HUMAN CAPITAL AND ECONOMIC ACTIVITY IN URBAN AMERICA

Jaison R. Abel*
Federal Reserve Bank of New York
E-mail: jaison.abel@ny.frb.org

Todd M. Gabe
School of Economics, University of Maine
E-mail: todd.gabe@umit.maine.edu

ABSTRACT. We examine the relationship between human capital and economic activity in U.S. metropolitan areas, extending the existing literature in two important 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 a 2.3 percent increase in metropolitan area GDP per capita. Second, we develop new measures of human capital that reflect the types of knowledge within U.S. metropolitan areas. Knowledge related to the provision of producer services and information technology are particularly important determinants of economic vitality.

Key words: Human Capital, Knowledge, New Economy, Productivity

JEL Classification: R11, J24, O40

* Corresponding author: 716-849-5010 (phone), 716-849-5021 (fax).

The views and opinions expressed here are solely those of the authors and do not necessarily reflect those of the Federal Reserve Bank of New York, the Federal Reserve System, or the University of Maine.

HUMAN CAPITAL AND ECONOMIC ACTIVITY IN URBAN AMERICA

ABSTRACT. We examine the relationship between human capital and economic activity in U.S. metropolitan areas, extending the existing literature in two important 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 a 2.3 percent increase in metropolitan area GDP per capita. Second, we develop new measures of human capital that reflect the types of knowledge within U.S. metropolitan areas. Knowledge related to the provision of producer services and information technology are particularly important determinants of economic vitality.

Key words: Human Capital, Knowledge, New Economy, Productivity

JEL Classification: R11, J24, O40

I. BACKGROUND

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).

There are two primary explanations for these empirical findings. First, human capital increases individual-level productivity and idea generation (Becker 1964). Thus, a higher level of human capital within a region raises regional productivity. Second, 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.

Gross domestic product (GDP), the measure of economic activity used in our analysis, 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 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 new data are available for the years 2001 to 2005, and cover 363 metropolitan areas in the United States.[1] The availability of this new information provides an opportunity to analyze the factors that explain differences in the amount of economic activity generated by U.S. metropolitan areas.

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 metropolitan areas in the United States. In 2005, for example, the metropolitan area with the largest GDP—New York city—produced over $1 trillion in final goods and services, while the smallest metropolitan area—Lewiston, Idaho—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. Table 1

---

[1] Metropolitan area definitions correspond to those issued by the Office of Management and Budget in June 2003, and last revised in December 2006. See Panek, Baumgardner, and McCormick (2007) for more information.

presents a list of the top and bottom 20 U.S. metropolitan areas based on average GDP per capita between 2001 and 2005. With an average GDP per capita of nearly $75,000, 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; Washington, DC; Boston, MA) and a few unexpected locations (e.g., Casper, WY; Sioux Falls, SD). The lowest ranking U.S. metropolitan area based on GDP per capita is McAllen-Edinburg-Mission, Texas, 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 significantly reduces the variation in the level of economic activity across metropolitan areas, a more than five-fold difference in GDP per capita still remains.

II. 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 and productivity 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 et al. 1995), rather than the individual (e.g., Moretti 2004; Acemoglu and Angrist 2000; Rauch 1993). As such, we cannot separately identify the private and social benefits arising from human capital accumulation. Rather, our work focuses only on the aggregate contribution of human capital to economic activity in urban America.

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 that exist between countries. 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 economic activity 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 published by the U.S. Bureau of Economic Analysis, as described above, and data on metropolitan area population from the U.S. Census Bureau. We use average GDP per capita 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).[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,

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

based on formal education, likely fails to capture the full array of knowledge and cognitive skills within a metropolitan area, educational attainment is a conventional measure of human capital that is widely used by others. In the next section of the paper, we extend our analysis to include additional measures of human capital 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. Bureau of Economic Analysis.[3] The first control variable, CAPEQUIP, is the estimated annual investment in capital equipment and software; the 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. Our final control variable, POP, is the 2000 population for each metropolitan area, and is included in our analysis to account for the effects of city size on productivity (see, e.g., Yankow 2006; Glaeser and Mare 2001; Segal 1976; and Sveikauskas 1975).[4]

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

4 Ciccone and Hall (1996) show that density is an important determinant of labor productivity in U.S. states. Our results remain unchanged if population density—rather than size—is used to measure and control for agglomeration economies.

We use data covering 290 metropolitan areas in the United States for our empirical analysis.[5] Our 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 total U.S. GDP and nearly 80 percent of the population. Table 2 presents the descriptive statistics for the variables used in the 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 the metropolitan areas in our dataset:

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

where $i \equiv$ MSA and $\varepsilon_i \equiv$ disturbance term that is assumed to be independently and identically distributed (N $(0, \sigma^2)$).

