

Federal Reserve Bank of New York
Staff Reports

Knowledge in Cities

Todd Gabe
Jaison R. Abel
Adrienne Ross
Kevin Stolarick

Staff Report no. 470
September 2010

This paper presents preliminary findings and is being distributed to economists and other interested readers solely to stimulate discussion and elicit comments. The views expressed in this paper are those of the authors and are not necessarily reflective of views at the Federal Reserve Bank of New York or the Federal Reserve System. Any errors or omissions are the responsibility of the authors.

Knowledge in Cities

Todd Gabe, Jaison R. Abel, Adrienne Ross, and Kevin Stolarick

Federal Reserve Bank of New York Staff Reports, no. 470

September 2010

JEL classification: R11, O18, J24

Abstract

This study identifies clusters of U.S. and Canadian metropolitan areas with similar knowledge traits. These groups—ranging from Making Regions, characterized by knowledge about manufacturing, to Thinking Regions, noted for knowledge about the arts, humanities, information technology, and commerce—can be used by analysts and policymakers for the purposes of regional benchmarking or comparing the types of programs and infrastructure available to support closely related economic activities. In addition these knowledge-based clusters help explain the types of regions that have levels of economic development that exceed, or fall short of, other places with similar amounts of college attainment. Regression results show that Engineering, Enterprising, and Building Regions are associated with higher levels of productivity and earnings per capita, while Teaching, Understanding, Working, and Comforting Regions have lower levels of economic development.

Key words: knowledge, occupations, economic development

Gabe: School of Economics, University of Maine. Abel: Federal Reserve Bank of New York. Ross: Institute for Competitiveness and Prosperity. Stolarick: Martin Prosperity Institute, University of Toronto. Address correspondence to Todd Gabe (e-mail: todd.gabe@umit.maine.edu). The views expressed in this paper are those of the authors and do not necessarily reflect the position of the institutions represented by the authors, the Federal Reserve Bank of New York, or the Federal Reserve System.

KNOWLEDGE IN CITIES

1. INTRODUCTION

It would be an understatement to suggest that knowledge plays a key role in today's economy; for much of the developed world, it might be more accurate to assert that knowledge *is* today's economy. Many observers have noted that the importance of natural resources, buildings and machinery as the means to produce goods and deliver services has been overshadowed by the primacy of knowledge, skills and creativity (Drucker 1968; Knight 1995; Florida 2002; Lever 2002). Facing this realization, researchers of state and regional economic policy (and some policymakers themselves) have a heightened interest in programs that fall under the broad umbrella of human capital-based economic development. These strategies include enhancing and promoting regional amenities to attract talented and creative workers (Florida 2002), workforce education and training, and incentives for R&D and entrepreneurship (Mathur 1999).

Human capital-based strategies are often backed by research that suggests educational attainment, typically measured as the percentage of adult residents with a college degree, increases regional economic development (Rauch 1993; Glaeser, Scheinkman and Shleifer 1995; Moretti 2004; Abel and Gabe 2010). But the number of years of formal education is a somewhat crude measure of human capital (Goldin and Katz 1996; Ingram and Neumann 2006). By simply counting up a region's residents with a college degree, equal weights are applied to individuals regardless of their area of expertise. Surely, the knowledge and skills required to graduate with a degree in, for

example, mechanical engineering or physics are different than the knowledge and skills needed in, say, history or political science.¹

Recent occupational-based approaches to economic development have provided a broader view of a region's stock of human capital (Florida 2002; Feser 2003; Markusen 2004; Bacolod, Blum and Strange 2009; Scott 2009). Florida, Mellander and Stolarick (2008, p. 618) suggest that, whereas formal education "measures potential talent or skill," an emphasis on occupations provides an idea of how "human talent or capability is absorbed by and used by the economy." Thus, if we want to know about differences in the levels of creative talent across cities or regions, we can compare places based on the proportion of the workforce employed in creative occupations (Florida 2002). Likewise, with information on the skills and knowledge that are important to job performance, we can use regional occupational data to say something about the mix of skills (e.g., cognitive, motor and people skills) and knowledge (e.g., engineering and technology, history and archaeology) used in the workforce (Feser 2003; Ingram and Neumann 2006; Bacolod, Blum and Strange 2009; Gabe 2009; Scott 2009; Abel and Gabe 2010).

This study takes such an approach to examine the knowledge economies of U.S. and Canadian metropolitan areas. Our goal in the paper is to identify and analyze a set of metropolitan area clusters that share similar knowledge traits. After joining a large sample of U.S. and Canadian metropolitan areas into eleven distinct clusters based on the types of knowledge used in the workforce, we provide descriptive information about inter-cluster differences in regional gross domestic product (GDP) and earnings per

¹ Ingram and Neumann (2006, p. 38) nicely summarize this line of thinking, "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."

capita. In addition, we estimate several metropolitan-level human capital regression models to investigate the effects of educational attainment on GDP and earnings per capita—with and without including fixed effects to control for the metropolitan area’s knowledge-based cluster. Inclusion of these fixed effects indicating the types of knowledge used in the workforce substantially enhances the goodness of fit (e.g., adjusted r-squared) in each of the regression models, and increases the estimated coefficients corresponding to the effects of educational attainment on both measures of regional economic development. These results suggest that it is important for analysts and policymakers to consider the types of knowledge available in the workforce as well as a region’s level of college attainment when developing and evaluating human capital-based economic development strategies.

2. KNOWLEDGE AS AN INDICATOR OF HUMAN CAPITAL

Human capital is generally thought of as the skills, talents and knowledge that people use in their role as workers to produce goods and deliver services. Until recent years, researchers have largely used the receipt of a college degree as the primary indicator of human capital (Becker 1964, Willis 1986). Simply put, a person with a degree is said to possess human capital, while someone without a degree does not. But this is a rather narrow and simplistic view of human capital. Many jobs—even some that offer reasonably high wages—do not require skills or talents that are typically covered in a college degree program. Likewise, even those skills that are learned initially in school are continuously honed through self study, experience, and formal and informal interactions with others.

Determining the types of knowledge available in U.S. and Canadian metropolitan areas presents a challenge to empirical researchers because, unlike the traditional approach of measuring “generic” human capital by counting up the number of residents with a college degree, such information is not directly observable. Following the method used by Feser (2003) and Abel and Gabe (2010), our approach allows us to infer the knowledge present in each metropolitan area using its occupational structure and data on the knowledge requirements of the region’s workforce. Information on the knowledge requirements of occupations is from the U.S. Department of Labor’s Occupational Information Network (O*NET).² The O*NET system contains detailed occupational-level data, collected via interviews of incumbent workers and input from professional occupational analysts, about job-related knowledge requirements pertinent to the 33 subjects shown in Table 1. These areas cover a wide range of topics from aspects of business (e.g., *Administrative and Management*, *Sales and Marketing*) to basic sciences (e.g., *Physics*, *Chemistry*, and *Biology*) and production-oriented tasks (e.g., *Food Production*, *Production and Processing*).

The O*NET survey asks respondents to rate the importance of the knowledge type to their job (e.g., on a scale of 1 to 5) and then rate the level of knowledge needed (e.g., on a scale of 1 to 7). The follow-up question on the “level” of knowledge, which provides a different set of “anchors” for each of the knowledge areas, is only required for types of knowledge that are rated as at least “somewhat” important (i.e., rating of “2” or higher on the first question). For the subject area of *Chemistry*, as an example, a knowledge level rating of “2” is equivalent to “use a common household bug spray,” a

² O*NET is discussed in detail by Peterson et al (2001) and Feser (2003).

rating of “4” is similar to “use the proper amount of chlorine to purify a water source” and the anchor for a knowledge level of “6” is “develop a safe commercial cleaner.”

