

**Beyond Educational Attainment:
Knowledge-Based Investments to Enhance a Region's
Human Capital and Resident Earnings**

Todd Gabe

© 2010 Lincoln Institute of Land Policy

**Lincoln Institute of Land Policy
Working Paper**

The findings and conclusions of this Working Paper reflect the views of the author(s) and have not been subject to a detailed review by the staff of the Lincoln Institute of Land Policy.

Contact the Lincoln Institute with questions or requests for permission to reprint this paper. help@lincolnst.edu

Lincoln Institute Product Code: WP10TG1

Abstract

For decades, economists have investigated the private returns to human capital by examining the effects of educational attainment on earnings. However, given the wide range of knowledge and skills that are important to job performance, the number of years of formal education provides a rather simplistic view of human capital. Study findings show that, although educational attainment has a substantial positive effect on the earnings of U.S. workers, the types of knowledge required in an occupation play an equally important role in wage determination. Knowing a lot about subjects such as Medicine and Dentistry, Administration / Personnel, Law and Government, Sales and Marketing, and Computers and Electronics leads to a sizable positive effect on earnings. Knowledge that is obtained through on-the-job experience appears to be especially well-rewarded in the U.S. labor market.

About the Author

Todd Gabe is Associate Professor of Economics at the University of Maine. He has a Ph.D. in Agricultural Economics from The Ohio State University and a M.S. in Applied Economics from the University of Minnesota. Gabe teaches courses in regional economic development and applied data analysis, and conducts research on topics related to regional economic development. Gabe won the University of Maine Presidential Public Service Award in 2004, and the College of Natural Sciences, Forestry and Agriculture Outstanding Public Service Award in 2005. His recent projects have studied aspects of the knowledge and creative economies; the impacts of agglomeration; cruise ship passengers in Portland and Bar Harbor, Maine; and various fiscal policy issues.

School of Economics
University of Maine
5782 Winslow Hall
Orono, ME 04469-5782
todd.gabe@umit.maine.edu
Phone: (207) 581-3307
Fax: (207) 581-4278

Acknowledgments

I would like to thank the Lincoln Institute of Land Policy for supporting this research through the “Race to the Top” program. This manuscript benefited from the helpful comments provided by Lynn McCormick (discussant) and other participants of the “Race to the Top” workshop held at the Lincoln Institute of Land Policy in September 2009.

Table of Contents

I. Introduction	1
II. Educational Attainment versus Knowledge	3
Figure 1. Human Capital: Educational Attainment versus Knowledge	5
Table 1. U.S. Knowledge Workers, 2006	6
Figure 2. Sample Question from the O*NET Survey	7
III. Returns to Human Capital	9
Table 2. Summary Statistics	10
Table 3. Effects of Human Capital on Individual Wages and Salaries, 2006.....	11
IV. How People Acquire and Share Knowledge	15
Table 4. How U.S. Workers Acquire and Disseminate Knowledge.....	17
Table 5. Relationship between Knowledge-based Wage Premium and How it is Acquired.....	21
V. Conclusions	22
References	24

Beyond Educational Attainment: Knowledge-Based Investments to Enhance a Region's Human Capital and Resident Earnings

I. Introduction

“Race to the top” economic development policies and programs should attempt to increase the long-term well being of their intended recipients without adversely impacting others in the region or elsewhere. Initiatives aimed at enhancing human capital almost certainly meet these criteria. Timothy Bartik (1990) makes a market failure-based argument to suggest that regional policymakers should invest in programs that help individuals acquire human capital. The types of market failure that might cause people to under invest in human capital, compared to what is optimal from society's standpoint, are that lenders cannot repossess human capital, education may enhance “social stability,” individuals have a hard time valuing the benefits of human capital before it is acquired, and the spillover benefits related to human capital (Bartik 1990). Several empirical studies have uncovered evidence of these positive externalities associated with human capital (Moretti 2004; Acemoglu and Angrist 2000; Rauch 1993). The inability of markets, without policy intervention, to arrive at a socially optimal outcome provides a rationale for public sector involvement in the provision of human capital.

At the local level, the public sector is deeply involved in providing K-12 education. In addition, regional governments subsidize the cost of higher education through state appropriations to public universities. These types of investments – aimed primarily at formal education – appear to be warranted given the multitude of studies that find a positive relationship between earnings and a person's level of educational attainment (e.g., receipt of a college degree) (Card 1999). But the number of years of formal education is a somewhat crude measure of human capital (Ingram and Neumann 2006). By focusing on educational attainment and the receipt of a college degree, the emphasis is on “how long” a person spent acquiring human capital as opposed to exactly “what” he or she knows.

Recent occupational-based approaches to economic development have provided a broader view, beyond educational attainment, 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 a person's occupation to say something about the types of skills (e.g., cognitive, motor and people skills) and knowledge (e.g., engineering and technology, history and archaeology) that he or she possess (Feser 2003;

Ingram and Neumann 2006; Bacolod, Blum and Strange 2009; Gabe 2009; Abel and Gabe 2008; Scott 2009).

This study takes such an approach to examine the returns to human capital. Our ultimate goal, supported by the empirical results presented in the paper, is to encourage policymakers to go beyond educational attainment as an (or, in some cases, “the”) indicator of human capital, and to think more broadly about the types of knowledge that people possess. The research questions that we attempt to address are (1) how do the returns to knowledge about specific subjects (e.g., computers and electronics, biology, administration and management) compare to the additional earnings associated with a college degree; and (2) does the way in which an individual acquires knowledge (e.g., educational attainment, experience, training) influence the return to knowing a lot about a particular subject?

The answers to these questions will extend the literature on the occupational-based approach to regional and community economic development. Ann Markusen (2004) argues that regional policies should target occupations along with industries, which have traditionally been the focus of economic development efforts (e.g., industry cluster initiatives). Some of the more desirable occupational characteristics for policymakers to consider include a high level of “capturability,” high past and expected future growth, occupations that are highly connected and integrated across industries, and occupations characterized by high levels of entrepreneurship (Markusen 2004). Markusen (2004, p. 254) notes that “occupational analysis can... be used to tie education and training options together with firm recruitment and retention at the community level.” Our analysis, which considers education and training as two of the paths to acquiring knowledge, will explore the ways in which these tools and others contribute to human capital and individual earnings.

Richard Florida’s (2002, 2008) extensive work on the creative economy is perhaps the best-known example of occupational-based regional development analysis. In his research, Florida uses several broad occupational categories (e.g., Computer and Mathematical Occupations; Arts, Design, Entertainment, Sports, and Media Occupations) to define members of the “creative class.” This information is used, along with other indicators such as measures of tolerance and technology, to rank metropolitan areas in terms of their creativity (Florida 2002). In addition, Florida (2002) demonstrates the “economic power” of the creative class by comparing the earnings of its members (\$48,752 average annual salary) to individuals counted among the ranks of the “working class” (\$27,799), “service class” (\$22,059) and agriculture (\$18,000). Using a regression-based approach, our analysis will attempt to estimate the additional earnings associated with knowledge about a wide range of subjects.