We begin by estimating equation (1) using ordinary least squares (OLS) and then re-estimate the model with controls for regional effects not captured by the explanatory variables.[6] Columns (1) and (2) of Table 3 present the results of our initial regression analysis. Overall, the empirical models perform quite well, explaining approximately 50 percent of the variation in the natural logarithm of metropolitan area GDP per capita. In addition, after controlling for regional effects, the expected relationship holds for all of

---

5 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. Specifically, 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.

6 We construct nine dummy variables based on U.S. Census Bureau regional divisions to control for unobserved regional effects.

the variables in our model, and three of the four variables are significant at conventionally accepted levels in both specifications.

In the initial analysis shown in Table 3, the conventional proxy for human capital, i.e., COLLEGE, is the primary variable of interest. 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 2.3 percent increase in GDP per capita. Other results show that increasing the population of a metropolitan area by one-million people results in a 3.3 percent increase in GDP per capita. This finding is consistent with research that has demonstrated the presence of scale economies in city size (Glaeser and Mare 2001; Segal 1976; Sveikauskas 1975). 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 20 percent increase in GDP per capita, while increasing investment in capital structures does not have a statistically effect on economic activity.

To compare the 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 results in an approximately 17 percent, 11 percent, 1 percent, and 5 percent, increase in GDP per capita, respectively. Thus, a metropolitan area's amount of human capital appears to play a leading role in explaining observed differences in the level of economic activity.

The endogeneity of a metropolitan area's college-educated workforce is a 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 related to human capital. 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).

To address this potential concern, we re-estimate our regression models using two-stage least squares (2SLS). Following Moretti (2004), we use the presence of a land-grant university within a metropolitan area as an instrumental variable for the proportion of a metropolitan area's working-age population with a college degree.[7] Moretti shows that this instrument 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 such an institution 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 largely established in the nineteenth century following the land-grant movement, and thus are unlikely to be influenced by current levels of economic activity.

The results of this two-stage analysis are also provided in Table 3; again excluding and including the regional dummy variables. Our first-stage regression results indicate that the presence of a land-grant university in a metropolitan area increases college share by over 5 percentage points.[8] This is a sizeable effect since, on average, the metropolitan areas in our sample have a college share of just over 23 percent. Columns

7 The Morrill Acts of 1862 and 1890 are credited for establishing the major land-grant universities that exist in the United States. In total, 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, but these have not been included in our analysis. See Appleby (2007) for more information on the history of land-grant universities.

8 This finding is consistent with Moretti (2004, Table 7).

(3) and (4) of Table 3 show that our second-stage results are nearly identical in sign and magnitude to those estimated using OLS, which provides further confidence in the robustness of our empirical results.

III. KNOWLEDGE AND URBAN ECONOMIC ACTIVITY

Our initial regression results show that educational attainment has a positive effect on GDP per capita in urban America. This finding, consistent with an extensive literature on the returns to education, suggests that human capital raises the level of economic activity in metropolitan areas. However, 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 areas in which urban residents possess knowledge and skills (i.e., "horizontal differentiation" of human capital) (Bacolod, Blum, and Strange 2007).

Previous studies have suggested that the number of years of formal education provides an incomplete picture of a person's 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, along with the attainment of a college degree, the types of knowledge and cognitive skills possessed by a regional workforce may have an impact on a metropolitan area's GDP per capita.

Measuring the types of knowledge and cognitive skills 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. For this reason, we utilize two complementary approaches that allow 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), based on surveys of incumbent workers and occupational analysts.[9] Table 4 shows the 33 knowledge areas for which this information is available, which includes a wide range of topics such as clerical, engineering and technology, public safety and security, and sales 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. For the topic of sales and marketing, an importance rating of 2 has an anchor of "sell cakes at a bake sale," a rating of 4 is "call a list of clients to introduce them to a new product line" and a rating of 6 is "develop a marketing plan for a nationwide telephone system."

---

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

To arrive at the knowledge variables used in our analysis, we matched 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. Following the general approach used by Ingram and Neumann (2006) and Lakdawalla and Philipson (2007), we utilized the average value of the knowledge importance or level across multiple occupations in the O*NET data. With this information then available for 470 Census occupations, we calculated a knowledge index that is the product of the knowledge importance and the knowledge level. Feser (2003) used the same approach, noting that it places a greater emphasis on high knowledge that is relevant to a given occupation.

