we are not able to make causal inferences when interpreting our results. However, as with our initial analyses, we construct the knowledge variables using information from 2000 and relate them to average GDP per capita during the 2001 to 2005 period and include state fixed effects to mitigate any endogeneity bias.

Table 5 summarizes information on the relationship between GDP per capita and a metropolitan area's average index value for each of the 33 knowledge areas. Results show that a metropolitan area's average knowledge index value in 13 areas have a positive and statistically significant effect on GDP per capita. Some of the knowledge areas that are positively associated with economic activity include administration and management, economics and accounting, mathematics, and computers and electronics. On the other hand, knowledge areas such as education and training, therapy and counseling, and food production are negatively associated with GDP per capita.

These results provide insight about the types of knowledge associated with high levels of economic activity. First, the importance of knowledge about topics related to business, management, and commerce is clear. This finding is captured by the knowledge areas of administration and management, economics and accounting, personnel and human resources, customer and personal service, and sales and marketing. Another key finding supported by this analysis is the importance of information dissemination using computers and advanced forms of communications. This finding encompasses knowledge areas such as computers and electronics, and telecommunications.

Of equal significance are findings related to the types of knowledge that do not appear to boost economic activity. We note that the knowledge areas of mechanical, building and construction, and food production do not have a significant effect on GDP per capita in urban America. Similarly, we do not find a positive and statistically significant relationship between GDP per capita and the knowledge areas of medicine and dentistry, and public safety and security. These results are somewhat surprising given the importance of health and safety to economic vitality and overall quality-of-life. One potential reason for these findings is that occupations that utilize this type of knowledge tend to be distributed evenly across U.S. metropolitan areas, and thus may not exhibit sufficient variation to explain differences in GDP per capita.

It is important to note that these results—namely, those related to the knowledge area of education and training—do not diminish the importance of educational attainment to metropolitan area GDP per capita. A key finding from our initial regression analyses is the substantial contribution of educational attainment to economic activity. However, results presented in this section show that knowledge related to education and training is associated with lower levels of GDP per capita, other things being equal. While the end-result of a college degree is an increase in economic activity, the process of delivering such an education does not significantly enhance a region's GDP per capita.

This may be explained by the fact that our measure of economic activity relies on the market value of final goods and services produced within a metropolitan area.[17] In the case of the knowledge area of education and training, the final goods and services that are counted in GDP statistics are the revenues generated by a university or college such as tuition, fees, and grants and contracts. On the other hand, the most valuable output of an educational institution, arguably its graduates, is not directly connected in metropolitan area GDP statistics to the level of knowledge about education and training. The extent to which the acquisition of a K-12 education is captured in GDP statistics is likely to be even smaller.

While our aggregate measure of knowledge has an effect on economic activity similar to the effect of educational attainment, our empirical analysis of the knowledge stocks of U.S. metropolitan areas shows that there is considerable variation in the effects of the individual knowledge areas. Thus, along with educational attainment it is useful to consider the types of knowledge that are available in a regional workforce. Table 6 lists the top 25 U.S. metropolitan areas in terms of both measures of human capital, with the knowledge-based measure calculated using each metropolitan area's standardized knowledge value for each topic, weighted by the coefficients in Table 5.

The two rankings of metropolitan areas shown in Table 6 reveal some noteworthy differences in the U.S. metropolitan areas characterized as "high" human capital. First, only six places (San Jose, Boulder, Austin, Bridgeport, Washington, D.C., and San Francisco) appear on both lists. Furthermore, metropolitan areas with a high proportion of college educated include, as expected, major "university towns" such as Iowa City, IA;

[17] Florida, Mellander and Stolarick (2008) also suggest that a high regional share of educators may reflect a large population of students, which typically contribute less to regional economic activity.

Corvalis, OR; and Lawrence, KS. In the list that rates places based on the types of knowledge used in the workforce these areas are replaced by cities such as Charlotte, NC and Seattle, WA, which are characterized by workers knowledgeable about business services and technology. The basic idea conveyed here is that conclusions about the amount of human capital present in a region depend on the chosen metric, whether it is based on the generic receipt of a college degree or the specific types of knowledge used in the workplace.