In a review of Florida’s book *The Rise of the Creative Class*, Edward Glaeser (2004) asks whether creativity has an effect on regional growth “over and above the effect of human capital.” To investigate this question, Glaeser (2004) reports the results from several basic regression models that include a region’s percent of the adult population with a 4-year college degree (i.e., educational attainment) and the proportion of employment in

Florida's "super creative core" (i.e., an occupational-based measure of creativity) as two of the determinants of U.S. metropolitan area population growth. The results, subject to several caveats acknowledged by Glaeser (2004), suggest that educational attainment generally has a positive and statistically significant effect on population growth, whereas the occupational-based measure of creativity does not. In our analysis, we ask the question of whether knowing a lot about a wide range of subjects has an effect on earnings over and above the return to a college degree. Our application is different – Glaeser (2004) looks at population growth and we focus on individual earnings – but the spirit of the inquiry is similar.

II. Educational Attainment versus Knowledge

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, economists 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 possesses human capital; and someone without a degree does not. But this is a rather narrow and simplistic view of human capital. Lots of jobs – even some that offer reasonably high wages – do not require skills or talents that are typically covered in a university degree program.

As an extreme example, Lebron James, arguably one of the most talented and well-paid basketball players of his generation, possesses extraordinarily high levels of human capital for his chosen profession – yet did not obtain these skills through a college degree. As a more mundane example, many taxi cab drivers possess the skills (e.g., ability to fearlessly dart in and out of traffic) and knowledge (e.g., general layout of the city where they work) they need to perform their jobs well. But – like Lebron James – many taxi cab drivers would be counted among the ranks of "low human capital" using the receipt of a college degree as the single criterion. The purpose of these examples is not to argue that cabbies and athletes should be counted as high human capital professions, only that there is a wide range of talents that are not obtained through a formal education and, thus, are not captured in studies that use the receipt of a degree to measure human capital.

Even for those with a college degree (or a Ph.D. for that matter), the skills and knowledge acquired through their years of formal education likely represent a small fraction of what they use in the workplace. Doctors learn a tremendous amount of information and techniques in medical school, yet the ongoing changes and important scientific breakthroughs in medicine render much of this schooling as inadequate within a relatively short time period. But, as is the case with many university degree programs, medical school trains doctors how to continue learning on their own after obtaining a degree. So, like Lebron James and most New York City cab drivers, doctors learn a lot of what they use in their daily jobs through practice and experience.

We define knowledge as the stocks of information and practical understandings that people possess and ultimately use in their jobs. Figure 1 shows a sampling of the ways in

which people acquire knowledge (bottom panel), as well as an illustration of how economists typically measure human capital (top panel). The two panels shown in the figure differ in a couple of key ways. First, the top panel focuses on “generic” human capital whereas the bottom panel considers a wide range of topics, listed in Table 1. Second, the top panel emphasizes one route to obtain “high” human capital, discussed at length above, while the bottom panel allows for a lot of ways to obtain knowledge.

Table 1 shows a list of the 33 knowledge areas considered in the paper. They range from aspects of business (e.g., sales and marketing, administration and management) to science (e.g., biology, chemistry) to the liberal arts (e.g., history and archaeology, philosophy and theology). These subject areas are from the U.S. Department of Labor’s Occupational Information Network (O*NET), which is the source of most of the occupational-related data used in the study. Peterson et al. (2001) describe the O*NET system and explain how these exact 33 topics were chosen. In the listing of the knowledge areas presented in Table 1, several of the subjects are combined into groups. This is because in our subsequent analysis we found considerable overlap in the occupations that require high knowledge about these topics.

The O*NET is based on information collected through surveys of workers and the input of professional occupational analysts. In the case of the knowledge variables, the survey asked 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 required (e.g., on a scale of 1 to 7). The follow-up question on the level of knowledge required, which provides a different set of “anchors” for each of the knowledge areas, is only required for types of knowledge that are at least “somewhat” important (rating of “2” or higher on the first question). Figure 2 shows an example of one of the O*NET survey questions. The anchors attached to the knowledge “level” ratings (about the subject of *Chemistry*) suggest that a score of “2” is equivalent to “use a common household bug spray,” while a rating of “6” is equivalent to “develop a safe commercial cleaner.”

Following Feser (2003), we constructed knowledge indices that are the product of the “importance” and “level” of the knowledge needed to perform a particular job. To identify individuals who possess “high knowledge” about a particular subject, we focus on those working in occupations with a knowledge index value that is at least one-standard deviation above the mean calculated across all U.S. workers. To arrive at this information, we first matched 1.6 million individuals aged 18 to 64 from the one-percent sample of the 2007 U.S. Community Survey (Ruggles et al. 2008) to knowledge index scores, based on his or her occupation. The U.S. Community Survey, conducted by the U.S. Census Bureau, provides a code that identifies an individual’s occupation among a list of about 470 jobs. After matching people to their knowledge index scores, we calculated a mean and standard deviation for each of the 33 knowledge areas. Once again, a person is said to possess high knowledge in an area if his or her knowledge score is at least one-standard deviation above the mean.