Table 2 shows, as illustrative examples of the information used in the cluster analysis, standardized knowledge scores for several U.S. and Canadian metropolitan areas. We used a 4-step process to construct these metropolitan-level knowledge scores. Step one involved calculating occupational-level knowledge indices. Following Feser (2003), we constructed these indices as the product of the knowledge importance (i.e., scale of 1 to 5) and level (i.e., scale of 1 to 7) ratings for each of the occupations. Step two involved developing knowledge indices for each metropolitan area. These variables are averages of the occupational-level knowledge indices, weighted by the proportion of a metropolitan area’s workforce in each occupation.³ Metropolitan area workforce information is from the 2006 Canadian Census and the 3-year (2005 to 2007) one-percent sample of the American Community Survey administered by the U.S. Census Bureau (Ruggles et al. 2010).⁴

The third step involved using the knowledge indices for 255 U.S. and 32 Canadian metropolitan areas to calculate average knowledge scores (and corresponding standard deviations) for each country in each of the 33 subject areas. The final step involved transforming the metropolitan-level indices into standardized knowledge scores,

³ This calculation required matching occupational categories from the O*NET system to those used in the data sets of metropolitan area employment. For the Canadian metropolitan areas, we used an occupational concordance to convert 520 Canadian NOC occupations to 821 U.S. SOC occupational codes. From there we matched the 6-digit SOC occupations to O*NET knowledge scores. For the U.S. metropolitan areas, we matched the O*NET occupations to one of 470 occupations used in the American Community Survey administered by the U.S. Census Bureau.

⁴ For the Canadian metropolitan areas, 2.7 million dwellings—or 6.5 million individuals—were sampled in the 2006 Census long-form that covers 20 percent of the population. For the U.S. metropolitan areas, the workforce knowledge variables are constructed using individual-level information on 3.7 million workers that are covered in the 2005-07 one-percent sample of the American Community Survey.

such as those shown in Table 2, which are expressed in terms of the number of standard deviations that a metropolitan area lies above (i.e., positive values) or below (i.e., negative values) its national average.⁵ For example, the information presented in Table 2 indicates that Athens, Georgia, has a *History and Archeology* knowledge score that is 3.51 standard deviations above the mean value across all U.S. metropolitan areas, Toronto has an *Economics and Accounting* knowledge score that is 2.12 standard deviations above the mean value across all Canadian metropolitan areas, and Washington D.C. has a *Mechanical* knowledge score that is 2.26 standard deviations below the mean value across all U.S. metropolitan areas.

The knowledge profiles shown in Table 2 provide a broad view of the types of human capital that are used in the selected metropolitan areas. Athens, Georgia, has a workforce that is knowledgeable about *Education and Training*, the sciences (e.g., *Biology* and *Chemistry*), the humanities (e.g., *History and Archeology*, *Foreign Language*, and *Philosophy and Theology*), and mental health (e.g., *Psychology*, and *Therapy and Counseling*). These types of knowledge are indicative of the region's economic identity that is heavily influenced by the presence of the University of Georgia. On the other hand, Calgary is characterized by a workforce that has low knowledge about topics such as *Therapy and Counseling*, *Philosophy and Theology*, and *History and Archeology*, but is highly knowledgeable about *Engineering and Technology*, *Mathematics*, *Physics*, and *Design*. Whereas the types of knowledge available in Athens, Georgia, immediately suggest “college town,” Calgary's knowledge profile points to a

⁵ All of the variables used in the paper are expressed as standardized values relative to a metropolitan area's home country because of differences in U.S. and Canadian occupational categories, slight differences in the time periods over which information is available, and—for variables expressed in dollar terms—differences in U.S. and Canadian currencies.

region that is strong in engineering and technology, presumably related to its energy-based economy.

New York, Toronto and Washington D.C. share the similar traits of high knowledge about *Fine Arts, Clerical, Communications and Media*, and *Economics and Accounting*. Further, these major metropolitan areas are characterized by low knowledge about *Food Production, Chemistry and Mechanical* (things). But there are some knowledge areas in which New York and Washington D.C. are quite different than Toronto. New York and Washington D.C. have positive standardized knowledge scores in the areas of *Education and Training, Geography, History and Archeology, Foreign Language, Philosophy and Theology, Psychology, Sociology and Anthropology*, and *Therapy and Counseling*, while Toronto has negative standardized knowledge scores in these subject areas. On the other hand, Toronto has a positive knowledge score in the area of *Production and Processing*, while New York and Washington D.C. have negative standardized knowledge scores on this topic. These differences suggest that the New York and Washington D.C. economies have greater emphases on humanities and mental health, whereas Toronto's workforce is more oriented towards manufacturing-type activities.

In addition, the table reveals some interesting differences in the knowledge profiles of New York and Washington D.C. The standardized knowledge scores in the subject areas of *Computers and Electronics, Design, Engineering and Technology, Mathematics*, and *Telecommunications* are much higher in Washington D.C. than in New York. On the other hand, the New York workforce is more knowledgeable than its Washington D.C. counterpart in the subject areas of *Medicine and Dentistry, Psychology*,

and *Therapy and Counseling*. These differences suggest that Washington D.C. has a greater emphasis on technology and engineering (similar to Calgary), while New York's workforce is more knowledgeable about the areas of physical and mental health.

3. CLUSTER ANALYSIS

We used the standardized knowledge scores for the 33 subject areas to reduce our sample of 287 U.S. and Canadian metropolitan areas into a smaller set of regions that share similar knowledge traits. To do this, we employed Ward's (1963) hierarchical clustering method that forms groups by minimizing the sum of the squared differences among places based on the standardized knowledge scores.⁶ The method starts by joining the two metropolitan areas with the most similar knowledge profiles into a cluster, and then—in subsequent iterations—combines other metropolitan areas with similar knowledge profiles into new clusters or adds places to existing clusters.

As an example, the first two metropolitan areas that were identified as a cluster (i.e., the two places with the greatest similarity in knowledge profiles) were Chicago and Kansas City. After this first iteration, we went from the original 287 metropolitan areas (i.e., 287 “clusters” made up of one metropolitan area) to 286 clusters: the cluster that combined Chicago and Kansas City, and the remaining 285 metropolitan areas. With each subsequent iteration, the number of clusters falls by one, until all of the metropolitan areas are joined into a single cluster. Choosing the exact number of clusters to maintain is somewhat subjective, depending on the intended use of the information. In our analysis, we found that 11 clusters provided metropolitan area groups with reasonably similar knowledge requirements (based on a diagnostics coefficient that measures the sum of the

⁶ Feser (2003) provides a detailed account of how Ward's clustering method can be applied to the O*NET knowledge areas. Unlike our application that focuses on metropolitan area knowledge profiles, Feser (2003) joins individual jobs into occupational clusters based on similar knowledge requirements.

squared Euclidean distance among clusters) as well as a manageable number of groups for the subsequent analysis.⁷

Table 3 provides names and brief descriptions of these metropolitan area clusters, along with a list of subjects that are characterized as “high” and “low” knowledge. The full list of metropolitan areas in each cluster is provided in the appendix. A cluster is said to have “very high knowledge” in a particular subject area if the mean value of standardized knowledge scores calculated across its members is greater than 1.0. These knowledge areas are underlined in Table 3. We refer to a cluster as possessing “high knowledge” about a topic if the mean value of standardized knowledge scores calculated across its members is between 0.5 and 1.0. Clusters that are characterized as “very low knowledge” or “low knowledge” in a particular subject are defined similarly, except they refer to standardized knowledge scores that are, on average, less than -1.0 or between -0.5 and -1.0, respectively.