Our first approach to examining the relationship between different types of human capital and the level of economic activity utilizes knowledge-based occupation clusters (Feser 2003). To arrive at these clusters, we used the knowledge indexes described above and Ward's (1963) hierarchical clustering method to reduce the set of 470 occupations to a more manageable number. This method provides groupings of occupations with similar knowledge indices, which can then in turn be combined with other groups of occupations to reduce further the number of clusters. The exact number of clusters to maintain is largely subjective, depending on the particular application. In our analysis, the split from 13 to 14 clusters resulted in the additional cluster consisting of a single occupation: miscellaneous media and communications workers. Upon examining the knowledge requirements of the occupations joined in the 13-cluster solution, we decided to use these groupings in the subsequent regression analysis.

Table 5 provides a descriptive title, based on our assessment of the occupations included in the cluster, and average knowledge indices for the 13 clusters. The largest cluster in terms of the proportion of the U.S. workforce is “unskilled service workers,” followed by “executives and managers,” “financial and legal,” and “laborers.” For each of the knowledge clusters, we calculated the mean index values in the 33 knowledge areas. Of the 13 clusters, the group of “executives and managers” consists of jobs that have the highest average knowledge index values in the areas of administration and management, economics and accounting, personnel and human resources, and sales and marketing. As another example from Table 5, the group of occupations in the “engineers and scientists” cluster has the highest average knowledge index values (among the 13 clusters) in the areas of mathematics, design, engineering and technology, and physics. In contrast, the group of occupations included in the “laborers” cluster has the lowest average index value in 19 of the 33 knowledge areas.

Table 6 summarizes regression results on the relationship between GDP per capita and the proportion of metropolitan area employment in each of the knowledge-based occupation clusters. Here, we estimated 13 separate models with each one focusing on a single knowledge cluster. These models also included, as additional controls not shown in the table, the explanatory variables from Table 3 along with the dummy variables to account for regional effects.[10] To facilitate comparisons of the results associated with the different clusters, the knowledge variables are “standardized” as the number of standard deviations that a metropolitan area is above or below the average proportion of employment in the cluster.

[10] Educational attainment, used as the indicator of human capital in the base case analysis, has a positive and statistically significant effect in each of the 13 regression models.

Empirical results from OLS regressions show that the proportions of the metropolitan area workforce in the clusters of "executives and managers," "financial and legal," "information technology," and "artists and designers" have a positive and statistically significant effect on GDP per capita. For example, an increase in the relative size of the "executives and managers" cluster equivalent to one standard deviation relative to the mean is associated with a 10.4 percent increase in GDP per capita. This is a sizable impact on economic activity, although smaller than the 17 percent increase from a similar change in educational attainment estimated in the base case regression analyses. However, the boost to economic activity associated with the "executives and managers" cluster is similar to the 11 percent increase from a one-standard deviation increase in the estimated annual investment in capital equipment.

On the other hand, the proportions of employment in the knowledge-based occupation clusters of "public safety," "agriculture and food services," "counselors and social workers," and "educators, librarians, and writers" have a negative and statistically significant effect on GDP per capita. Other things being equal, an increase in the relative size of the "educators, librarians, and writers" cluster equivalent to one standard deviation relative to the mean is associated with a 12.5 percent decrease in GDP per capita. It appears from this analysis that, other things being equal, a regional workforce possessing high knowledge about education and training, foreign language, and history and archaeology—areas that are relatively important in the cluster of "educators, librarians, and writers"—actually diminishes the amount of measured economic activity in urban America.

Our second approach to examining the relationship between different types of human capital and the level of economic activity directly utilizes the 33 knowledge areas, instead of the knowledge-based occupational clusters. Table 7 presents information on the relationship between GDP per capita and a metropolitan area's average index value for each of the 33 knowledge areas. These variables are averages of the knowledge indices for the 470 Census occupations considered in the analysis, weighted by the proportion of a metropolitan area's workforce in each occupation. As in the previous analysis, the results shown in Table 7 are from separate regression models that include the knowledge variable of interest along with the same group of control variables, not shown in the table.[11] Similar to the analysis of the occupational clusters, the knowledge variables are standardized to facilitate comparisons across the 33 knowledge areas.

OLS regression results show that a metropolitan area's average knowledge index value in 12 areas have a positive and statistically significant effect on GDP per capita. Some of the knowledge areas that tend to enhance economic activity include administration and management, economics and accounting, mathematics, and computers and electronics. These findings help to explain, for example, the positive effects on GDP per capita associated with the proportion of employment of the "executives and managers" and "information technology" clusters. On the other hand, knowledge areas such as education and training, therapy and counseling, and food production have a negative and statistically significant effect on GDP per capita. These results shed light onto the negative effects on GDP per capita associated with the proportion of

[11] Educational attainment has a positive and statistically significant effect in each of the 33 regression models.

employment in the "educators, librarians, and writers," "counselors and social workers," and "agriculture and food service" knowledge clusters.