V. CONCLUSIONS

Previous research spanning the literature from cross-country macroeconomic studies of productivity and economic growth to labor economics studies focusing on individual-level earnings have uncovered strong evidence related to the importance of human capital as a key determinant of economic vitality. Our results focusing on differences in the levels of GDP per capita across U.S. metropolitan areas provide new evidence on the importance of human capital to regional economies. Using educational attainment as an indicator of human capital, we find that a one-percentage point increase in the proportion of residents with a college degree is associated with about a two percent increase in U.S. metropolitan area GDP per capita. This finding is robust across several model specifications, some of which treat educational attainment as an endogenous variable explained by the presence of a land grant university and climate.

Further results show that it is not only the amount of education that matters, but that the level of economic activity is also determined by the types of knowledge possessed by workers in a region. Specifically, we find that knowledge about subjects such as administration and management, economics and accounting, mathematics, computers and electronics, and telecommunications are particularly important drivers of economic activity. Florida, Mellander, and Stolarick (2008) reached similar conclusions, finding that computer science-, management and business-, and financial operations-based occupations are key determinants of regional economic development.

These results point to the importance of producer services to the economies of U.S. metropolitan areas. Collectively, the knowledge areas of administration and management, economics and accounting, personnel and human resources, customer and personal service, clerical, and law and government contribute to the provision of producer services. Similar to our results, Hansen (1990) and Gatrell (2002) found that producer services enhance regional productivity and wages. An explanation for these findings is that producer services allow for a greater division of labor (Hansen 1990), and that service providers use their “creativity” and “abilities to undertake research and development” to deliver “unstandardized” work products that provide value to their clients and the overall economy (Lindahl and Beyers 1999, p. 18).

Other results suggest that activities associated with the “new economy” are important determinants of economic activity in urban America. Specifically, we find that the specific knowledge areas of telecommunications, and computers and electronics have a positive and statistically significant effect on metropolitan area GDP per capita. Oliner and Sichel (2000) and Nordhaus (2002) have uncovered similar results showing positive effects of information technology, i.e., computers and telecommunications, on U.S. macroeconomic growth during the late 1990s.

Study findings suggest that the keys to a vibrant metropolitan area in the early 21st century likely differ from characteristics of success in earlier decades. With the exception of the positive relationship found between GDP per capita and the knowledge area of production and processing, we find no evidence of manufacturing-, agricultural- or basic scientific-related knowledge contributing to differences in GDP per capita across U.S. metropolitan areas. These types of activities, at different times believed to determine the fates of cities, now appear to have been overshadowed in importance by human capital associated with the provision of producer services and information technology.

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Table 1: Descriptive Statistics for Base Case Analysis

Variable	Mean	Std Dev	Minimum	Maximum
GDP Per Capita	$33,856	$9,062	$14,728	$74,261
College	23.41	7.38	11.05	52.38
Capital Equipment	$6.05	$0.54	$4.67	$9.02
Capital Structure	$4.29	$0.94	$2.76	$9.77
Population Density	2.88	3.37	0.12	27.30

Notes: GDP Per Capita is 2001-2005 average. All other variables are from 2000. College represents the percentage of each MSA's working population (i.e., 25+) with a four-year degree. Capital Equipment and Capital Structure are estimated annual investments expressed in thousands on a per worker basis. Population Density is expressed in hundreds of people per square mile. N=290.

Sources: Current Dollar Gross Domestic Product by Metropolitan Statistical Area, U.S. Bureau of Economic Analysis; Annual Estimates of the Population of Metropolitan and Micropolitan Statistical Areas, U.S. Bureau of Census; United States Census (2000), U.S. Bureau of Census; Business Investment by Industry in the U.S. Economy, U.S. Bureau of Economic Analysis.