Figure 1. Human Capital: Educational Attainment versus Knowledge

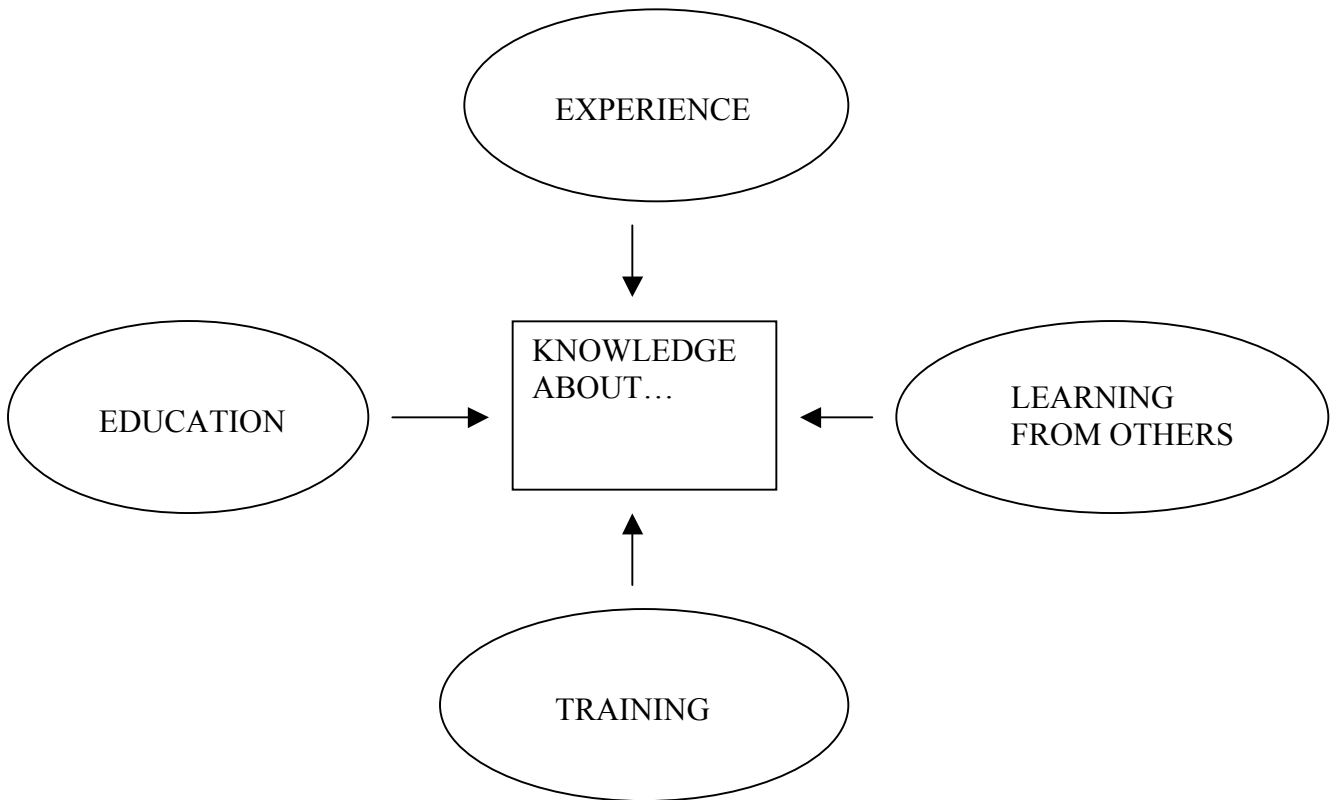
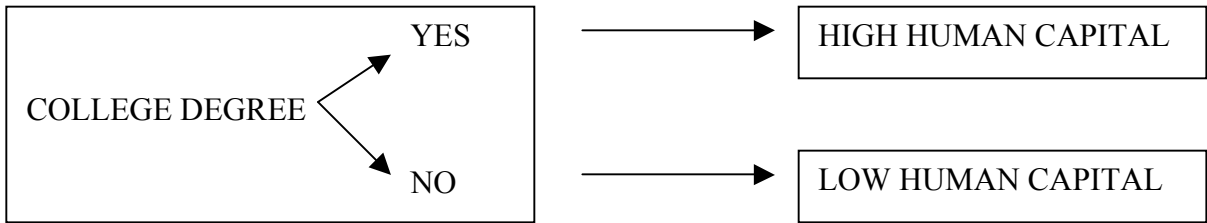


Table 1. U.S. Knowledge Workers, 2006

Knowledge Area	% of U.S. Workforce	% w/ 4-year Degree	Average Age	Average Earnings
<i>Administration and Management</i>	13.6%	55.6%	44.8	\$65,642
<i>Personnel and Human Resources</i>	11.7%	58.0%	45.4	\$65,650
<i>Clerical</i>	13.5%	41.3%	43.8	\$35,219
<i>Economics and Accounting</i>	9.5%	57.7%	44.3	\$63,961
<i>Law and Government</i>	9.8%	67.3%	44.2	\$65,817
<i>Communications and Media</i>	11.2%	78.4%	43.7	\$49,759
<i>Sales and Marketing</i>	12.0%	50.6%	42.5	\$54,436
<i>Customer and Personal Service</i>	14.4%	57.0%	42.7	\$47,160
<i>Production and Processing</i>	13.1%	32.7%	43.1	\$41,857
<i>Food Production</i>	9.5%	22.2%	37.9	\$22,056
<i>Mechanical</i>	15.2%	21.3%	42.0	\$35,287
<i>Building and Construction</i>	10.5%	26.0%	42.2	\$36,274
<i>Computers and Electronics</i>	8.5%	71.4%	42.6	\$60,976
<i>Engineering and Technology</i>	11.9%	41.0%	42.0	\$47,277
<i>Design</i>	12.7%	39.3%	41.8	\$45,151
<i>Mathematics</i>	10.3%	63.8%	43.4	\$64,854
<i>Physics</i>	11.7%	42.3%	41.7	\$50,133
<i>Telecommunications</i>	7.9%	56.1%	42.1	\$56,650
<i>Biology</i>	9.3%	64.9%	42.7	\$48,001
<i>Chemistry</i>	12.2%	51.8%	43.1	\$48,068
<i>Medicine and Dentistry</i>	6.4%	70.4%	42.7	\$54,193
<i>Psychology</i>	15.0%	73.6%	43.2	\$43,748
<i>Sociology and Anthropology</i>	13.3%	79.9%	43.6	\$44,346
<i>Therapy and Counseling</i>	12.4%	76.2%	43.8	\$45,210
<i>Education and Training</i>	13.4%	72.5%	43.6	\$46,670
<i>English Language</i>	17.0%	59.9%	42.7	\$49,537
<i>Foreign Language</i>	13.7%	45.5%	39.9	\$35,971
<i>Fine Arts</i>	6.1%	52.9%	43.2	\$38,815
<i>Geography</i>	11.8%	69.8%	43.3	\$40,028
<i>History and Archeology</i>	8.8%	79.7%	43.6	\$35,826
<i>Philosophy and Theology</i>	16.1%	73.1%	43.6	\$46,093
<i>Public Safety and Security</i>	11.1%	36.0%	42.3	\$44,318
<i>Transportation</i>	13.8%	25.2%	42.0	\$36,136

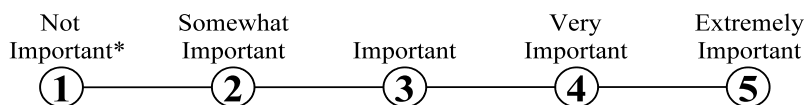
Sources: Occupational Information Network (O*NET), U.S. Department of Labor; 2007 American Community Survey, U.S. Census Bureau.

Figure 2. Sample Question from the O*NET Survey

16. Chemistry

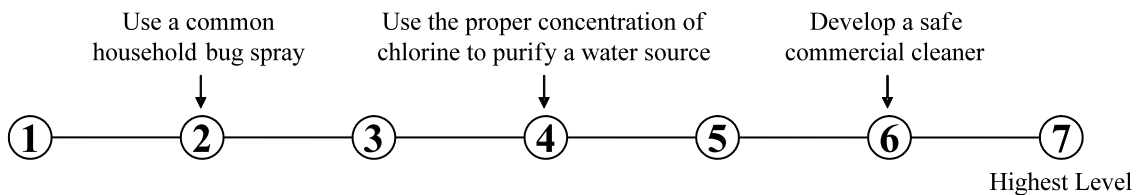
Knowledge of the chemical composition, structure, and properties of substances and of the chemical processes and transformations that they undergo. This includes uses of chemicals and their interactions, danger signs, production techniques, and disposal methods.