For example, the cluster of *Making Regions*—described as “very high knowledge about manufacturing; very low knowledge about commerce and humanities”—has a workforce characterized by very high knowledge about the subject areas of *Mechanical* and *Production and Processing*, and very low knowledge about subjects such as *Customer and Personal Service*, *English Language*, *Geography* and *Economics and Accounting*. This cluster is comprised of metropolitan areas such as Canton, Ohio; Detroit, Michigan; and Windsor, Ontario. The metropolitan areas included in the *Making Regions* cluster are generally regarded as some of the more important U.S. and Canadian manufacturing regions.

⁷ Going from the 11-cluster solution to the 12-cluster solution, a group of relatively homogeneous metropolitan areas (e.g., the cluster of *Working Regions*) split into two categories.

Whereas the cluster of *Making Regions* contains places with a long history of manufacturing, a group of *Teaching Regions* is made up of mostly “college towns.” These metropolitan areas—such as Bloomington, Indiana; Columbia, Missouri; and Kingston, Ontario—are characterized by very high knowledge about subjects such as *Education and Training*, *Biology*, *Chemistry*, *History and Archeology*, and *Philosophy and Theology*. In addition, *Teaching Regions* have very low knowledge about *Production and Processing*, and *Mechanical* (things). The information for Athens, Georgia, presented in Table 2 provides a reasonably close representation of the knowledge profiles of the metropolitan areas included in this cluster. A cluster of *Understanding Regions* is also made up of metropolitan areas (e.g., Charlottesville, Virginia; Iowa City, Iowa) that are home to major research universities. This group is characterized by very high knowledge about arts, sciences, humanities and IT; and very low knowledge about manufacturing. These two clusters of primarily college-dominated metropolitan areas differ in that there is a stronger emphasis on the knowledge topics of *Fine Arts*, *Medicine and Dentistry*, and IT (i.e., *Computers and Electronics*, *Telecommunications*) in the *Understanding Regions*.

A cluster of *Thinking Regions* includes the major U.S. metropolitan areas of New York, Philadelphia and San Diego, as well as some smaller places such as Halifax, Nova Scotia; Las Cruces, New Mexico; and Portland, Maine. These regions are characterized by high knowledge about arts, humanities, IT and commerce, and low knowledge about manufacturing. Many of the other major metropolitan areas in our sample—such as Chicago, Los Angeles, Miami, Montreal and Toronto—are included in a cluster of *Enterprising Regions*, which are characterized by high knowledge about commerce (e.g.,

Sales and Marketing, Economics and Accounting, Customer and Personal Service) and IT (i.e., *Computers and Electronics, Telecommunications*). These groups differ in that the *Thinking Regions* (e.g., New York, Philadelphia) have high knowledge in a broader range of topics related to the humanities (e.g., *Geography, History and Archeology, Philosophy and Theology*) and mental health (e.g., *Psychology, Therapy and Counseling*), while the *Enterprising Regions* (e.g., Chicago, Toronto) have deeper knowledge about commerce.

Metropolitan areas such as Anchorage, Alaska; Houston, Texas; Lake Charles, Louisiana; and Oshawa, Ontario; are included in a cluster of *Building Regions*. This group is noted for its very high knowledge about construction and transportation, as well as high knowledge about *Mechanical* (things). Many of the places that make up this cluster serve as key transportation hubs (e.g., Mobile, Alabama; Saint John, New Brunswick) and some have economies that are dominated by tourism (e.g., Myrtle Beach, South Carolina; Naples, Florida). In addition, other metropolitan areas included in the *Building Regions* cluster have strong connections to energy-related production and distribution (e.g., Edmonton, Alberta; Houston, Texas).

A cluster of *Innovating Regions* is made up of metropolitan areas such as Austin, Boston, Seattle and Washington D.C. These places are generally regarded as some of the cities with the highest levels of human capital and innovative activity. Indeed, this cluster is characterized by very high knowledge about IT, arts, commerce and engineering. In addition, *Innovating Regions* have high knowledge about education and the humanities (e.g., *English Language, Geography, History and Archaeology*). Given its strong presence in the humanities, the *Innovating Regions* cluster has high knowledge in many of the same subject areas that are emphasized in *Teaching Regions* (e.g., Athens,

Georgia; Kingston, Ontario) and *Understanding Regions* (e.g., Gainesville, Florida; Rochester, Minnesota). However, the cluster of *Innovating Regions* distinguishes itself with very high knowledge about *Engineering and Technology*, and *Economics and Accounting*. These knowledge areas related to engineering and commerce are less emphasized in the other two clusters of college-oriented metropolitan areas.

High knowledge about IT, commerce and engineering are also defining characteristics of a cluster of *Engineering Regions*, which is made up of metropolitan areas such as Calgary and San Jose. This small group of metropolitan areas is similar to the cluster of *Innovating Regions* (e.g., Boston, Ottawa, San Francisco) in its strong emphasis on engineering and science, but it does not have very high knowledge scores in the subject areas of *Education and Training*, *History and Archaeology*, and *Philosophy and Theology*. In addition, the metropolitan areas that make up the *Engineering Regions* cluster are characterized by low knowledge about physical (e.g., *Medicine and Dentistry*) and mental (e.g., *Psychology, Therapy and Counseling*) health.

4. KNOWLEDGE-BASED CLUSTERS AND ECONOMIC DEVELOPMENT

One of the basic ideas of this paper is that it is useful to go beyond the share of the population with a college degree as the single indicator of human capital in a region and to think more broadly about the types of knowledge that are used in the workforce. The knowledge-based metropolitan area clusters provide a convenient way to make finer distinctions about the specific types of human capital present in a region, especially in cases where levels of educational attainment are similar. In this section, we examine the extent to which incorporating information about the knowledge-based clusters into basic regressions of metropolitan-level productivity and wages deepens our understanding

about the role of human capital in raising indicators of economic development. More specifically, we identify the knowledge-based clusters that are associated with enhanced regional productivity and earnings, while accounting for levels of college attainment.

Table 4 presents information on average GDP and earnings per capita—two key indicators of regional economic development—for each of the 11 knowledge-based metropolitan area clusters.⁸ In addition, the table shows average levels of college attainment for each of the clusters. As with the metropolitan area-level knowledge scores, the regional economic development indicators and educational attainment data are reported as standardized values, which are interpreted as the number of standard deviations that a metropolitan area falls above (i.e., positive values) or below (i.e., negative values) its national average. For example, the average GDP per capita value of 1.27 for the cluster of *Innovating Regions* suggests that the metropolitan areas in this group have, on average, productivity figures that are 1.27 standard deviations above the mean calculated across all of the metropolitan areas in the same nation.

Figures shown in the table suggest that the clusters of *Innovating* and *Engineering Regions* have the highest values of GDP and earnings per capita among the eleven knowledge-based metropolitan area clusters. Both of these clusters are characterized by very high knowledge about IT (e.g., *Computers and Electronics, Telecommunications*), commerce (e.g., *Economics and Accounting, Sales and Marketing*) and engineering (e.g., *Engineering and Technology, Design*). In addition, the clusters of *Thinking* and *Enterprising Regions*, which also have average standardized GDP and earnings per capita values that exceed zero, are also noted for a significant presence of IT, commerce and

⁸ 2005 GDP figures for U.S. metropolitan areas are from the U.S. Bureau of Economic Analysis (BEA). Educational attainment figures for U.S. metropolitan areas are from the 2000 U.S. Census. For the Canadian metropolitan areas, these figures are from Statistics Canada 2006 Census.

engineering, which are important for economic growth and regional economic development (Oliner and Sichel 2000; Florida, Mellander and Stolarick 2008; Gabe 2009; Abel and Gabe 2010).

