IMPACT OF HUMAN CAPITAL TO ECONOMIC GROWTH IN U.S. COUNTIES

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ABSTRACT

The aim of this paper is to evaluate the interplay between human capital and economic growth. Unlike previous studies that mostly focused on educational attainment and the average years of schooling as measurements of human capital, this study explores highly educated and specialized human capital as attributes to GDP per worker and the poverty rate that are considered as proxies of economic growth. This article also contributes to the literature by focusing on smaller economic entities (i.e. U.S. counties) that have not been popularly studied in the past. The regression results of this study imply that higher-level and specialized human capital are key determinants of U.S. counties' economic growth. In addition, human capital contributes differently in regions across the U.S. **JEL Classification:** O10, O15, R11

INTRODUCTION

Building on the antecedent neoclassical growth model (Solow, 1956; Swan, 1956), voluminous literature has revealed that the accumulation of human capital is a key factor to the economic growth of a nation (Nelson & Phelps, 1966; Mankiw et al, 1992; Ciccone, 2002; Papageorgiou, 2003; Caselli & Wilson, 2004). Riley (2011) summarized five key contributions of human capital to an economy: 1) there ought to be positive spillover effects on labor productivity/output per person which contributes to higher trend economic growth; 2) A higher skilled and more flexible labor force will be better able to adjust to changing technologies and changing patterns of demand leading to lower levels of structural employment; 3) Better human capital ought to lead to higher wages and higher expected lifetime earnings (providing that people are being paid fairly their contribution to economic value) and improved incentives to find work and reduced dependence on the welfare system; 4) Stronger knowledge and skills will promote invention and innovation - two further ingredients of long-term growth. Little wonder that there remains a global war for talent among countries seeking to attract the brightest students and workers; 5) If more people have the skills, qualifications and competencies to remain active in an ever-changing economy, this ought to support progress in combatting high levels of relative poverty and social exclusion.

Nevertheless, empirical studies on this topic have mainly focused on three avenues: national (Bassanini and Scarpetta, 2001; Glaeser et al, 2004; Klenow and Rodriguez-

Clare, 2005; Pelinescu, 2015), metropolitan (Rauch, 1993; Simon, 1998; Gottlieb & Fogarty, 2003), and industrial (Feldman & Audretsch, 1999; Glass & Saggi, 2002; Porter, 2003) levels. At the national level, Costar (2011) built a general equilibrium model to prove that variations among skilled laborers create income differences between countries. He collected data from 58 market economies from 1950-1985, which explained cross-country and within-country differences by measuring the GDP per worker. With the cross-country data, Costar discovered that developed countries have lower income levels than the U.S. because they have significantly fewer scientist and engineers in the workforce. He also calibrated the within-country income differences between skilled and unskilled workers, and asserted that skilled labor is potentially more important for development. Instead of evaluating multiple countries, Fleisher et al (2010) specifically explained that China's economic growth has strong ties to total factor productivity (TFP) growth. They found that human capital has both direct and indirect effects on TFP growth in which the direct effect comes from domestic innovation activities and the indirect impact is a spillover effect of human capital on TFP growth.

At the metropolitan level, Gottlieb and Fogarty (2003) explored the relationship between human capital at the bachelor's degree level and subsequent economic growth in 75 large U.S. metropolitan areas. Within a 17-year period, data found that a 1 percent increase in the number of individuals who obtained a bachelor's degree was associated with a 0.04% increase in the income or employment growth rate. In addition, their results showed that an income growth inequality existed across U.S. regions driven by cumulative differences in human capital stocks. Likewise, Florida (2002) outlined that the stock of high human capital individuals is fundamental to attracting high-tech firms in metropolitan economic outcomes. Furthermore, qualitative and quantitative research has indicated that talent prefers to live in areas with diversity and quality of life. Moreover, talent is attracted to high-tech industries that generate higher per capita incomes.

At the industrial level, Xu (2000) demonstrated that the level of human capital is a key factor in explaining the level of technology diffusion from U.S. multinational enterprises (MNEs) to their host countries. He found that developed countries received more benefits from the technology transfer provided by the U.S. MNEs than less developed countries, which did not meet the minimum human capital threshold level. Falk (2007) estimated a dynamic empirical growth model using panel data for 58 manufacturing sectors from 19 OECD countries between 1970 and 2004. The results concluded that the ratio of firms' R&D expenditures to GDP and the share of R&D investment in the high-tech sector have strong positive effects on GDP per capita and GDP per hour worked.

Past research has focused on national, metropolitan, or industrial levels and mostly ignored the smaller scope of the economy (e.g. counties, smaller cities, and rural areas) because of difficulty obtaining data. In order to fill the gap in literature and with the new availability of information in U.S. county databases, this paper extends its research to new areas (i.e. U.S. counties) and determines what human capital factors matter to a county's particular growth. Rather than using human capital, most existing research at the county level looks at factors associated with tax policy (Carlino & Mills, 1987), natural resource amenities (Deller et al., 2001), Social and institutional factors (Rupasingha et al., 2002), infrastructure spending (Fan et al., 2000), and metropolitan spillover effect (Zhong, 2016). Zhong (2017) studied the impact of innovation to the economic growth of U.S. counties. However, the definition of innovation in his study includes other business, economic, and social parameters, in addition to human capital factor.