A. How important is knowledge of CHEMISTRY to the performance of *your current job*?



* If you marked Not Important, skip LEVEL below and go on to the next knowledge area.

B. What level of CHEMISTRY knowledge is needed to perform *your current job*?



The first column of figures presented in Table 1 shows the percentage of the U.S. workforce who are identified as possessing high knowledge about the 33 topics. If these knowledge scores were distributed normally across workers, we would expect about 16 percent to fall one-standard deviation above the mean. This is roughly the case for only a few of the knowledge areas. However, we would not expect all of the topics to have knowledge index values that are normally distributed across the workforce for a couple of reasons. First, as noted above, we matched 1.6 million people to knowledge scores based on their revealed occupation, among roughly 470 jobs. This means that the knowledge scores are quite “lumpy.” Second, we might expect the distribution of some of the knowledge scores to be skewed. It is not surprising that, for a topic such as *Medicine and Dentistry*, either you need a lot of knowledge to perform your job (e.g., doctor, nurse, x-ray technician) or very little at all (e.g., economist, sales person, brick mason). Thus, the distribution of knowledge in the area of *Medicine and Dentistry* (and many other topics) is skewed to the right. This leads to a smaller proportion of individuals with knowledge requirements that are more than one-standard deviation above the mean.

The other three columns in Table 1 provide descriptive information about individuals working in high-knowledge occupations. The percentage of workers with at least a four-year college degree reveals a wide variation in the formal education that goes along with high knowledge about the various topics. Over three-fourths of the workers who know a lot about the subjects of *Communications and Media*, *Sociology and Anthropology*, *Therapy and Counseling*, and *History and Archeology* have at least a college degree. On the other end of the educational attainment spectrum, less than one-quarter of those who are highly knowledgeable about *Food Production* or *Mechanical (things)* have a four-year college degree. This information is consistent with a basic premise of this paper, expressed above, that educational attainment is an incomplete measure of human capital.

The next column shows the average age of those who know a lot about the selected topics. For the areas of *Food Production* and *Foreign Language*, the average age is less than 40 years old. A quite different pattern emerges for workers highly knowledgeable about *Law and Government* and various aspects of business (e.g., *Administration and Management*, *Personnel and Human Resources*, and *Economics and Accounting*); the average age of workers in these knowledge areas is approaching 45 years old.

The far-right column of Table 1 reveals substantial differences in earnings across the 33 knowledge areas. It pays to know a lot about *Law and Government*, *Personnel and Human Resources*, or *Administration and Management*. Other knowledge areas that are rewarded in the labor market include *Mathematics*, *Economics and Accounting* and *Computers and Electronics*. People with high knowledge about *Food Production* do not generally make very much money; nor do those who are highly knowledgeable about the topics of *Clerical (tasks)*, *Mechanical (things)*, *History and Archeology*, *Foreign Language*, *Transportation*, and *Building and Construction*. It is interesting to note that, despite the very high proportion of workers with at least a four-year college degree, workers who know a lot about *History and Archeology* are not particularly well paid. In fact, their earnings are similar to workers who are highly knowledgeable about

Mechanical (things), the subject with the lowest percentage of workers who have completed a four-year college degree.

III. Returns to Human Capital

A common approach to measuring the private returns to human capital is econometric analysis of individual-level data using a wage regression model (Mincer 1974, Willis 1986, Card 1999). This typically involves examining the effect of educational attainment (i.e., receipt of a college degree) on wages and salaries, while controlling for the effects of other factors such as age (i.e., a proxy for experience), gender, marital status, and other socioeconomic characteristics. A similar approach is used in this paper; however, we examine the effects of college attainment as well as the effects of possessing high knowledge about the various subjects. The control variables that are unrelated to human capital are described in Table 2.

Table 3 presents regression results from three models that examine the effects of human capital on individual earnings. The knowledge areas enter into the regressions as dummy variables indicating whether or not the individual's occupation has a knowledge index value that is one or more standard deviations above the average U.S. worker (i.e., whether or not an individual possesses "high knowledge"). As shown in Table 1, several of the topics are combined into groups due to the overlap of occupations that require high knowledge. Along with these 26 knowledge areas and a dummy variable indicating the receipt of a college degree, the regressions also control for a person's age (an indicator of potential experience), gender, marital status and race. The regression models are estimated using earnings information and other pertinent data on 812,290 individuals from the 2007 American Community Survey of the U.S. Census Bureau. We focus on the annual earnings of full-time workers, defined as those who worked 50 or more weeks and typically 36 or more hours per week. Thus, our results cannot be generalized to all workers, both full- and part-time, or the entire working-age population.

We estimated three regression models as a way to compare the returns associated with knowledge about the various subjects to the additional earnings related to the receipt of a college degree. The first column of results (model 1) shows the effect of college attainment on earnings, controlling for the other socioeconomic characteristics but not the 26 knowledge areas. This wage regression model follows the general approach used by economists to measure the returns to human capital (Willis 1986; Card 1999). In the regression model shown in the center column of results (model 2), we replace college attainment as the sole indicator of human capital with the 26 knowledge variables. The third regression model, shown in the far right column, includes variables representing the receipt of a 4-year college degree as well as the knowledge variables.

Table 2. Summary Statistics (n = 812,290)

Variable	Definition	Mean	Standard Deviation
<i>Wages and Salaries</i>	Individual's total pre-tax wage and salary, and business and farm income, 2006	56,266	56,542
<i>ln (Wages and Salaries)</i>	Natural logarithm of Wages and Salaries	10.66	0.696
<i>College Degree</i>	= 1 if individual's highest level of educational attainment is a bachelor's degree or higher; 0 otherwise	0.434	NA
<i>Age</i>	Individual's age in years	42.81	11.40
<i>Male</i>	= 1 if the individual is a male; 0 otherwise	0.584	NA
<i>White</i>	= 1 if individual reported a race of "white," regardless of additional race(s) reported; 0 otherwise	0.814	NA
<i>Married</i>	= 1 if individual is married; 0 otherwise	0.646	NA

Notes: Information is from the 2007 American Community Survey, U.S. Census Bureau. Sample includes full-time workers, defined as those who worked 50 or more weeks and typically 36 or more hours per week. Mean values for the knowledge variables are shown, as percentages, in Table 1.