Results from both sets of analysis reveal similar findings concerning the types of knowledge associated with high levels of economic activity in urban America. First and foremost, the importance of knowledge about topics related to business, management, and commerce is clear. This finding is captured by the workforce clusters of "executives and managers" and "financial and legal," as well as 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 both sets of regressions is the importance of information dissemination using computers and advanced forms of communications. This finding encompasses the cluster of "information technology" occupations, and 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. Here, we note that the knowledge-based occupation clusters of "unskilled service workers" and "laborers" do not have a statistically significant effect on GDP per capita in urban America. These are two of the larger groups of occupations in terms of the proportion of U.S. workers. Laborers represent the "old economy" characterized by high manufacturing activity, while the share of the economy made up of unskilled service providers has grown remarkably in recent decades. Similarly, we do not find a statistically significant relationship between GDP per capita and the clusters of "engineers and scientists" and "medicine and health" occupations. These results are particularly surprising given the importance of scientific innovations and healthcare to economic vitality and overall quality-of-life. One potential reason for this finding is that innovations of these sorts tend to provide global benefits, and thus may not be captured fully by differences across metropolitan areas.

It is important to note that these results—namely, those related to the cluster of "educators, librarians, and writers" and 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 urban economic activity. However, results presented in this section show that the existence of a high proportion of educators in a metropolitan area is associated with lower levels of GDP per capita, other things being equal. While the end result of a college degree is a substantial increase in economic activity, the process of obtaining such an education does not significantly enhance a region's GDP per capita.

This result can be explained by the fact that GDP per capita, the variable used to measure economic activity, is defined as the market value of all final goods and services produced within a metropolitan area.[12] 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. Similarly, the output generated by knowledge about subjects such as history and archeology,

[12] 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.

philosophy and theology, and fine arts appears to contribute relatively little to measured GDP.

IV. SUMMARY AND CONCLUSIONS

Previous research spanning the literature from cross-country macroeconomic studies of economic growth and worker productivity 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 presented in this paper, 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 a 2.3 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 partially explained by the presence of a land grant university.

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 located within the region. Specifically, we find that the percentage of a metropolitan area's workforce in the knowledge-based occupation clusters of "executives and managers," "financial and legal," "information technology" and "artists and designers" have a positive and statistically significant effect on GDP per capita. Empirical analysis shows that knowledge in specific areas such as administration and management, economics and accounting, mathematics, computers and electronics, and telecommunications are particularly important drivers of economic activity in urban America. Florida, Mellander, and Stolarick (2008) reached similar conclusions, finding that computer science-, management and business-, and financial operations-based occupations are important drivers of regional economic development.

These results point to the importance of producer services as a key determinant of metropolitan area GDP per capita. 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).

Our results also suggest that activities associated with the "new economy" are important determinants of economic activity in urban America. Specifically, we find that the knowledge-based occupation cluster of "information technology" and 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.

REFERENCES

Acemoglu, Daron and Joshua Angrist. 2000. "How Large Are Human-Capital Externalities? Evidence from Compulsory Schooling Laws," *NBER Macroeconomics Annual*, Vol. 15, pp. 9-59.

Appleby, Arnold P. 2007. "Milestones in the Legislative History of U.S. Land-Grant Universities," Unpublished Mimeo, Oregon State University, pp. 1-26.

Bacolod, Marigee, Bernardo S. Blum, and William C. Strange. 2007. "Skills in the City," Unpublished Mimeo, University of California-Irvine, pp. 1-45.

Becker, Gary S. 1964. *Human Capital*, New York: Columbia University Press.

Berry, Christopher R. and Edward L. Glaeser. 2005. "The Divergence of Human Capital Levels Across Cities," *Papers in Regional Science*, Vol. 84, No. 3, pp. 407-444.

Ciccone, Antonio and Robert E. Hall. 1996. "Productivity and the Density of Economic Activity," *American Economic Review*, Vol. 86, No. 1, pp. 54-70.

Feser, Edward J. 2003. "What Regions Do Rather Than Make: A Proposed Set of Knowledge-based Occupation Clusters," *Urban Studies*, Vol. 40, No. 10, pp. 1937-1958.

Florida, Richard, Charlotta Mellander, and Kevin Stolarick. 2008. "Inside the Black Box of Regional Development – Human Capital, the Creative Class and Tolerance," *Journal of Economic Geography*, Vol. 8, No. 5, pp. 615-649.