This paper is organized as follows. The next section presents a literature review.

Followed by a data and methodology description in section 3. Section 4 evaluates statistical results and discussion. Finally, conclusion remarks are presented at the end of this paper.

LITERATURE REVIEW ON HUMAN CAPITAL

This study aims to examine the relationship between human capital and the economic growth of U.S. counties. Although there is a large body of literature on this topic, various measurements of human capital have been used in the past. An early measure of human capital appeared in the famous Mankiw, Romer and Weil (1992) model (M-R-W model). They created a human capital version of the neoclassical Solow-Swan growth model to explicitly argue the importance of human capital in economic growth. In this model, they constructed a proxy for the rate of human capital accumulation that measures the approximate percentage of working-age populations in secondary schools. Based on this human capital measure, they concluded that the output and the marginal product of capital was lower in poor countries because they have less human capital than in rich countries. Furthermore, the difference were also attributed to variations in human capital, physical capital, and productivity.

Unlike the M-R-W model, some other scholars have focused on the average number of formal education years among populations (Psacharopoulos & Arriagada, 1986; Barro and Lee, 1993; Islam, 1995; Bassanini and Scarpetta, 2001). Benhabib and Spiegel (1994) used data based on the average years of schooling from 58 countries to indicate insignificant or negative relationships between human capital and income growth, but still found that human capital influenced the growth of total factor productivity. Bassanini and Scarpetta (2001) found that one extra year of average schooling influenced a rise in human capital by 10 percent and GDP per capita by 4-7 percent. Due to a lack of average number of years schooling in many countries, some researchers have replaced this data with enrollment rates in primary, secondary, and post-secondary schools (Murthy & Chien, 1997).

Nevertheless, school attainment has not guaranteed improved economic conditions (Benhabib & Spiegel, 1994), and some studies have argued that education quality is more important than quantity. Hanushek & Woessmann (2008) reviewed the role of cognitive skills in promoting economic well-being. They relied on information from several cognitive achievement tests (e.g. TIMSS, PISA, and IALS), and concluded that there is strong evidence that cognitive skills are more powerful than school attainment in relation to individuals earning potential, their distribution of income, and economic growth. For example, Hanushek & Schultz (2012) showed a deviation of 100 points in a PISA test resulted in a difference of 2 percent in the growth rate of GDP per capita. Similarly, Hanushek & Zhang (2008) used 13-country IALS scores and revealed that cognitive skills play an important role in determining an individual's earning potential. Likewise, cognitive skills had a positive effect in all but one country (i.e. Poland). Cognitive skills also received the highest return in the U.S., and the return to cognitive skills correlated positively with the level of education attainment across nations.

Other miscellaneous measurements of human capital include the number of patents (Pelinescu, 2015), human capital index (Ederer at al., 2007; Slaper et al., 2011), the share of education expenditure in GDP (Nonnemen & Vanhoudt, 1996; Hanushek & Kimko, 2000), and educational capital share of wage bill (Pritchett, 2001). The majority of these measurements confirmed that human capital leads to economic growth.

In today's competitive environment, primary and secondary education is not enough to meet the job requirements in many industries. Employers, particularly in high-tech industries and STEM occupations, seek qualified candidates with a bachelor's degree or higher. Therefore, employment in high-tech and STEM fields is a good measure of human capital stock. For example, Florida (2002) examined the relationship between talent (defined as population with a bachelor's degree and above), high-tech industry, and regional economic outcomes. He stated that high concentrations of high-tech industries generate the demand and thick labor markets that talented high human capital individuals prefer. The correlation coefficient between talent and high-tech industry is quite high at 0.723. Together, talent and technology based industries generate positive regional economic outcomes in the form of higher per capita incomes. The correlation coefficient between talent and per capita income level is 0.588. Similarly, workers in STEM occupations drive innovation, productivity and competitiveness. Higher educational attainment in STEM fields is well recognized as an important component of economic development (Atkinson & Mayo, 2010; Winters, 2014).

Based on the argument above, this study now turns its focus on human capital with a bachelor's degree as it relates to high-tech and STEM industries. As such, highly educated and specialized individuals are more likely to be vital to economic growth because they provide general and specific knowledge and skills that facilitate the creation, diffusion, and adoption of new knowledge and technologies. Such a contribution is not only beneficial to one firm or one county, but creates a wider impact on the economy as a whole.