Table 2: Regression Results for Education and Urban Economic Activity

	OLS		2SLS	
	(1)	(2)	(3)	(4)
Dependent Variable is Log of Average GDP Per Capita				
Constant	8.577 ***	9.781 ***	8.837 ***	8.755 ***
	(55.64)	(131.72)	(31.65)	(34.24)
College	0.024 ***	0.018 ***	0.018 ***	0.020 ***
	(13.29)	(10.17)	(3.67)	(4.47)
Capital Equipment	0.187 ***	--	0.149 ***	0.161 ***
	(7.35)		(3.54)	(4.14)
Capital Structure	0.009	--	0.025	0.020
	(0.53)		(1.13)	(0.95)
Population Density	0.018 ***	0.025 ***	0.022 ***	0.021 ***
	(5.07)	(6.17)	(4.58)	(4.60)
Adj. R^2	0.612	0.485	--	--
First Stage: Dependent Variable is College				
Land Grant	--	--	5.921 ***	5.729 ***
			(5.94)	(5.82)
Climate	--	--	--	0.142 ***
			--	(2.87)
Adj. R^2	--	--	0.436	0.453
F -statistic of Excluded Instruments	--	--	--	22.30 ++
p -value of Overidentification Test	--	--		0.385
Hausman Test for Endogenity (H_0: γ_1 = 0)				
First Stage Residuals	--	--	0.006	0.004
			(1.15)	(0.88)
Interpretation	--	--	Fail to Reject	Fail to Reject
Preferred Estimator	--	--	OLS	OLS

Notes: All model specifications include state fixed effects. *t* -statistics reported in parentheses. *** and ** denote significance at the .01 and .05 levels, respectively. Full results from first stage regressions omitted for brevity. ++ denotes that we can reject the null hypothesis of weak instruments based on the Stock and Yogo (2005) test (α = 0.05) using a 5 percent size distortion. *First Stage Residuals* reports the coefficient (γ_1) and corresponding *t* -statistic when the estimated residuals obtained from the first stage regression are included in the second stage regression. N=290.

Table 3: Knowledge Areas

Administration and Management	Engineering and Technology	Personnel and Human Resources
Biology	English Language	Philosophy and Theology
Building and Construction	Fine Arts	Physics
Chemistry	Food Production	Production and Processing
Clerical	Foreign Language	Psychology
Communications and Media	Geography	Public Safety and Security
Computers and Electronics	History and Archeology	Sales and Marketing
Customer and Personal Service	Law and Government	Sociology and Anthropology
Design	Mathematics	Telecommunications
Economics and Accounting	Mechanical	Therapy and Counseling
Education and Training	Medicine and Dentistry	Transportation

Sources: Occupational Information Network (O*NET), U.S. Department of Labor.

Table 4: Regression Results for Knowledge and Urban Economic Activity

	OLS		2SLS	
	(1)	(2)	(3)	(4)
Dependent Variable is Log of Average GDP Per Capita				
Constant	9.150 ***	10.142 ***	9.033 ***	8.960 ***
	(57.16)	(141.66)	(34.22)	(35.46)
Knowledge	0.136 ***	0.097 ***	0.163 ***	0.180 ***
	(8.84)	(6.99)	(3.24)	(3.83)
Capital Equipment	0.167 ***	--	0.197 ***	0.215 ***
	(5.52)		(3.24)	(3.74)
Capital Structure	0.013	--	-0.001	-0.010
	(0.64)		(-0.04)	(-0.33)
Population Density	0.025 ***	0.031 ***	0.024 ***	0.023 ***
	(6.29)	(7.06)	(4.85)	(4.73)
Adj. R^2	0.490	0.387	--	--
First Stage: Dependent Variable is Knowledge				
Land Grant	--	--	0.664 ***	0.645 ***
			(4.97)	(4.85)
Climate	--	--	--	0.014 **
				(2.09)
Adj. R^2	--	--	0.447	0.455
F -statistic of Excluded Instruments	--	--	--	14.69 +
p -value of Overidentification Test	--	--	--	0.343
Hausman Test for Endogenity (H_0: $\gamma_1 = 0$)				
First Stage Residuals	--	--	-0.029	-0.049
			(-0.56)	(-1.00)
Interpretation	--	--	Fail to Reject	Fail to Reject
Preferred Estimator	--	--	OLS	OLS

Notes: All model specifications include state fixed effects. *t* -statistics reported in parentheses. *** and ** denote significance at the .01 and .05 levels, respectively. Full results from first stage regressions omitted for brevity. + denotes that we can reject the null hypothesis of weak instruments based on the Stock and Yogo (2005) test (α = 0.05) using a 10 percent size distortion. *First Stage Residuals* reports the coefficient (γ_1) and corresponding *t* -statistic when the estimated residuals obtained from the first stage regression are included in the second stage regression. N=290.