Gatrell, Jay D. 2002. "Business Services, Productivity, and Wages: Metropolitan and Nonmetropolitan Michigan Counties, 1977-1997," *The Professional Geographer*, Vol. 54, No. 3, pp.365-378.

Glaeser, Edward L. 2005. "Reinventing Boston: 1640-2003," *Journal of Economic Geography*, Vol. 5, No. 2, pp. 119-153.

Glaeser, Edward L. and Albert Saiz. 2004. "The Rise of the Skilled City," *Brookings-Wharton Papers on Urban Affairs*, Vol. 5, pp. 47-94.

Glaeser, Edward L. and David C. Mare. 2001. "Cities and Skills," *Journal of Labor Economics*, Vol. 19, No. 2, pp. 316-342.

Glaeser, Edward L., Jose A. Scheinkman, and Andrei Shleifer. 1995. "Economic Growth in a Cross-Section of Cities," *Journal of Monetary Economics*, Vol. 36, No. 1, pp. 117-143.

Goldin, Claudia and Lawrence F. Katz. 1996. "Technology, Skill and the Wage Structure: Insights from the Past," *American Economic Review*, Vol. 86, No. 2, pp. 252-257.

Hall, Robert E. and Charles I. Jones. 1999. "Why Do Some Countries Produce So Much More Output Per Worker Than Others?" *Quarterly Journal of Economics*, Vol. 114, No. 1, pp. 83-116.

Hansen, Niles. 1990. "Do Producer Services Induce Regional Economic Development?" *Journal of Regional Science*, Vol. 30, No. 4, pp. 465-476.

Ingram, Beth F. and George R. Neumann. 2006. "The Returns to Skill," *Labour Economics*, Vol. 13, No. 1, pp. 35-59.

Jacobs, Jane. 1969. *The Economy of Cities*, New York: Vintage.

Lakdawalla, Darius and Tomas Philipson. 2007. "Labor Supply and Weight," *Journal of Human Resources*, Vol. 42, No. 1, pp. 85-116.

Lindahl, David P. and William B. Beyers. 1999. "The Creation of Competitive Advantage by Producer Service Establishments," *Economic Geography*, Vol. 75, No. 1, pp. 1-20.

Lucas, Robert E. 1988. "On the Mechanics of Economic Development," *Journal of Monetary Economics*, Vol. 22, No. 1, pp. 3-42.

Lucas, Robert E. 1977. "Hedonic Wage Equations and Psychic Wages in the Returns to Schooling," *American Economic Review*, Vol. 67, No. 4, pp. 549-558.

McGranahan, David A. and Timothy Wojan. 2007. "Recasting the Creative Class to Examine Growth Processes in Rural and Urban Counties," *Regional Studies*, Vol. 41, No. 2, pp. 197-216.

Marshall, Alfred. 1890. *Principles of Economics*, London: Macmillan.

Meade, Douglas S., Stanislaw J. Rzeznik, and Darlene C. Robinson-Smith. 2003. "Business Investment by Industry in the U.S. Economy for 1997," *Survey of Current Business*, Vol. 83, No. 11, pp. 18-70.

Moretti, Enrico. 2004. "Estimating the Social Return to Higher Education: Evidence from Longitudinal and Repeated Cross-Sectional Data," *Journal of Econometrics*, Vol. 121, No. 1-2, pp. 175-212.

Nordhaus, William D. 2002. "Productivity Growth and the New Economy," *Brookings Papers on Economic Activity*, Vol. 2002, No. 2, pp. 211-244.

Oliner, Stephen D. and Daniel E. Sichel. 2000. "The Resurgence of Growth in the Late 1990s: Is Information Technology the Story?" *Journal of Economic Perspectives*, Vol. 14, No. 4, pp.3-22.

Panek, Sharon D., Frank T. Baumgardner, and Matthew J. McCormick. 2007. "Introducing New Measures of the Metropolitan Economy: Prototype GDP-by-Metropolitan-Area Estimates for 2001-2005," *Survey of Current Business*, Vol. 87, No. 11, pp. 79-114.

Peterson, Norman, Michael Mumford, Walter Borman, Richard Jeanneret, Edwin Fleishman, Kerry Levin, Michael Campion, Melinda Mayfield, Frederick Morgeson, Kenneth Pearlman, Marilyn Gowing, Anita Lancaster, Marilyn Silver, and Donna Dye. 2001. "Understanding Work Using the Occupational Information Network (O*NET): Implications for Practice and Research," *Personnel Psychology*, Vol. 54, No. 2, pp. 451-492.

Rauch, James E. 1993. "Productivity Gains from Geographic Concentration of Human Capital: Evidence from the Cities," *Journal of Urban Economics*, Vol. 34, No. 3, pp. 380-400.