Table 3. Effects of Human Capital on Individual Wages and Salaries, 2006

Variable	Estimated Coefficients		
	Model 1	Model 2	Model 3
Constant	8.456*** (1,025)	8.581*** (984.3)	8.573*** (966.9)
<i>Age</i>	0.071*** (163.9)	0.069*** (160.6)	0.064*** (155.8)
<i>Age</i> ²	-0.001*** (-140.8)	-0.001*** (-139.8)	-0.001*** (-133.2)
<i>Male</i>	0.282*** (208.8)	0.285*** (189.0)	0.268*** (185.0)
<i>White</i>	0.125*** (73.42)	0.113*** (66.34)	0.098*** (60.28)
<i>Married</i>	0.120*** (82.47)	0.109*** (75.62)	0.098*** (70.78)
<i>College Degree</i>	0.525*** (392.49)	NA	0.386*** (267.4)
<i>Administration / Personnel</i>	NA	0.278*** (143.8)	0.239*** (128.9)
<i>Clerical</i>	NA	0.001 (0.535)	0.002 (1.104)
<i>Economics and Accounting</i>	NA	0.058*** (20.41)	0.060*** (21.89)
<i>Law and Government</i>	NA	0.238*** (95.06)	0.180*** (74.79)
<i>Communications and Media</i>	NA	0.028*** (10.72)	-0.002 (-0.933)

Table is continued on the following page.

Table 3. Effects of Human Capital on Individual Wages and Salaries, 2006, continued

Variable	Estimated Coefficients		
	Model 1	Model 2	Model 3
<i>Sales and Marketing</i>	NA	0.160*** (63.87)	0.134*** (55.77)
<i>Customer and Personal Service</i>	NA	0.014*** (6.444)	0.002 (1.116)
<i>Production and Processing</i>	NA	-0.027*** (-13.42)	-0.009*** (-4.825)
<i>Food Production</i>	NA	-0.202*** (-77.03)	-0.171*** (-67.81)
<i>Mechanical</i>	NA	-0.095*** (-37.19)	-0.028*** (-11.50)
<i>Building and Construction</i>	NA	-0.019*** (-6.320)	-0.007** (-2.266)
<i>Computers and Electronics</i>	NA	0.210*** (70.93)	0.127*** (44.46)
<i>Engineering / Design</i>	NA	0.096*** (34.34)	0.066*** (24.44)
<i>Mathematics</i>	NA	0.111*** (43.59)	0.069*** (28.43)
<i>Physics</i>	NA	0.152*** (52.97)	0.109*** (39.74)
<i>Telecommunications</i>	NA	0.051*** (18.52)	0.065*** (24.48)
<i>Biology / Chemistry</i>	NA	0.013*** (5.243)	-0.007*** (-2.892)

Table is continued on the following page.

Table 3. Effects of Human Capital on Individual Wages and Salaries, 2006, continued

Variable	Estimated Coefficients		
	Model 1	Model 2	Model 3
<i>Medicine and Dentistry</i>	NA	0.275*** (74.36)	0.248*** (69.87)
<i>Psychology / Sociology / Therapy</i>	NA	0.059*** (18.13)	-0.009*** (-2.808)
<i>Education and Training</i>	NA	-0.024*** (-8.735)	-0.032*** (-12.25)
<i>English Language</i>	NA	-0.056*** (-23.05)	-0.043*** (-18.53)
<i>Foreign Language</i>	NA	-0.062*** (-28.35)	-0.039*** (-18.47)
<i>Fine Arts</i>	NA	0.014*** (4.760)	0.009*** (3.010)
<i>Geography / History / Philosophy</i>	NA	0.156*** (61.78)	0.072*** (29.36)
<i>Public Safety and Security</i>	NA	-0.145*** (-53.83)	-0.074*** (-28.62)
<i>Transportation</i>	NA	-0.068*** (-33.03)	-0.028*** (-13.96)
R-squared	0.271	0.287	0.344
Adjusted R-squared	0.271	0.287	0.344
Number of Observations	812,290	812,290	812,290

Notes: Dependent variable is $\ln(\text{Wages and Salaries})$. Sample includes full-time workers, defined as those who worked 50 or more weeks and typically 36 or more hours per week. t-statistics are shown in parentheses. *** and ** denote significance at the 1- and 5-percent levels, respectively.

A comparison of adjusted R-squared values between models 1 and 2 suggests that a slightly larger percentage of the variation in individual earnings is explained by the knowledge variables, collectively, than by the receipt of a college degree. The adjusted R-squared value corresponding to model 3, which exceeds the goodness-of-fit in models 1 and 2, suggests that the inclusion of the educational attainment and knowledge variables together explain a substantially higher percentage of the variation in earnings than either of the human capital measures alone. It is also interesting to compare the effects of the human capital variables on earnings between models 1 and 3, and 2 and 3. Here, the emphasis is on how the effect of one of the human capital variables – say educational attainment – differs depending on whether or not the regression model controls for the other measure of human capital; in this case, the knowledge variables. When comparing models 1 and 3, we find that the estimated effect of a college degree on earnings falls by over 25 percent, from 0.525 (model 1) to 0.386 (model 3), when the regression controls for the knowledge variables along with educational attainment. Looking at models 2 and 3, we also see that the estimated effects of most of the knowledge variables change markedly when the regression model controls for educational attainment. For instance, the estimated effect of high knowledge about *Computers and Electronics* on earnings decreases by about 40 percent, from 0.210 (model 2) to 0.127 (model 3), when the regression controls for the receipt of a college degree.

Regression results from model 3 show that, other things being equal, the knowledge areas of *Medicine and Dentistry*, *Administration / Personnel*, *Law and Government*, *Sales and Marketing*, and *Computers and Electronics* have sizable effects on individual earnings. High knowledge about these topics, controlling for the receipt of a 4-year college degree, increases the annual wages and salaries of full-time workers by more than 10 percent. On the other hand, individuals who are well versed in the topics of *Food Production*, *Public Safety and Security*, and *Education and Training* appear to be penalized in the workforce. Other things being equal, possessing high knowledge about these topics lowers annual full-time earnings by more than five percent.

To conclude this section of the paper, we return to our original research question: how do the returns to knowledge about specific subjects compare to the additional earnings associated with a college degree? First, we find that educational attainment has a substantial effect on the annual earnings of full-time workers, ranging from a 38.6-percent to 52.5-percent wage premium. This means that the amount of education a person acquires matters in the labor market. However, the high-end estimate of 52.5-percent is likely biased upward because the regression model does not control for the types of knowledge that people possess. In other words, the wage premium attributed to educational attainment estimated in the traditional human capital earnings model likely overstates the return to the amount of education because it also captures – in part – the additional earnings associated with the types of knowledge that people possess.

Second, based on a comparison of the goodness-of-fit of the models we estimated, we find that the knowledge variables as a group perform slightly better than educational attainment at explaining the variation in individual earnings. However, an approach that combines information about the amount of human capital (i.e., educational attainment)

along with the type (i.e., knowledge areas) appears to perform considerably better than either of the human capital measures individually. Another advantage of using both human capital measures in a wage regression model is that it eliminates some of the bias, mentioned above, that might result from a singular focus on either the amount or type of human capital that an individual possesses.