Table 5 shows the results from OLS regression models that examine the effects of educational attainment on metropolitan-level GDP and earnings per capita. For each of these indicators of regional economic development, we estimate two regression models: one includes the (standardized) share of the population with at least a college degree as the only measure of human capital, and the other regression model includes the educational attainment variable and controls for fixed effects related to the metropolitan areas' knowledge-based clusters.

Results from the model focusing on GDP per capita, without the fixed effects, suggest that college attainment has a positive and statistically significant effect on regional productivity.⁹ A one-standard deviation increase in the share of the metropolitan area population with a college degree is associated with a 0.56-standard deviation increase in GDP per capita. The adjusted r-squared of 0.311 suggests that the educational attainment measure alone explains about one-third of the variation observed in regional productivity. In the model that includes the fixed effects indicating a metropolitan area's knowledge-based cluster, the effect associated with a one-standard deviation increase in college attainment rises from a 0.56- to a 0.66-standard deviation increase in regional productivity. In addition, the model's goodness of fit (i.e., adjusted r-squared) increases from 0.311 to 0.442, which suggests that educational attainment along with the

⁹ This finding is consistent with a well-established literature emphasizing the importance of the geographic concentration of human capital to regional economies (see, e.g., Lucas 1988; Rauch 1993; Glaeser, Scheinkman, and Shleifer 1995; Glaeser and Saiz 2004; Moretti 2004; Abel and Gabe 2010).

knowledge-based cluster assignments explain almost one-half of the variation observed in GDP per capita.

Our results on the effects of educational attainment on earnings per capita reveal similar patterns. First, in the model without the fixed effects, we find that educational attainment has a positive and statistically significant effect on regional earnings. More specifically, regression results show that a one-standard deviation increase in college attainment is associated with a 0.47-standard deviation increase in earnings per capita. The adjusted r-squared of 0.217 suggests that, by itself, educational attainment explains less than one-quarter of the variation in earnings per capita observed across metropolitan areas. As we found in our analysis of regional productivity, the inclusion of the fixed effects indicating the knowledge-based cluster increases the adjusted r-squared markedly; in this case, from 0.217 to 0.387. In addition, the estimated coefficient corresponding to educational attainment increases—from 0.469 to 0.544—in the model that controls for fixed effects associated with the metropolitan area’s knowledge-based cluster.

Estimated coefficients corresponding to the fixed effects included in the regression models suggest that, controlling for the share of residents with a college degree, *Engineering Regions* have significantly higher levels of productivity and earnings than places in the other knowledge-based clusters. Similarly, Florida, Mellander and Stolarick (2008) found that engineering-related occupations have a high association with regional development, and Gabe (2009) uncovered positive private and external (i.e., spillover effects) returns associated with engineering-based knowledge. Fixed-effects results corresponding to *Building* and *Enterprising Regions* suggest that metropolitan areas in these groups also have measures of regional economic development that are

significantly higher, controlling for differences in college attainment, than the other knowledge-based clusters.

On the other hand, regression results suggest that *Teaching* and *Understanding Regions* have significantly lower levels of productivity and earnings per capita than other places with similar levels of college attainment. In previous studies, Abel and Gabe (2010) and Florida, Mellander and Stolarick (2008) found that the presence of educators in a region do not enhance indicators of economic development. Explanations for these findings are that places dominated by large universities (reflected in high knowledge about *Education and Training*) have smaller shares of residents engaged in other productive activities, and that—whereas the end result of a college education increases productivity—the process of delivering a college education does not lift a region’s GDP per capita (Florida, Mellander and Stolarick 2008; Abel and Gabe 2010). Results from the fixed-effects models also suggest that, controlling for educational attainment, *Comforting* and *Working Regions* have less favorable indicators of regional economic development than the other knowledge-based clusters.

Our fixed-effects results corresponding to the *Innovating*, *Teaching*, *Understanding* and *Engineering Regions* demonstrate the utility of the knowledge-based clusters at differentiating levels of regional economic development across places with high levels of education. According to the figures shown in Table 4, these clusters have the highest average shares of college attainment; yet the economic development indicators vary widely among these clusters. As noted above, the clusters of *Innovating* and *Engineering Regions* have the highest average values of GDP and earnings per capita. On the other hand, the *Teaching* and *Understanding Regions*, despite their high

levels of college attainment, have productivity and earnings figures that are in the middle to the bottom of the pack among the 11 knowledge-based clusters.

In our regression analysis of regional economic development, we found positive estimated coefficients on the fixed effects corresponding to *Engineering Regions*, and that the clusters of *Teaching* and *Understanding Regions* are associated with lower levels of productivity and earnings per capita. The *Innovating Regions* are about where you would expect in terms of these indicators, given the share of the population with a college degree. Membership in this cluster is associated with a 0.335-standard deviation increase in output per capita and a 0.033-standard deviation decrease in earnings; neither of these effects is statistically significant. The fact that *Teaching* and *Understanding Regions* have modest levels of economic development, in light of their high shares of college attainment, helps explain the increase in the estimated effect of educational attainment on economic development in the fixed-effects regressions. Without accounting for the knowledge-based clusters, the effects of education on economic development are likely to diminish at high levels of college attainment in the *Teaching* and *Understanding Regions*. After controlling for the fixed effects associated with these and the other clusters, the estimated effects of education on economic development increase markedly.

To investigate these ideas in more depth, we examine the effects of educational attainment on regional economic development only in those metropolitan areas with standardized college attainment scores that exceed zero (i.e., places with shares that exceed the national average). As shown in Table 6, the adjusted r-squared values from the regressions that do not include the fixed effects are about 0.06. This suggests that, for metropolitan areas with “above average” shares of the population with a college degree,

educational attainment—although exerting a statistically significant effect on GDP and earnings per capita—explains very little of the variation observed in these indicators of regional economic development. However, as was the case in our analysis that examined all of the metropolitan areas in our sample, the adjusted r-squared values increase substantially—by about a factor of 5.0—when we control for the knowledge-based regional clusters. Additionally, as discussed previously, the estimated coefficients corresponding to college attainment increase substantially in the fixed-effects regression models.

5. SUMMARY AND CONCLUSIONS

In recent years, several studies have used information on the occupations present in a region to gain a sense of the types of skills and knowledge used in the workforce (Florida 2002; Feser 2003; Florida, Mellander and Stolarick 2008; Bacolod, Blum and Strange 2009; Gabe 2009; Scott 2009; Abel and Gabe 2010). Such an approach has allowed researchers to go beyond college attainment as the indicator of human capital in a region. This study extends the existing literature by identifying clusters of Canadian and U.S. metropolitan areas with similar knowledge profiles. These groups range from *Comforting Regions*—noted for high knowledge about topics such as *Therapy and Counseling* and *Philosophy and Theology*—to *Engineering Regions* that are characterized by very high knowledge about engineering, IT and commerce.