Romer, Paul M. 1990. "Endogenous Technological Change," *Journal of Political Economy*, Vol. 98, No. 5, pp. S71-S102.

Segal, David. 1976. "Are there Returns to Scale in City Size?" *Review of Economics and Statistics*, Vol. 58, No. 3, pp. 339-350.

Simon, Curtis J. 1998. "Human Capital and Metropolitan Employment Growth," *Journal of Urban Economics*, Vol. 43, No. 2, pp. 223-243.

Sveikauskas, Leo A. 1975. "The Productivity of Cities," *Quarterly Journal of Economics*, Vol. 89, No. 3, pp. 393-413.

Ward, Joe H. 1963. "Hierarchical Groupings to Optimize an Objective Function," *Journal of the American Statistical Association*, Vol. 58, No. 301, pp. 236-244.

Yankow, Jeffrey. 2006. "Why Do Cities Pay More? An Empirical Examination of Some Competing Theories of the Urban Wage Premium," *Journal of Urban Economics*, Vol. 60, No. 2, pp. 139-161.

Table 1: Average GDP Per Capita for Top and Bottom 20 MSAs, 2001-2005

Rank	MSA	Average GDP Per Capita
1	Bridgeport-Stamford-Norwalk, CT	$74,261
2	San Jose-Sunnyvale-Santa Clara, CA	$66,708
3	Charlotte-Gastonia-Concord, NC-SC	$64,195
4	Washington-Arlington-Alexandria, DC-VA-MD-WV	$59,087
5	San Francisco-Oakland-Fremont, CA	$58,362
6	Casper, WY	$57,558
7	Sioux Falls, SD	$56,350
8	Boston-Cambridge-Quincy, MA-NH	$54,587
9	Anchorage, AK	$53,252
10	Trenton-Ewing, NJ	$52,843
11	Des Moines-West Des Moines, IA	$52,778
12	Seattle-Tacoma-Bellevue, WA	$52,628
13	Durham, NC	$52,327
14	Boulder, CO	$51,562
15	New York-Northern New Jersey-Long Island, NY-NJ-PA	$51,440
16	Denver-Aurora, CO	$51,424
17	Houston-Sugar Land-Baytown, TX	$51,250
18	Hartford-West Hartford-East Hartford, CT	$51,143
19	Minneapolis-St. Paul-Bloomington, MN-WI	$50,612
20	Dallas-Fort Worth-Arlington, TX	$50,140
344	Florence-Muscle Shoals, AL	$21,220
345	Visalia-Porterville, CA	$21,068
346	Deltona-Daytona Beach-Ormond Beach, FL	$20,976
347	El Centro, CA	$20,890
348	Gadsden, AL	$20,771
349	Logan, UT-ID	$20,614
350	Kingston, NY	$20,296
351	Hanford-Corcoran, CA	$20,188
352	Laredo, TX	$19,963
353	Yuma, AZ	$19,899
354	Merced, CA	$19,861
355	Cumberland, MD-WV	$19,627
356	Las Cruces, NM	$19,540
357	Ocala, FL	$19,367
358	Madera, CA	$18,861
359	Punta Gorda, FL	$17,577
360	Prescott, AZ	$16,974
361	Lake Havasu City-Kingman, AZ	$15,539
362	Brownsville-Harlingen, TX	$15,398
363	McAllen-Edinburg-Mission, TX	$14,728

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.

Table 2: Descriptive Statistics for Base Case Analysis

Variable	Mean	Std Dev	Minimum	Maximum
GDP Per Capita	$33,856	$9,062	$14,728	$74,261
College Degree	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	0.75	1.64	0.07	18.36

Notes: GDP Per Capita is 2001-2005 average. All other variables are from 2000. Population is expressed in millions. College Degree 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 and expressed in thousands on a per worker basis. Based on 290 observations.

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 3: Regression Results for Base Case Models

Variable	OLS (1)	OLS (2)	2SLS (3)	2SLS (4)
First Stage: Dependent Variable is College Degree Percentage				
Land Grant	--	--	5.493 ***	5.423 ***
			(5.32)	(5.56)
Second Stage: Dependent Variable is Log of Average GDP Per Capita				
Intercept	8.866 ***	8.788 ***	8.900 ***	8.776 ***
	(58.62)	(55.20)	(28.28)	(26.71)
College Degree	0.023 ***	0.023 ***	0.022 ***	0.023 ***
	(13.72)	(13.09)	(4.00)	(4.19)
Capital Equipment	0.174 ***	0.183 ***	0.170 ***	0.185 ***
	(7.22)	(7.52)	(4.24)	(4.57)
Capital Structure	-0.019	0.009	-0.018	0.008
	(-1.49)	(0.61)	(-1.17)	(0.46)
Population	0.033 ***	0.032 ***	0.034 ***	0.032 ***
	(4.70)	(4.64)	(3.79)	(3.67)
Regional Effects	No	Yes	No	Yes
Adj. R^2	0.483	0.527	0.252	0.368
N	290	290	290	290

Notes: "Regional Effects" indicates whether dummy variables based on nine Census divisions have been included in the model . T-statistics reported in parentheses. ***, **, and * denote significance at the .01, .05, and .10 levels, respectively. Based on 290 observations.