Finally, we find a fairly sizable variation in the estimated returns to knowledge across the 26 subject areas. Possessing high knowledge about *Medicine and Dentistry*, and *Administration and Management* enhances earnings by over 20 percent, while knowing a lot about *Food Production* carries a wage penalty of over 15 percent. This does not imply, however, that a college degree in a field related to *Food Production* (or another knowledge area with a negative effect on earnings), when it leads to subsequent employment in a job that uses such knowledge, actually lowers a person's earning potential compared to someone without a 4-year degree. Rather, it suggests that part of the college wage premium might be offset by the type of degree obtained. Although our analysis does not explicitly examine the statistical interaction between a college degree and the high knowledge variables, it suggests that the type of degree (e.g., major) determines a person's earnings in the labor market.

IV. How People Acquire and Share Knowledge

In this section, we look at the ways in which people acquire and disseminate knowledge. As illustrated earlier in the paper, knowledge and formal education do not always go hand in hand. Looking back at Table 1, we see that the percentage of high-knowledge workers with at least a 4-year college degree ranges from 80 percent (*Sociology and Anthropology*, and *History and Archeology*) to less than 25 percent (*Mechanical and Food Production*). So, from this information, it appears that formal education is not the only route to knowledge in (at least) some of the subjects. Along with formal education, people can acquire and spread knowledge through work experience, on-the-job training, and via interactions with others.

Table 4 provides descriptive information about some of the ways in which workers acquire and disseminate knowledge. All of the variables shown in the table are constructed using data from the O*NET. The variables *Years Education* and *Years Work Experience* are constructed by transforming categorical variables into numerical measures. For example, the O*NET survey asks respondents to select the amount of "related work experience" required by someone in the occupation from a set of 11 options, such as "Up to and including 1 month" and "Over 8 years, up to and including 10 years." Using this information, we calculated an average number of years using midpoints of the categories and information on the proportion of respondents who selected each category. The variable *%w/More than 1 Year Job Training* is constructed using information from an O*NET question that asks, "If someone were being hired to perform this job, how much ON-THE-JOB TRAINING would be required?" Our measure of on-the-job training is simply the average proportion of individuals, by

knowledge area, who selected response categories that indicate more than one year of training.

The variable *Importance of Updating Knowledge* provides an idea of the extent to which workers are required to keep up with new developments and trends. To construct this variable, we first calculated an index score (similar to the knowledge variables described above) for the O*NET work activity titled “Using and Updating Relevant Knowledge.” With this information in hand, we then identified those occupations with index values (i.e., importance multiplied by level) that are one standard deviation or more above the mean across all jobs. The figures shown in Table 4 are the proportion of occupations, in each knowledge area, that have index values one standard deviation or more above the mean. For example, 65.6 percent of the occupations that require high knowledge (i.e., a knowledge index value that is one or more standard deviations above the mean) about *Computers and Electronics* also require that workers keep current with new information and trends (i.e., an index score for “Using and Updating Relevant Knowledge” that is one or more standard deviations above the mean).

The next two variables, *Communication w/in Firm* and *Communication Outside Firm*, attempt to capture patterns of information flow. Both measures are constructed in a similar manner as the variable that captures the importance of updating knowledge. In this case, the variables are based on O*NET survey questions related to work activities titled “Communicating with Supervisors, Peers, or Subordinates” and “Communicating with People Outside the Firm.” The values shown in Table 4 are interpreted as the percentages of occupations, by knowledge category, with index values that are at least one standard deviation above the mean. For example, 2.3 percent of occupations that require knowledge about *Economics and Accounting* exhibit high amounts of communication within the firm, while 20.4 percent of these occupations involve substantial communication outside the firm. The final variables shown in Table 4, % *Constant Contact w/ Others*, is from the O*NET work context question that reads, “How much contact with others (by telephone, face-to-face, or otherwise) is required to perform *your current job*?” This measure is the average proportion of individuals, by knowledge area, who selected the option indicating that their job requires “constant contact with others.”

Looking at the variable *Years of Education*, we see that the knowledge areas with the highest amounts of formal education include *Communications and Media*, *History and Archeology*, and *Sociology and Anthropology*. Considerably less formal education is required in the knowledge areas of *Food Production*, *Mechanical*, and *Transportation*. These findings, which are very similar to the Census-based data from Table 1 about the percentage of high-knowledge workers with at least a 4-year college degree, instill confidence in the information contained in the O*NET.

Table 4. How U.S. Workers Acquire and Disseminate Knowledge

Knowledge Area	Years Education	Years Work Experience	% w/More than 1 Year Job Training	Importance of Updating Knowledge	Communication w/in Firm	Communication Outside Firm	% Constant Contact w/others
<i>Administration and Management</i>	13.8	4.15	19.0%	0.102	0.587	0.344	71.8%
<i>Personnel and Human Resources</i>	14.0	4.04	19.3%	0.151	0.611	0.341	75.0%
<i>Clerical</i>	13.5	2.17	9.3%	0.023	0.156	0.186	72.7%
<i>Economics and Accounting</i>	13.8	3.08	15.4%	0.018	0.023	0.204	75.2%
<i>Law and Government</i>	15.3	2.62	21.8%	0.375	0.158	0.632	63.1%
<i>Communications and Media</i>	16.1	2.33	19.2%	0.394	0.201	0.144	72.2%
<i>Sales and Marketing</i>	14.0	2.16	11.4%	0.073	0.044	0.403	75.7%
<i>Customer and Personal Service</i>	14.3	1.96	12.6%	0.392	0.118	0.326	84.7%
<i>Production and Processing</i>	12.8	2.61	22.1%	0.093	0.186	0.146	56.1%
<i>Food Production</i>	12.4	1.11	8.0%	0.060	0.054	0.053	71.7%
<i>Mechanical</i>	12.4	2.78	34.5%	0.167	0.126	0.037	54.4%
<i>Building and Construction</i>	12.6	3.00	38.5%	0.116	0.108	0.135	58.1%
<i>Computers and Electronics</i>	15.1	3.43	24.8%	0.656	0.349	0.181	48.1%
<i>Engineering and Technology</i>	13.4	3.42	36.9%	0.335	0.151	0.089	51.9%
<i>Design</i>	13.3	3.33	36.3%	0.280	0.140	0.056	52.5%
<i>Mathematics</i>	14.8	3.54	30.1%	0.402	0.176	0.173	57.3%
<i>Physics</i>	13.7	3.09	35.6%	0.341	0.105	0.073	57.0%
<i>Telecommunications</i>	14.4	3.08	20.1%	0.460	0.279	0.209	60.7%
<i>Biology</i>	14.9	2.07	18.5%	0.609	0.075	0.101	70.4%
<i>Chemistry</i>	14.2	2.05	18.1%	0.475	0.105	0.069	69.4%
<i>Medicine and Dentistry</i>	15.2	1.63	11.1%	0.615	0.047	0.033	84.0%