Table 5: Regression Results for Knowledge Areas

Knowledge Area, Standardized	Est. Coeff	*t*-Statistic
Administration and Management	0.170 ***	8.43
Economics and Accounting	0.150 ***	9.75
Mathematics	0.136 ***	7.67
Computers and Electronics	0.135 ***	5.79
Sales and Marketing	0.130 ***	7.39
Personnel and Human Resources	0.118 ***	5.12
Customer and Personal Service	0.116 ***	6.21
Clerical	0.085 ***	4.93
Telecommunications	0.084 ***	5.00
Law and Government	0.067 ***	3.21
Production and Processing	0.051 ***	2.62
Design	0.050 ***	3.75
Engineering and Technology	0.034 ***	2.62
English Language	0.031	1.07
Physics	-0.003	-0.24
Building and Construction	-0.005	-0.35
Communications and Media	-0.006	-0.19
Transportation	-0.009	-0.54
Mechanical	-0.020	-1.07
Public Safety and Security	-0.021	-1.31
Medicine and Dentistry	-0.035 ***	-2.97
Chemistry	-0.049 ***	-4.29
Food Production	-0.061 ***	-4.74
Biology	-0.068 ***	-5.99
Therapy and Counseling	-0.075 ***	-5.15
Psychology	-0.081 ***	-4.52
Fine Arts	-0.112 ***	-5.46
Foreign Language	-0.123 ***	-6.93
Geography	-0.136 ***	-7.99
Philosophy and Theology	-0.139 ***	-9.28
Sociology and Anthropology	-0.150 ***	-8.92
History and Archeology	-0.154 ***	-11.39
Education and Training	-0.174 ***	-7.45

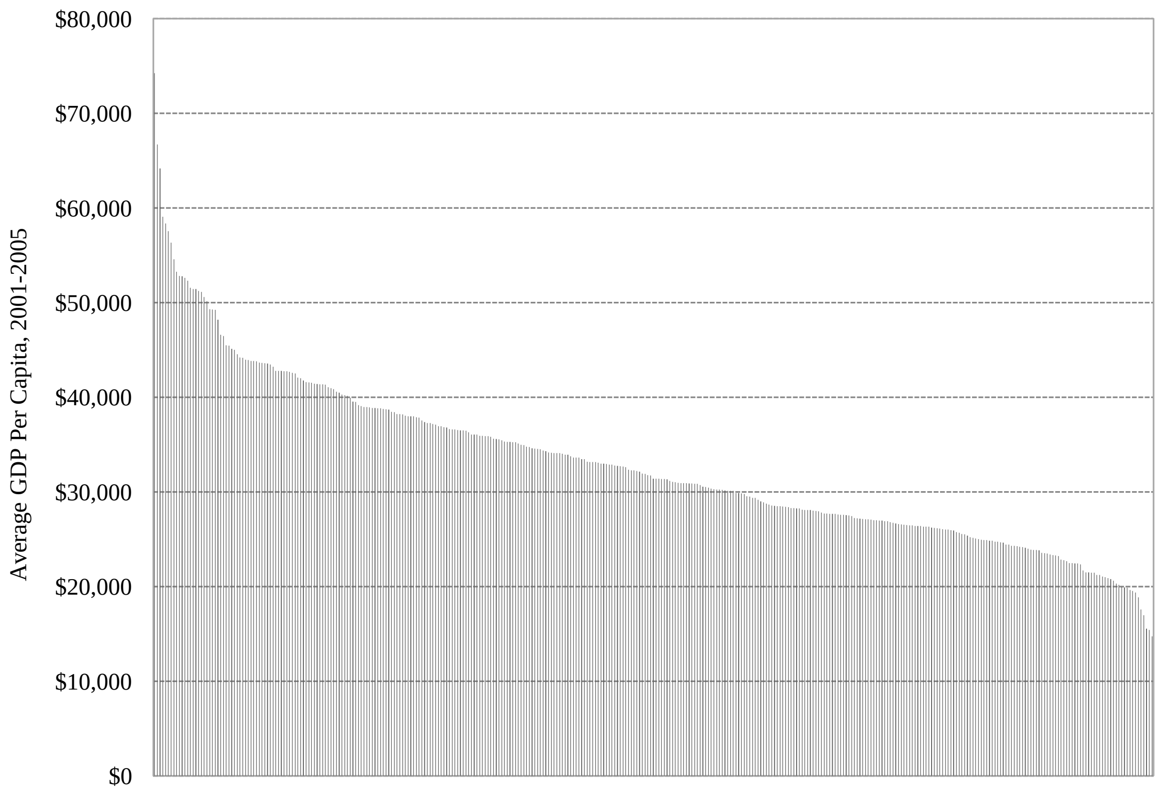
Notes: Results summarzied in the table are from 33 different regression models, which also include the explanatory variables shown in Table 2 and state fixed effects. *** denotes significance at the .01 level. N=290.