Table 4: 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 5: Summary of Knowledge-based Occupation Clusters

	Executives and Managers	Information Technology	Agriculture and Food Service	Engineers and Scientists	Counselors and Social Workers	Financial and Legal	Public Safety	Laborers	Construction and Mechanical	Medicine and Health	Educators, Librarians, and Writers	Artists and Designers	Unskilled Service Workers
# Occupations	35	13	23	31	17	51	12	106	44	19	17	12	90
%U.S. Workforce	13.1%	3.1%	8.5%	2.6%	2.8%	12.4%	1.4%	9.7%	7.5%	3.3%	5.8%	1.3%	27.7%
Administration and Management	17.4	9.1	10.1	12.1	13.1	8.7	11.6	4.1	9.0	7.8	8.9	8.3	6.4
Biology	0.8	0.3	2.0	4.7	2.7	0.2	1.7	0.8	1.3	14.4	4.0	0.6	1.1
Building and Construction	1.9	1.1	1.4	12.3	1.3	0.5	2.6	3.6	14.6	0.3	1.2	1.6	0.8
Chemistry	1.8	0.8	3.1	8.8	2.5	0.4	3.6	4.0	5.6	10.2	2.9	1.5	2.4
Clerical	12.5	8.8	4.7	8.8	11.0	18.9	10.5	2.8	4.8	6.4	10.9	7.8	5.9
Communications and Media	6.6	7.3	2.8	5.6	8.0	4.7	8.0	1.5	2.7	4.6	9.2	8.9	3.1
Computers and Electronics	11.3	26.6	4.0	14.2	10.2	11.9	10.7	5.1	5.1	6.9	12.2	10.8	4.6
Customer and Personal Service	20.1	14.8	14.2	13.0	20.1	16.0	17.2	4.8	11.5	22.0	12.6	10.9	13.6
Design	3.4	11.3	1.0	17.5	1.3	0.8	2.2	5.2	9.9	1.2	3.0	11.2	1.1
Economics and Accounting	10.7	4.8	4.3	5.3	5.0	9.7	2.2	0.9	3.0	2.6	2.1	2.5	2.7
Education and Training	12.0	10.8	6.9	9.3	18.3	5.7	13.7	4.9	9.0	14.4	21.0	7.1	6.6
Engineering and Technology	3.5	13.1	2.1	19.2	1.3	1.0	3.2	6.6	9.7	2.3	2.6	4.1	1.4
English Language	15.6	14.3	8.3	15.0	17.5	14.9	16.0	6.1	8.7	16.3	20.8	12.6	9.2
Fine Arts	0.4	0.7	0.3	0.7	1.5	0.2	0.2	0.4	0.5	0.4	3.9	12.1	0.5
Food Production	0.8	0.1	9.9	0.9	1.1	0.2	0.5	0.5	0.7	0.9	0.9	0.2	1.0
Foreign Language	1.5	1.4	1.4	1.1	2.0	0.9	3.1	0.5	1.4	2.8	2.9	1.2	1.5
Geography	2.6	1.6	1.1	6.4	2.7	1.3	5.5	0.7	2.5	1.6	8.9	2.2	1.9
History and Archeology	0.8	0.8	0.4	1.4	2.8	0.5	1.4	0.2	0.8	1.2	7.9	1.8	0.7
Law and Government	8.6	4.3	3.2	8.3	8.9	7.7	17.0	1.4	5.7	7.2	6.3	2.3	3.1
Mathematics	13.6	14.1	7.9	18.5	8.5	11.5	7.5	7.5	11.6	11.6	11.7	7.0	6.8
Mechanical	3.5	5.4	4.2	10.6	1.3	1.0	4.1	11.6	17.4	3.6	2.3	3.3	2.8
Medicine and Dentistry	1.4	0.4	1.2	1.0	5.5	0.8	3.7	0.7	1.9	21.7	2.9	0.4	2.1
Personnel and Human Resources	12.1	3.4	6.3	6.1	11.1	5.3	8.1	1.6	5.1	7.1	5.3	4.2	3.4
Philosophy and Theology	2.4	0.8	1.0	1.0	9.5	1.2	4.5	0.5	1.1	7.2	7.2	2.0	1.3
Physics	1.4	3.7	1.1	11.0	1.0	0.3	3.0	3.1	7.0	4.1	2.5	1.4	1.0
Production and Processing	8.0	5.1	7.3	7.6	3.0	3.2	2.3	8.5	7.7	2.9	2.3	6.4	3.3
Psychology	7.5	4.3	4.1	4.6	19.7	3.1	12.2	1.6	5.4	21.9	13.3	5.1	4.5
Public Safety and Security	6.6	5.9	5.3	10.3	8.3	2.9	23.0	4.5	10.5	7.7	6.8	2.5	6.2
Sales and Marketing	14.5	3.2	7.5	6.5	5.7	4.2	1.4	1.3	3.7	3.4	3.2	8.4	5.1
Sociology and Anthropology	3.1	1.5	1.3	1.9	12.5	1.3	5.6	0.7	1.6	9.9	9.8	3.0	2.0
Telecommunications	3.0	12.8	1.1	4.1	3.0	2.7	9.7	1.1	3.0	2.7	2.6	3.3	2.3
Therapy and Counseling	3.3	1.1	1.2	0.9	17.3	1.0	5.2	0.5	1.7	15.6	7.1	0.8	1.9
Transportation	4.3	2.4	2.1	4.8	3.3	2.0	8.8	1.8	6.5	2.4	2.7	2.2	4.5