Table 4. How U.S. Workers Acquire and Disseminate Knowledge, continued

	<i>Years Education</i>	<i>Years Work Experience</i>	<i>% w/More than 1 Year Job Training</i>	<i>Importance of Updating Knowledge</i>	<i>Communi- cation w/in Firm</i>	<i>Communi- cation Outside Firm</i>	<i>% Constant Contact w/others</i>
<i>Psychology</i>	15.6	1.69	14.5%	0.406	0.042	0.060	83.0%
<i>Sociology and Anthropology</i>	15.9	1.90	15.0%	0.425	0.096	0.095	80.7%
<i>Therapy and Counseling</i>	15.6	1.58	13.4%	0.398	0.076	0.074	83.4%
<i>Education and Training</i>	15.7	2.53	18.8%	0.319	0.177	0.157	78.6%
<i>English Language</i>	14.3	1.77	11.0%	0.319	0.084	0.114	76.7%
<i>Foreign Language</i>	14.0	1.67	14.6%	0.316	0.048	0.071	76.8%
<i>Fine Arts</i>	14.3	2.89	17.2%	0.101	0.257	0.252	71.3%
<i>Geography</i>	15.6	2.03	20.3%	0.244	0.151	0.198	73.0%
<i>History and Archeology</i>	16.0	2.01	17.7%	0.259	0.107	0.103	74.5%
<i>Philosophy and Theology</i>	15.6	1.78	14.0%	0.363	0.073	0.074	79.5%
<i>Public Safety and Security</i>	12.9	2.48	28.2%	0.153	0.134	0.137	65.6%
<i>Transportation</i>	12.5	1.69	17.1%	0.049	0.051	0.152	63.5%

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

Work experience appears to play a key role in the knowledge areas of *Administration and Management*, *Personnel and Human Resources*, *Mathematics*, *Computers and Electronics*, and *Engineering and Technology*. Formal education appears to be a good substitute for experience in the areas of *History and Archeology*, *Sociology and Anthropology*, *Philosophy and Theology*, and *Therapy and Counseling*. Workers with high knowledge in these areas tend to have high levels of formal education, but relatively low levels of work experience. On-the-job training is important in the knowledge areas of *Building and Construction*, *Engineering and Technology*, and *Design*. Although these knowledge areas also generally require high amounts of work experience, the knowledge areas with the highest experience requirements – *Administration and Management*, and *Personnel and Human Resources* – involve relatively little training. The lowest amounts of training are required in the knowledge areas of *Food Production*, *Clerical*, and *English Language*.

The practice of updating knowledge involves keeping up with current information and trends. Updating knowledge is particularly important in the subject areas of *Computers and Electronics*, *Medicine and Dentistry*, *Biology*, *Chemistry*, and *Telecommunications*. Interestingly, with the exception of *Computers and Electronics*, these knowledge areas require modest amounts of work experience and training. So it is likely that people keep current in these areas through regional networking, self-study (e.g., reading journals), and attending conferences and professional meetings.

Communicating with individuals inside and outside a worker's own firm are also key mechanisms for disseminating knowledge. As it pertains to matters within a company, workers with high knowledge about *Personnel and Human Resources*, *Administration and Management*, *Computers and Electronics*, and *Telecommunications* appear to be the most connected. When communicating with people outside the firm, those knowledgeable about *Law and Government*, and *Sales and Marketing* hold that distinction. Personal contact with others is another way in which knowledge may be shared. The knowledge areas of *Customer and Personal Service*, *Medicine and Dentistry*, *Therapy and Counseling*, *Psychology*, and *Sociology and Anthropology* involve the highest levels of contact with others. On the other hand, people knowledgeable about *Computers and Electronics*, *Engineering and Technology*, and *Design* spend less time on the job interacting with others.

The information presented in Table 4, as discussed above, paints an interesting picture of how U.S. workers acquire and share knowledge. Workers that know a lot about *Administration and Management*, and *Personnel and Human Resources* tend to be more experienced (both in terms of age, see Table 1, and years on the job) and are the primary communicators within the firm. Those knowledgeable about *Sales and Marketing*, and *Customer and Personal Service* have moderate education and experience, low amounts of training, and high levels of contact with others and communication with people outside the firm.

It is interesting to compare the areas of *Production and Processing*, *Mechanical*, and *Building and Construction* in terms of the indicators shown in Table 4. All three areas require similar amounts of formal education, but job training appears to be considerably less important in the knowledge area of *Production and Processing*. Of the three areas, it is relatively more important for those knowledgeable about *Mechanical* (things) to keep current with new information and trends. It is also interesting to compare the knowledge areas of *Computers and Electronics*, *Engineering and Technology*, and *Design*. All three areas require relatively high levels of experience, but while knowledge about *Computers and Electronics* appears to come from a formal education, job training contributes to knowledge in the areas of *Engineering and Technology*, and *Design*. Of these three knowledge areas, the subject of *Computers and Electronics* places a much higher importance on updating knowledge as well as considerably more communication with others inside the firm. As noted above, compared to the other 30 knowledge areas included in the analysis, none of these three subjects require much in the way of contact with others.

With this information along with the regression results from the previous section of the paper, we can investigate our second research question: does the way in which an individual acquires knowledge influence the return to knowing a lot about a particular subject? Table 5 reports regression results on the relationship between the knowledge-based wage premiums (from Table 3) and the information presented in Table 4 about how knowledge is acquired and disseminated. Since we examined the natural logarithm of earnings in the wage regression model and we transformed the values in Table 4 into natural logs, the estimated coefficients shown in Table 5 can be interpreted as elasticities.

Our regression results reveal a positive relationship between the knowledge-based wage premium and the years of work experience of those with high knowledge about a particular subject. A doubling of the amount of work experience associated with a given knowledge area increases the earnings premium by 36.1 percent. We also found, other things being equal, a positive relationship between the knowledge-based wage premium and the extent to which individuals with high knowledge about a given subject are required to keep current with new information and trends. A doubling of this variable (i.e., *Importance of Updating Knowledge*) is associated with a 5.5-percent increase in the knowledge-based wage premium.

On the other hand, we find a negative relationship between the knowledge-based wage premium and the amount of job training of people who are knowledgeable about a particular subject. A doubling of the percentage of workers in a knowledge area with more than one year of job training is associated with a 15.9 percent decrease in the knowledge-based wage premium. In addition, our results show a negative relationship between the knowledge-based wage premium and the variable that measures the amount of communication within a firm, although the estimated coefficient is statistically significant at slightly above the 10-percent level ($p = 0.1020$). It is also interesting to note that the amount of formal education associated with a knowledge area does not have a statistically significant effect on the knowledge-based wage premium.