These knowledge-based clusters provide a useful system for organizing metropolitan areas based on the region's economic identity and the types of cognitive skills used by workers. Many places with a long history of manufacturing (e.g., Canton, Ohio; Windsor, Ontario) are clustered in a group of *Making Regions*, while places such as

Boston, Raleigh-Durham, Ottawa, and San Francisco make up a cluster of *Innovating Regions*. Regional analysts and policymakers can use these clusters to identify “peer groups” with similar knowledge profiles for the purposes of benchmarking or comparing the types of government programs and infrastructure available to support closely-related economic activities. For example, officials from Athens, Georgia, would likely benefit more from a site visit to State College, Pennsylvania—a fellow *Teaching Region*—than from trying to emulate the policies that are effective in nearby Atlanta. Likewise, officials in Athens would be better off using State College and other *Teaching Regions* as benchmarks to gauge changes in regional economic indicators.

But beyond the utility of the knowledge-based metropolitan area clusters for these purposes, they also help deepen our understanding about the types of economic activities that are associated with regional productivity and earnings per capita. Our empirical results show that incorporating fixed effects indicating a metropolitan area’s cluster assignment substantially increases model goodness-of-fit measures (i.e., adjust r-squared) compared to regressions that include college attainment as the sole indicator of human capital. This means that the knowledge-based clusters are important predictors, above and beyond shares of college attainment, of regional economic development.

In addition, the fixed-effects regression results identify the types of regions that are likely to have levels of economic development that are greater (or less) than others with similar shares of college attainment. Here, our regression results show that *Engineering, Enterprising* and *Building Regions* are associated with higher levels of productivity and earnings per capita; while *Teaching, Understanding, Working* and *Comforting Regions* have lower levels of economic development. This does not suggest,

for example, that *Understanding Regions* are less productive than *Building Regions*. The cluster of *Understanding Regions* has an average standardized productivity score of 0.32, which is higher than the comparable score (-0.05) for *Building Regions*. However, in the fixed-effects regressions, the association with regional productivity is higher for *Building Regions* (estimated coefficient = 0.335) than *Understanding Regions* (estimated coefficient = -1.256) due to the fact that higher productivity in *Understanding Regions* (compared to *Building Regions*) is explained by the large difference in college attainment.

Finally, the knowledge-based clusters are especially helpful in explaining differences in the measures of regional economic development across metropolitan areas with similarly high shares of college attainment. Places that are dominated by large universities (e.g., Bloomington, Indiana), regions that are noted for vibrant innovative economies (e.g., San Francisco) and key engineering and technology centers (e.g., San Jose) typically have among the highest levels of college attainment. Our regression models allow us to isolate the effects of education on economic development by controlling for differences in the knowledge profiles of regions. This allows us to make a distinction between, for example, the types of knowledge used by the workforces of “college towns” as compared to places such as Silicon Valley. The end result is that incorporating this information increases the estimated effects of education on regional productivity and earnings per capita.

REFERENCES

- Abel, Jaison R. and Todd Gabe. 2010. "Human Capital and Economic Activity in Urban America," *Regional Studies*, forthcoming.
- Bacolod, Marigee, Bernardo Blum and William Strange. 2009. "Skills in the City," *Journal of Urban Economics*, 65, 136-153.
- Becker, Gary. 1964. *Human Capital*, New York: Columbia University Press.
- Drucker, Peter. 1968. *The Age of Discontinuity*, New York: Harper and Row.
- Feser, Edward. 2003. "What Regions Do Rather than Make: A Proposed Set of Knowledge-Based Occupation Clusters," *Urban Studies*, 40, 1937-1958.
- Florida, Richard. 2002. *The Rise of the Creative Class*, New York: Basic Books.
- 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*, 8, 615-649.
- Gabe, Todd. 2009. "Knowledge and Earnings," *Journal of Regional Science*, 49, 439-457.
- Glaeser, Edward, Jose Scheinkman, and Andrei Shleifer. 1995. "Economic Growth in a Cross-Section of Cities," *Journal of Monetary Economics*, 36, 117-143.
- Glaeser, Edward L. and Albert Saiz. 2004. "The Rise of the Skilled City," *Brookings-Wharton Papers on Urban Affairs*, 5, 47-94.

- Goldin, Claudia and Lawrence F. Katz. 1996. "Technology, Skill and the Wage Structure: Insights from the Past," *American Economic Review*, 86, 252-257.
- Ingram, Beth and George Neumann. 2006. "The Returns to Skill," *Labour Economics*, 13, 35-59.
- Knight, Richard. 1995. "Knowledge-Based Development: Policy and Planning Implications for Cities," *Urban Studies*, 32, 225-260.
- Lever, William F. 2002. "Correlating the Knowledge-Base of Cities with Economic Growth," *Urban Studies*, 39, 859-870.
- Lucas, Robert E. 1988. "On the Mechanics of Economic Development," *Journal of Monetary Economics*, 22, 3-42.
- Markusen, Ann. 2004. "Targeting Occupations in Regional and Community Economic Development," *Journal of the American Planning Association*, 70, 253-268.
- Mathur, Vijay. 1999. "Human Capital-Based Strategy for Regional Economic Development," *Economic Development Quarterly*, 13, 203-216.
- Moretti, Enrico. 2004. "Estimating the Social Return to Higher Education: Evidence from Longitudinal and Repeated Cross-Sectional Data," *Journal of Econometrics*, 121, 175-212.
- Oliner, Stephen and Daniel Sichel. 2000. "The Resurgence of Growth in the Late 1990s: Is Information Technology the Story?" *Journal of Economic Perspectives*, 14, 3-22.

- 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*, 54, 451-492.
- Rauch, James. 1993. "Productivity Gains from Geographic Concentration of Human Capital: Evidence from the Cities," *Journal of Urban Economics*, 34, 380-400.
- Ruggles, Steven, Matthew Sobek, Trent Alexander, Catherine A. Fitch, Ronald Goeken, Patricia Kelly Hall, Miriam King, and Chad Ronnander. 2010. Integrated Public Use Microdata Series: Version 4.0 [Machine-readable database]. Minneapolis, MN: Minnesota Population Center [producer and distributor].
- Scott, Allen. 2009. "Human Capital Resources and Requirements across the Metropolitan Hierarchy of the USA," *Journal of Economic Geography*, 9, 207-226.
- Ward, Joe. 1963. "Hierarchical Groupings to Optimize an Objective Function," *Journal of the American Statistical Association*, 58, 236-244.
- Willis, Robert. 1986. "Wage Determinants: A Survey and Reinterpretation of Human Capital Earnings Functions," in a O. Ashenfelter and R. Layard (eds), *Handbook of Labor Economics*. Amsterdam: Elsevier, pp. 525-602.

Table 1. Knowledge Areas

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

Source: Occupational Information Network, U.S. Department of Labor.