Notes: Ward's (1963) hierarchical clustering method was used to combine occupations into the 13 clusters. Numbers reported in table are mean index values for the occupations included in the knowledge-based clusters.

Sources: Occupational Information Network (O*NET), U.S. Department of Labor; United States Census (2000), U.S. Bureau of Census.

Table 6: Regression Results for Knowledge-based Occupation Clusters

% Workforce in Cluster, Standardized	Est. Coeff	T-Statistic
Executives and Managers	0.099 ***	7.54
Financial and Legal	0.070 ***	5.29
Information Technology	0.050 ***	2.74
Artists and Designers	0.039 **	2.19
Engineers and Scientists	0.018	1.07
Unskilled Service Workers	0.008	0.39
Laborers	0.006	0.36
Construction and Mechanical	-0.002	-0.11
Medicine and Health	-0.006	-0.50
Public Safety	-0.030 **	-2.43
Agriculture and Food Service	-0.055 ***	-4.37
Counselors and Social Workers	-0.069 ***	-5.07
Educators, Librarians, and Writers	-0.133 ***	-10.42

Notes: Results summarzied in the table are from 13 different regression models, which also include the explanatory variables shown in Table 3 and regional dummy variables. *** and ** denote significance at the .01 and .05 levels. Based on 290 observations.

Table 7: Regression Results for Knowledge Areas

Knowledge Area, Standardized	Est. Coeff	T-Statistic
Administration and Management	0.165 ***	7.75
Economics and Accounting	0.152 ***	9.39
Mathematics	0.133 ***	6.95
Personnel and Human Resources	0.128 ***	5.41
Customer and Personal Service	0.120 ***	6.29
Sales and Marketing	0.110 ***	6.19
Computers and Electronics	0.096 ***	3.94
Clerical	0.075 ***	4.16
Law and Government	0.060 ***	3.01
Telecommunications	0.052 ***	2.97
Production and Processing	0.032 *	1.71
Design	0.029 **	2.13
Engineering and Technology	0.017	1.24
English Language	0.010	0.35
Public Safety and Security	-0.012	-0.80
Transportation	-0.014	-0.80
Physics	-0.015	-1.23
Building and Construction	-0.020	-1.27
Communications and Media	-0.030	-0.91
Mechanical	-0.032 *	-1.71
Medicine and Dentistry	-0.035 ***	-2.92
Chemistry	-0.049 ***	-4.19
Food Production	-0.059 ***	-4.60
Psychology	-0.065 ***	-3.74
Therapy and Counseling	-0.066 ***	-4.62
Biology	-0.070 ***	-6.05
Fine Arts	-0.103 ***	-5.11
Foreign Language	-0.107 ***	-6.10
Geography	-0.118 ***	-6.86
Philosophy and Theology	-0.124 ***	-8.04
Sociology and Anthropology	-0.129 ***	-7.43
History and Archeology	-0.140 ***	-9.75
Education and Training	-0.164 ***	-7.08

Notes: Results summarzied in the table are from 33 different regression models, which also include the explanatory variables shown in Table 3 and regional dummy variables. ***, ** and * denote significance at the .01, .05 and .10 levels, respectively. Based on 290 observations.