Table 6: Top 25 U. S. Metropolitan Areas Based on Alternative Measures of Regional Human Capital Stocks

Rank	Educational Attainment	Types of Knowledge
1	Boulder, CO	San Jose-Sunnyvale-Santa Clara, CA
2	Iowa City, IA	Denver-Aurora, CO
3	Corvallis, OR	Dallas-Fort Worth-Arlington, TX
4	Lawrence, KS	Atlanta-Sandy Springs-Marietta, GA
5	Washington-Arlington-Alexandria, DC-VA-MD-WV	San Francisco-Oakland-Fremont, CA
6	Columbia, MO	Bridgeport-Stamford-Norwalk, CT
7	Madison, WI	Phoenix-Mesa-Scottsdale, AZ
8	San Jose-Sunnyvale-Santa Clara, CA	Washington-Arlington-Alexandria, DC-VA-MD-WV
9	Charlottesville, VA	Austin-Round Rock, TX
10	Santa Fe, NM	Salt Lake City, UT
11	Bloomington, IN	Seattle-Tacoma-Bellevue, WA
12	Fort Collins-Loveland, CO	Charlotte-Gastonia-Concord, NC-SC
13	Raleigh-Cary, NC	Cedar Rapids, IA
14	San Francisco-Oakland-Fremont, CA	Minneapolis-St. Paul-Bloomington, MN-WI
15	Gainesville, FL	Des Moines-West Des Moines, IA
16	Champaign-Urbana, IL	Jacksonville, FL
17	Bridgeport-Stamford-Norwalk, CT	Columbus, OH
18	Burlington-South Burlington, VT	Portland-Vancouver-Beaverton, OR-WA
19	College Station-Bryan, TX	Manchester-Nashua, NH
20	Ann Arbor, MI	Tulsa, OK
21	Tallahassee, FL	Huntsville, AL
22	Austin-Round Rock, TX	Boulder, CO
23	State College, PA	Detroit-Warren-Livonia, MI
24	Bloomington-Normal, IL	Kansas City, MO-KS
25	Boston-Cambridge-Quincy, MA-NH	Richmond, VA

Notes: The knowledge-based measure of human capital used for this ranking is calculated using each metropolitan area's standardized knowledge values for each knowledge area, weighted by the regression coefficients reported in Table 5.

Figure 1: Distribution of Economic Activity in U.S. Metropolitan Areas, 2001-2005



Sources: Current Dollar Gross Domestic Product by Metropolitan Statistical Area, U.S. Bureau of Economic Analysis; Annual Estimates of the Population of Metropolitan and Micropolitan Statistical Areas, U.S. Bureau of Census.