Table 2. Standardized Knowledge Scores for Selected Metropolitan Areas

Knowledge Area	Athens, Georgia	Calgary	New York	Toronto	Washington, DC
Administration & Management	0.71	2.20	0.66	1.81	2.23
Fine Arts	-0.43	-0.18	2.39	1.54	2.02
Biology	2.29	-0.64	-0.03	-1.90	0.24
Building & Construction	-0.49	1.27	-1.45	-1.15	-0.82
Chemistry	1.90	0.38	-1.66	-2.19	-1.87
Clerical	0.20	1.29	1.81	1.38	2.50
Communications & Media	1.70	0.65	1.78	1.09	3.33
Computers & Electronics	0.69	1.34	0.96	1.49	3.53
Customer & Personal Service	-0.11	0.40	1.04	0.30	1.10
Design	-0.15	2.76	-0.68	0.86	1.88
Economics & Accounting	-0.41	2.25	1.55	2.12	2.17
Education & Training	3.03	-0.48	0.50	-0.05	1.35
Engineering & Technology	-0.25	3.29	-1.14	0.35	1.72
English Language	1.15	1.08	1.31	0.99	2.39
Food Production	0.87	-1.08	-1.67	-1.67	-2.01
Geography	2.73	1.59	0.65	-1.23	1.99
History & Archeology	3.51	-0.90	1.07	-0.70	1.67
Foreign Language	2.40	-0.76	0.26	-0.77	0.93
Law & Government	0.75	1.82	1.78	0.92	3.69
Mathematics	0.76	3.02	-0.28	1.49	2.25
Mechanical	-0.53	-0.02	-2.33	-1.00	-2.26
Medicine & Dentistry	0.47	-1.16	0.51	-1.73	-0.46
Personnel & Human Resources	1.09	1.73	0.89	1.15	1.50
Philosophy & Theology	2.74	-1.19	1.07	-1.09	0.85
Physics	0.86	2.83	-1.31	-1.52	0.75
Production & Processing	-0.59	0.53	-1.86	0.56	-1.84
Public Safety & Security	-0.30	-0.06	-0.52	-1.89	-0.46
Psychology	1.42	-1.03	1.45	-1.33	0.81
Sales & Marketing	-0.02	1.56	0.80	1.88	0.78
Sociology & Anthropology	2.49	-1.15	1.22	-0.90	1.37
Telecommunications	-0.41	0.82	1.08	0.97	3.73
Therapy & Counseling	1.35	-1.24	1.19	-1.41	0.16
Transportation	-1.29	0.25	-0.69	-0.88	-1.03

Sources: Occupational Information Network, U.S. Department of Labor; 2005-07 American Community Survey of the U.S. Census Bureau (U.S. metropolitan areas) and Statistics Canada 2006 Census (Canadian metropolitan areas).

Table 3. Knowledge-Based Clusters

Name	Brief Cluster Description	High Knowledge in...	Low Knowledge in...
<i>Comforting Regions</i>	High knowledge about mental health; low knowledge about engineering and production.	Customer & Personal Service, Philosophy & Theology, Psychology, Sociology & Anthropology, Therapy & Counseling	Building & Construction, <u>Design</u> , Engineering & Technology, Mechanical, Physics, Production & Processing
<i>Working Regions</i>	Low knowledge about IT and commerce.	NA	Clerical, Computers & Electronics, Design, Economics & Accounting, Mathematics, Personnel & Human Resources, Sales & Marketing, Telecommunications
<i>Thinking Regions</i>	High knowledge about arts, humanities, IT and commerce; low knowledge about manufacturing.	Fine Arts, Biology, Clerical, Communications & Media, Computers & Electronics, Customer & Personal Service, Economics & Accounting, Education & Training, English Language, Geography, History & Archeology, Foreign Languages, Law & Government, Medicine & Dentistry, Personnel & Human Resources, Philosophy & Theology, Psychology, Sales & Marketing, Sociology & Anthropology, Telecommunications, Therapy & Counseling	Mechanical, Production & Processing

Table is continued on the following page.

Table 3. continued

Name	Brief Cluster Description	High Knowledge in...	Low Knowledge in...
<i>Building Regions</i>	Very high knowledge about construction and transportation.	<u>Building & Construction</u> , <u>Mechanical</u> , <u>Public Safety & Security</u> , <u>Transportation</u>	NA
<i>Innovating Regions</i>	Very high knowledge about IT, arts, commerce and engineering; low knowledge about manufacturing.	<u>Fine Arts</u> , <u>Biology</u> , <u>Clerical</u> , <u>Communications & Media</u> , <u>Computers & Electronics</u> , <u>Customer & Personal Service</u> , <u>Design</u> , <u>Economics & Accounting</u> , <u>Education & Training</u> , <u>Engineering & Technology</u> , <u>English Language</u> , <u>Geography</u> , <u>History & Archaeology</u> , <u>Foreign Language</u> , <u>Law & Government</u> , <u>Mathematics</u> , <u>Personnel & Human Resources</u> , <u>Philosophy & Theology</u> , <u>Physics</u> , <u>Psychology</u> , <u>Sales & Marketing</u> , <u>Sociology & Anthropology</u> , <u>Telecommunications</u>	Food Production, <u>Mechanical</u> , <u>Production & Processing</u> , <u>Public Safety & Security</u> , <u>Transportation</u>

Table is continued on the following page.

Table 3. continued

Name	Brief Cluster Description	High Knowledge in...	Low Knowledge in...
<i>Making Regions</i>	Very high knowledge about manufacturing; very low knowledge about commerce and humanities.	<u>Mechanical, Production & Processing</u>	Fine Arts, Biology, <u>Clerical, Communications & Media, Computers & Electronics, Customer & Personal Service, Economics & Accounting, Education & Training, English Language, Geography, History & Archaeology, Foreign Language, Law & Government, Mathematics, Medicine & Dentistry, Personnel & Human Resources, Philosophy & Theology, Psychology, Sales & Marketing, Sociology & Anthropology, Telecommunications, Therapy & Counseling</u>
<i>Teaching Regions</i>	Very high knowledge about the humanities and science; very low knowledge about manufacturing.	<u>Biology, Chemistry, Clerical, Communications & Media, Computers & Electronics, Education & Training, English Language, Geography, History & Archaeology, Foreign Language, Law & Government, Mathematics, Medicine & Dentistry, Personnel & Human Resources, Philosophy & Theology, Physics, Psychology, Sociology & Anthropology, Therapy & Counseling</u>	Building & Construction, <u>Mechanical, Production & Processing, Public Safety & Security, Transportation</u>

Table is continued on the following page.

Table 3. continued

Name	Brief Cluster Description	High Knowledge in...	Low Knowledge in...
<i>Enterprising Regions</i>	High knowledge about commerce and IT.	Fine Arts, Clerical, Computers & Electronics, Customer & Personal Service, <u>Economics & Accounting</u> , Mathematics, <u>Sales & Marketing</u> , Telecommunications	Chemistry, Food Production, Mechanical, Public Safety & Security,
<i>Farming Regions</i>	Very high knowledge about food production and manufacturing; very low knowledge about arts and humanities.	Biology, <u>Building & Construction</u> , Chemistry, <u>Food Production</u> , Geography, <u>Mechanical, Production & Processing</u> , <u>Public Safety & Security</u> , <u>Transportation</u>	<u>Fine Arts</u> , <u>Clerical</u> , <u>Communications & Media</u> , <u>Computers & Electronics</u> , <u>Customer & Personal Service</u> , Economics & Accounting, <u>Education & Training</u> , <u>English Language</u> , History, <u>Mathematics</u> , Personnel & Human Resources, <u>Philosophy & Theology</u> , <u>Psychology</u> , Sales & Marketing, <u>Sociology & Anthropology</u> , Telecommunication, <u>Therapy & Counseling</u>
<i>Understanding Regions</i>	Very high knowledge about arts, sciences, humanities and IT; very low knowledge about manufacturing.	<u>Fine Arts</u> , <u>Biology</u> , <u>Chemistry</u> , <u>Clerical</u> , <u>Communications & Media</u> , <u>Computers & Electronics</u> , <u>Customer & Personal Service</u> , <u>Education & Training</u> , <u>English Language</u> , <u>Geography</u> , <u>History & Archaeology</u> , <u>Foreign Language</u> , <u>Law & Government</u> , <u>Mathematics</u> , <u>Medicine & Dentistry</u> , <u>Personnel & Human Resources</u> , <u>Philosophy & Theology</u> , <u>Physics</u> , <u>Psychology</u> , <u>Sociology & Anthropology</u> , <u>Telecommunications</u> , <u>Therapy & Counseling</u>	<u>Building & Construction</u> , Food Production, <u>Mechanical</u> , <u>Production & Processing</u> , Public Safety & Security, <u>Transportation</u>

Table is continued on the following page.