Table 5. Relationship between Knowledge-based Wage Premium and How it is Acquired

How Knowledge is Acquired	Estimated Coefficient	t-stat
Constant	-0.503	-0.477
<i>Years Education</i>	-0.023	-0.059
<i>Years Work Experience</i>	0.361***	2.951
<i>% w/More than 1 Year Job Training</i>	-0.159*	-1.833
<i>Importance of Updating Knowledge</i>	0.055*	1.738
<i>Communication w/in Firm</i>	-0.056	-1.723
<i>Communication Outside Firm</i>	0.014	0.449
<i>% Constant Contact with Others</i>	-0.034	-0.187
R-squared	0.514	
Adjusted R-squared	0.325	
Number of Observations	26	

Notes: Dependent variable is the return to high knowledge about each of the 26 subjects, based on the estimated coefficients shown in the right-hand column of Table 3. Explanatory variables are the values shown in Table 4, transformed into natural logs. *** and * denote significance at the 1- and 10-percent levels, respectively.

V. Conclusions

This paper has examined the effects of human capital on individual earnings, with an emphasis on the returns to educational attainment (a measure of “how much” someone knows) as well as the types of knowledge required in a person’s occupation (a measure of “what” someone knows). The empirical approach involved regression analysis of a large sample of U.S. workers to estimate a wage premium associated with a college degree along with the additional earnings attributed to possessing high knowledge about a wide range of subjects. Our analysis centered around two research questions: (1) how do the returns to knowledge about specific subjects compare to the additional earnings associated with a college degree; and (2) does the way in which an individual acquires knowledge influence the return to knowing a lot about a particular subject?

The answer to the first question is that the college wage premium, estimated at between 38.6 percent (in a regression model that controls for the types of knowledge possessed) and 52.5 percent, exceeds the additional earnings associated with each of the individual knowledge areas. This means that in the U.S. labor market it pays to know “a lot” and possess a high level of human capital. That said, being knowledgeable about subjects such as *Medicine and Dentistry*, *Administration / Personnel*, *Law and Government*, *Sales and Marketing*, and *Computers and Electronics* leads to a sizable positive effect on individual earnings. This means that exactly “what” a person knows is an important predictor of earnings, too. In addition, the knowledge variables as a group perform slightly better, in terms of adjusted R-squared, than educational attainment alone at explaining the variation in the annual wages and salaries of full-time U.S. workers.

The answer to the second question is “yes,” the wage premium associated with high knowledge about a particular subject appears to be influenced by the way in which knowledge is acquired. Specifically, we find that knowledge-based wage premiums tend to be larger in those subjects (e.g., *Administration and Management*, *Computers and Electronics*) that require higher amounts of work experience. Likewise, knowledge areas that place a high importance on updating knowledge tend to have more lucrative wage premiums. On the other hand, knowledge that is acquired through job training does not appear to be rewarded in the labor market.

These results suggest that regional policymakers should use a multifaceted approach to measure human capital and determine appropriate policies and programs to enhance the skills and knowledge of the local workforce. Indeed, college attainment is important as evidenced by the high wage premium associated with a 4-year degree. This suggests that, as is current practice in many regions, policymakers should continue to make investments aimed at formal education. However, it is also useful for policymakers to consider the types of knowledge used in the economy and to recognize that knowing a lot about some topics, irrespective of whether or not a person obtained a college degree, can enhance a person’s earnings. This would support local programs and policies directed at enhancing knowledge about topics such as information technology (i.e., knowledge areas of *Computers and Electronics*, and *Telecommunications*) and aspects of business services

(i.e., *Administration / Personnel; Economics and Accounting; Sales and Marketing*). Knowledge appears to be acquired and disseminated in these subjects through work experience and the practice of keeping up with current information and trends, which points to the importance of local networking opportunities and other formal and informal venues to share experience. This strategy has often been cited as a key factor in Silicon Valley's IT success (Saxenian 1994).

Thinking along the lines discussed in this paper might provide a challenge to policymakers. When viewing regional human capital only in terms of educational attainment, the one-size-fits-all approach of turning out and attracting more college graduates makes all the sense in the world. When thinking about the types of knowledge present in a region along with those subjects that policymakers would like to see enhanced, the recommendations become much cloudier. There is still an emphasis on attracting the college educated, but it is not just "how much" these graduates know (e.g., whether or not they have a degree), it is even more importantly "what" they know (e.g., number of degrees by subject area). Furthermore, along with a desire to increase regional opportunities for formal education, policymakers should consider other ways (e.g., training, experience, networking) people acquire knowledge. Thus, knowledge-based investments require a good deal of understanding about a region's current and desired knowledge-based assets.

References

- Abel, Jaison and Todd Gabe. "Human Capital and Economic Activity in Urban America." Federal Reserve Bank of New York, Staff Report 332. July 2008.
- Acemoglu, Daron and Joshua Angrist. 2000. "How Large Are Human-Capital Externalities? Evidence from Compulsory Schooling Laws," *NBER Macroeconomics Annual*, 15, 9-59.
- Acs, Zoltan and Catherine Armington. 2004. "The Impact of Geographic Differences in Human Capital on Service Firm Formation Rates," *Journal of Urban Economics*, 56, 244-278.
- Bacolod, Marigee, Bernardo Blum and William Strange. 2009. "Skills in the City," *Journal of Urban Economics*, 65, 136-153.
- Bartik, Timothy. 1990. "The Market Failure Approach to Regional Economic Development Policy," *Economic Development Quarterly*, 4, 361-370.
- Becker, Gary. 1964. *Human Capital*, New York: Columbia University Press.
- Card, David. 1999. "The Causal Effects of Education on Earnings," in a O. Ashenfelter and D. Card (eds), *Handbook of Labor Economics*. Amsterdam: Elsevier, pp. 1801-1863.
- 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. 2008. *Who's Your City?* 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. 2004. Review of Richard Florida's *The Rise of the Creative Class*. [Online: retrieved September 16, 2009, available: http://post.economics.harvard.edu/faculty/glaeser/papers/Review_Florida.pdf]
- Ingram, Beth and George Neumann. 2006. "The Returns to Skill," *Labour Economics*, 13, 35-59.

Markusen, Ann. 2004. "Targeting Occupations in Regional and Community Economic Development," *Journal of the American Planning Association*, 70, 253-268.

Mincer, Jacob. 1974. *Schooling, Experience and Earnings*. New York: NBER Press.

Moretti, Enrico. 2004. "Estimating the Social Return to Higher Education: Evidence from Longitudinal and Repeated Cross-Sectional Data," *Journal of Econometrics*, 121, 175-212.

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. 2008. *Integrated Public Use Microdata Series: Version 4.0* [Machine-readable database]. Minneapolis, MN: Minnesota Population Center [producer and distributor].

Saxenian, AnnaLee. 1994. *Regional Advantage: Culture and Competition in Silicon Valley and Route 128*, Cambridge, MA: Harvard University Press.

Scott, Allen. 2009. "Human Capital Resources and Requirements across the Metropolitan Hierarchy of the USA," *Journal of Economic Geography*, 9, 207-226.

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.