Table 3. continued

Name	Brief Cluster Description	High Knowledge in...	Low Knowledge in...
<i>Engineering Regions</i>	Very high knowledge about engineering, IT, and commerce; low knowledge about physical and mental health.	Chemistry, Clerical, Communications & Media, <u>Computers & Electronics</u> , <u>Design</u> , <u>Economics & Accounting</u> , <u>Engineering & Technology</u> , English Language, Geography, Law & Government, <u>Mathematics</u> , <u>Physics</u> , Production & Processing, Sales & Marketing, <u>Telecommunications</u>	Medicine & Dentistry, Philosophy & Theology, Psychology, Sociology & Anthropology, <u>Therapy & Counseling</u> , Transportation

Table 4. Regional Economic Indicators, by Knowledge-Based Cluster

Name	Cluster Description	Average GDP Per Capita (Standardized)	Average Earnings Per Capita (Standardized)	Average College Attainment (Standardized)
<i>Comforting Regions</i>	High knowledge about mental health; low knowledge about engineering and production.	-0.37	-0.44	-0.19
<i>Working Regions</i>	Low knowledge about IT and commerce.	-0.45	-0.43	-0.39
<i>Thinking Regions</i>	High knowledge about arts, humanities, IT and commerce; low knowledge about manufacturing.	0.28	0.39	0.58
<i>Building Regions</i>	Very high knowledge about construction and transportation.	-0.05	-0.12	-0.58
<i>Innovating Regions</i>	Very high knowledge about IT, arts, commerce and engineering; low knowledge about manufacturing.	1.27	1.41	1.96
<i>Making Regions</i>	Very high knowledge about manufacturing; very low knowledge about commerce and humanities.	-0.41	-0.25	-0.80

Table is continued on the following page.

Table 4. continued

Name	Cluster Description	Average GDP Per Capita (Standardized)	Average Earnings Per Capita (Standardized)	Average College Attainment (Standardized)
<i>Teaching Regions</i>	Very high knowledge about the humanities and science; very low knowledge about manufacturing.	-0.40	-0.76	1.43
<i>Enterprising Regions</i>	High knowledge about commerce and IT.	0.74	0.50	0.49
<i>Farming Regions</i>	Very high knowledge about food production and manufacturing; very low knowledge about arts and humanities.	-0.98	-0.54	-1.27
<i>Understanding Regions</i>	Very high knowledge about arts, sciences, humanities and IT; very low knowledge about manufacturing.	0.32	-0.05	2.37

Table is continued on following page.

Table 4. continued

Name	Cluster Description	Average GDP Per Capita (Standardized)	Average Earnings Per Capita (Standardized)	Average College Attainment (Standardized)
<i>Engineering Regions</i>	Very high knowledge about engineering, IT, and commerce; low knowledge about physical and mental health.	1.63	2.20	1.20

Table 5. Effects of Education and Knowledge Clusters on Economic Development (n=287).

Variable	Dependent Variable: GDP Per Capita, Standardized		Dependent Variable: Earnings Per Capita, Standardized	
	Constant	1.61E-15 (0.000)	NA	3.74E-16 (0.000)
% Metropolitan Area Population w/ College Degree, Standardized	0.559*** (11.393)	0.663*** (8.445)	0.469*** (8.961)	0.544*** (6.611)
<i>Comforting Regions</i>	NA	-0.242* (-1.738)	NA	-0.341** (-2.335)
<i>Working Regions</i>	NA	-0.193* (-1.721)	NA	-0.215* (-1.838)
<i>Thinking Regions</i>	NA	-0.108 (-0.782)	NA	0.078 (0.544)
<i>Building Regions</i>	NA	0.335** (2.526)	NA	0.197 (1.423)
<i>Innovating Regions</i>	NA	-0.033 (-0.130)	NA	0.335 (1.307)

Table is continued on the following page.

Table 5. continued

Variable	Dependent Variable: GDP Per Capita, Standardized		Dependent Variable: Earnings Per Capita, Standardized	
<i>Making Regions</i>	NA	0.126 (1.072)	NA	0.185 (1.499)
<i>Teaching Regions</i>	NA	-1.355*** (-5.390)	NA	-1.537*** (-5.835)
<i>Enterprising Regions</i>	NA	0.416*** (3.531)	NA	0.231* (1.870)
<i>Farming Regions</i>	NA	-0.137 (-0.458)	NA	0.149 (0.476)
<i>Understanding Regions</i>	NA	-1.256*** (-3.013)	NA	-1.345*** (-3.080)
<i>Engineering Regions</i>	NA	0.831** (2.161)	NA	1.547*** (3.840)
Adjusted R-squared	0.311	0.442	0.217	0.388

Notes: t-statistics are shown in parentheses. *, ** and *** indicate statistical significance at the 0.10, 0.05 and 0.01 levels.

Table 6. Effects of Education and Knowledge Clusters on Economic Development in Places with High College Attainment (n=130).

Variable	Dependent Variable: GDP Per Capita, Standardized		Dependent Variable: Earnings Per Capita, Standardized	
	Constant	0.214 (1.583)	NA	0.074 (0.474)
% Metropolitan Area Population w/ College Degree, Standardized	0.368*** (3.110)	0.554*** (3.494)	0.406*** (2.978)	0.527*** (2.893)
<i>Comforting Regions</i>	NA	-0.350 (-1.331)	NA	-0.600** (-1.983)
<i>Working Regions</i>	NA	-0.214 (-0.875)	NA	-0.282 (-1.002)
<i>Thinking Regions</i>	NA	-0.032 (-0.160)	NA	0.122 (0.531)
<i>Building Regions</i>	NA	0.882*** (2.882)	NA	0.500 (1.422)
<i>Innovating Regions</i>	NA	0.182 (0.471)	NA	0.377 (0.850)

Table is continued on the following page.

Table 6. continued.

Variable	Dependent Variable: GDP Per Capita, Standardized		Dependent Variable: Earnings Per Capita, Standardized	
<i>Making Regions</i>	NA	-0.404 (-0.472)	NA	0.058 (0.059)
<i>Teaching Regions</i>	NA	-1.199*** (-3.485)	NA	-1.513*** (-3.827)
<i>Enterprising Regions</i>	NA	0.508*** (2.849)	NA	0.248 (1.209)
<i>Understanding Regions</i>	NA	-0.996* (-1.749)	NA	-1.305** (-1.993)
<i>Engineering Regions</i>	NA	0.963** (2.055)	NA	1.567*** (2.910)
Adjusted R-squared	0.063	0.303	0.057	0.303

Notes: t-statistics are shown in parentheses. *, ** and *** indicate statistical significance at the 0.10, 0.05 and 0.01 levels.

Appendix: List of U.S. and Canadian Metropolitan
Areas by Knowledge-Based Cluster

<i>Comforting Regions</i>	
Abilene, TX	Moncton, NB
Alexandria, LA	Monroe, LA
Amarillo, TX	Pueblo, CO
Asheville, NC	Quebec City, QC
Atlantic City, NJ	Savannah, GA
Buffalo-Niagara Falls, NY	Shreveport, LA
Chico, CA	Sioux Falls, SD
Columbus, GA/AL	Spokane, WA
El Paso, TX	Springfield-Holyoke-Chicopee, MA
Fayetteville, NC	Syracuse, NY
Hattiesburg, MS	Topeka, KS
Las Vegas, NV	Utica-Rome, NY
Lincoln, NE	Waco, TX
Lubbock, TX	Winnipeg, MB
Memphis, TN/AR/MS	

<i>Working Regions</i>	
Akron, OH	Laredo, TX
Albany, GA	London, ON
Allentown-Bethlehem-Easton, PA/NJ	McAllen-Edinburg-Pharr-Mission, TX
Altoona, PA	Medford, OR
Augusta-Aiken, GA-SC	Muncie, IN
Bellingham, WA	Peterborough, ON
Billings, MT	Providence-New Bedford-Fall River, RI-MA
Binghamton, NY	Rochester, NY
Brownsville-Harlingen-San Benito, TX	Saskatoon, SK
Dayton-Springfield, OH	Scranton-Wilkes-Barre, PA
Duluth-Superior, MN/WI	Sherbrooke, QC
Eugene-Springfield, OR	Sioux City, IA/NE
Fresno, CA	South Bend-Mishawaka, IN
Glens Falls, NY	Springfield, MO
Goldsboro, NC	Sudbury, ON
Greensboro-Winston Salem-High Point, NC	Texarkana, TX/AR
Guelph, ON	Thunder Bay, ON
Hamilton, ON	Trois-Rivieres, QC
Harrisburg-Lebanon--Carlisle, PA	Tuscaloosa, AL
Jackson, TN	Tyler, TX
Johnson City-Kingsport-Bristol, TN/VA	Vineland-Milville-Bridgetown, NJ
Johnstown, PA	Waterloo-Cedar Falls, IA
Lafayette-W. Lafayette, IN	Wichita Falls, TX
Lansing-E. Lansing, MI	Wichita, KS

Thinking Regions

Albany-Schenectady-Troy, NY	Philadelphia, PA/NJ
Albuquerque, NM	Portland, ME
Barnstable-Yarmouth, MA	Redding, CA
Baton Rouge, LA	Regina, SK
Bridgeport-Stamford-Norwalk, CT	Salinas-Sea Side-Monterey, CA
Charleston-N.Charleston, SC	San Antonio, TX
Columbia, SC	San Diego, CA
Halifax, NS	San Luis Obispo-Atascad-P Robles, CA
Honolulu, HI	Santa Barbara-Santa Maria-Lompoc, CA
Jackson, MS	Santa Cruz, CA
Knoxville, TN	Santa Rosa-Petaluma, CA
Las Cruces, NM	St. Johns, NL
Little Rock--North Little Rock, AR	Tucson, AZ
New Haven-Meriden, CT	Victoria, BC
New Orleans, LA	Wilmington, NC
New York-Northeastern NJ	Worcester, MA
Olympia, WA	

Building Regions

Anchorage, AK	Kileen-Temple, TX
Barrie, ON	Lafayette, LA
Beaumont-Port Arthur-Orange,TX	Lake Charles, LA
Biloxi-Gulfport, MS	Lakeland-Winterhaven, FL
Bremerton, WA	Macon-Warner Robins, GA
Clarksville- Hopkinsville, TN/KY	Mobile, AL
Corpus Christi, TX	Myrtle Beach, SC
Dothan, AL	Naples, FL
Dover, DE	Norfolk-Virginia Beach-Newport News, VA
Edmonton, AB	Ocala, FL
Fayetteville-Springdale, AR	Odessa, TX
Fort Myers-Cape Coral, FL	Oshawa, ON
Fort Walton Beach, FL	Panama City, FL
Grand Junction, CO	Pensacola, FL
Hagerstown, MD	Punta Gorda, FL
Houston-Brazoria, TX	Reno, NV
Jacksonville, NC	Riverside-San Bernardino,CA
Kelowna, BC	Saint John, NB

Innovating Regions

Ann Arbor, MI	Raleigh-Durham, NC
Austin, TX	San Francisco-Oakland-Vallejo, CA
Boston, MA-NH	Santa Fe, NM
Colorado Springs, CO	Seattle-Everett, WA
Fort Collins-Loveland, CO	Tallahassee, FL
Madison, WI	Trenton, NJ
Ottawa-Gatineau, ON	Washington, DC/MD/VA

Making Regions

Anniston, AL	Kokomo, IN
Appleton-Oskosh-Neenah, WI	Lancaster, PA
Benton Harbor, MI	Lima, OH
Brantford, ON	Longview-Marshall, TX
Canton, OH	Lynchburg, VA
Danville, VA	Mansfield, OH
Davenport, IA-Rock Island -Moline, IL	Modesto, CA
Decatur, AL	Peoria, IL
Decatur, IL	Racine, WI
Detroit, MI	Reading, PA
Eau Claire, WI	Rockford, IL
Elkhart-Goshen, IN	Rocky Mount, NC
Erie, PA	Saginaw-Bay City-Midland, MI
Evansville, IN/KY	Salem, OR
Flint, MI	Sheboygan, WI
Florence, AL	St. Catharines, ON
Fort Wayne, IN	St. Cloud, MN
Gadsden, AL	St. Joseph, MO
Grand Rapids, MI	Stockton, CA
Green Bay, WI	Sumter, SC
Greenville-Spartanburg-Anderson SC	Terre Haute, IN
Hickory-Morgantown, NC	Toledo, OH/MI
Jackson, MI	Wausau, WI
Janesville-Beloit, WI	Williamsport, PA
Joplin, MO	Windsor, ON
Kalamazoo-Portage, MI	York, PA
Kankakee, IL	Youngstown-Warren, OH-PA
Kitchener, ON	Yuba City, CA

Teaching Regions

Athens, GA	Greenville, NC
Auburn-Opekika, AL	Kingston, ON
Bloomington, IN	Lexington-Fayette, KY
Bryan-College Station, TX	Springfield, IL
Champaign-Urbana-Rantoul, IL	State College, PA
Columbia, MO	

Enterprising Regions

Atlanta, GA	Milwaukee, WI
Birmingham, AL	Minneapolis-St. Paul, MN
Bloomington-Normal, IL	Montgomery, AL
Boise City, ID	Montreal, QC
Charlotte-Gastonia-Rock Hill, NC-SC	Nashville, TN
Chattanooga, TN/GA	Oklahoma City, OK
Chicago, IL	Omaha, NE/IA
Cincinnati-Hamilton, OH/KY/IN	Orlando, FL
Cleveland, OH	Phoenix, AZ
Columbus, OH	Portland, OR-WA
Dallas-Fort Worth, TX	Provo-Orem, UT
Daytona Beach, FL	Richmond-Petersburg, VA
Denver-Boulder, CO	Roanoke, VA
Des Moines, IA	Sacramento, CA
Fargo-Morehead, ND/MN	Salt Lake City-Ogden, UT
Hartford-Bristol-Middleton- New Britain, CT	Sarasota, FL
Indianapolis, IN	St. Louis, MO-IL
Jacksonville, FL	Tampa-St. Petersburg-Clearwater, FL
Kansas City, MO-KS	Toronto, ON
Los Angeles-Long Beach, CA	Tulsa, OK
Louisville, KY/IN	Vancouver, BC
Manchester-Nashua, NH	Ventura-Oxnard-Simi Valley, CA
Miami-Hialeah, FL	

Farming Regions

Abbotsford, BC	Richland-Kennewick-Pasco, WA
Bakersfield, CA	Yakima, WA
Houma-Thibodoux, LA	Yuma, AZ
Merced, CA	

<i>Understanding Regions</i>	
Charlottesville, VA	Iowa City, IA
Gainesville, FL	Rochester, MN

<i>Engineering Regions</i>	
Calgary, AB	Melbourne-Titusville-Cocoa-Palm Bay, FL
Huntsville, AL	San Jose, CA