DATA AND METHODOLOGY

In this section, we will test the relationship between human capital factors and the economic growth of U.S. counties. Data is retrieved from the Innovation Index 2.0, which is developed by the Indiana Business Research Center in the Kelley School of Business at Indiana University[1]. This innovation index is comprised of five major categorical indexes (three based on innovation inputs and two based on innovation outputs) organized thematically: Human Capital (input), Business Dynamics (input), Business Profile (input), Employment & Productivity (output), and Economic Well-Being (output). These five major indexes are also calculated from several sub-indexes that are built up from several measures that are also organized thematically along more precisely defined concepts. For instance, the input factor of Human Capital index alone has 12 measures that include population growth rate for ages 25-44, high school attainment for ages 18-24, some college education for age 25+, associate degree attainment for age 25+, bachelor's degree for age 25+, graduate degree for age 25+, patent technology diffusion, university-based knowledge spillovers, business incubator spillovers, STEM degree creation, technology-based knowledge occupation clusters, and high-tech industry employment share. The output factors of Employment and Productivity Index and Economic Welling-Being index describe economic growth and standard of living, as well as other economic outcomes, such as job growth, GDP per Worker, per capita personal income growth, poverty rate and unemployment rate.

Since the common conceptualization of economic growth is the growth of gross domestic product (GDP), we adopt GDP per Worker data from the Innovation Index 2.0 as one of the dependent variables to measure the overall economic conditions in each county. As matter of fact, economic growth is not only measured by the dollar value of output, named GDP, but can also be measured by other economic and social indicators, such as poverty rate. The well-known classic growth theory has firmly explained the positive nexus between poverty and growth (Solow, 1959; Roemer & Gugerty, 1997; Adams, 2004) to some extent. Therefore, the second conceptualization of economic growth in this analysis is the poverty index from the Innovation Index 2.0.

The independent variables in this analysis are measures of human capital. As stated previously, we focus on highly educated and specialized human capital measurements that are deemed to contribute more to economic growth. From the Innovation Index 2.0, we selected bachelor's degree, educational attainment, high-tech industry employment, patent technology diffusion, STEM education and occupations, and technology-based knowledge occupation as measures of human capital stock in each county. All data are valued in an index rate.

Table 1 gives an overview of the data and some sample statistics. Included are the means, standard deviations, minimums and maximums for all dependent and independent variables. Table 1 shows that there is a large variation in county-specific characteristics for the sample. New York (NY) and Midland (TX), along with several Alaska counties, lead the GDP per worker index in the nation at 200, and Blaine (NE) ranks on the bottom at 51.5. Borden (TX) has the highest poverty index at 198.7[2] and several Midwestern and Southern counties have the lowest poverty index at 50. In term of all human capital measurements, it is not a surprise that many coastal counties lead the indexes and that many Midwestern and Southern counties rank at the bottom. In total, the data pool contained 3,106 observations. The regression specification is as follows:

$$GDP/Worker_i \text{ or } Poverty_i = \beta_0 + \beta_1 BA_i + \beta_2 Education\_Attainment_i + \beta_3 High\_Tech\_Emp_i + \beta_4 Patent_i + \beta_5 STEM_i + \beta_6 Tech\_Occupation_i + \beta_7 Region\_Dummy_i + \mu_i \quad (1)$$

In regressions, we specifically examine the relationships between economic growth and human-capital-measured indexes individually and aggregately. Since more coastal states (e.g. California, Massachusetts) lead the human-capital-related indexes and more Midwestern and Southern states (e.g. Mississippi, Nebraska) rank at the bottom, it seems that a county's location could matter to its economic growth. In order to capture the heterogeneity of a county's location, we also added a regional dummy variable. We rely on the US Census Bureau's region definition to divide the nation into four statistical regions: Northeast (9 states), Midwest (12 states), South (17 states), and West (13 states).

RESULTS AND DISCUSSION

Table 2 presents eleven OLS models analyzing the connection between human-capital-related measures and GDP per worker as proxy of economic growth. Not surprisingly, most human capital measurements (in the form of BA and other high-tech and STEM factors) have a positive and statistically significant association with the change of GDP per worker. For example, when the Bachelor's Degree index increases by 1 index point, the GDP per worker index will go up by around 0.2 point, which means a growth on GDP per worker. Surprisingly, the Education Attainment index has a negative impact on GDP per worker. The Education Attainment index includes measures for high school attainment and postsecondary education. Since more people have a high school diploma than have a bachelor's degree or higher in U.S., high school attainment has more weight in the Education Attainment index. However, high school graduates might not have enough to be considered as human capital, thus an increase in the Education Attainment index might not contribute the growth of GDP per worker. This result, along with the coefficient of Bachelor's Degree index, affirms that highly educated individuals (the bachelor's degree and higher) are more attributable to economic growth. Another interesting result is the differential between regional dummies. Coefficients on Northeast and West dummies are positive, but are negative on Midwest and South dummies. A county that locates in the Northeast or West region can receive more benefit from human capital, while the economic growth in counties located in the Midwest or South regions are much weaker than their peers in the Northwest and West. Our results are in line with Prichett (2001) and Slaper et al. (2011), which both found that the quantity and quality of human capital positively correlated to increase GDP per worker.

Table 3 presents regression results when using the poverty index as dependent variable. Again, most coefficients of human-capital-related factors are as expected, positive and significant. Coefficients in Table 3 are generally larger than that in Table 2, which indicates human-capital-related factors have a bigger impact on poverty than to productivity. For instance, a 1 point increase on the Bachelor's Degree index leads to about a 0.4 point rise on the poverty index. Thus, a decrease on the poverty rate. Education attainment, measuring population with a high school diploma and above, now show a positive impact in relation to the poverty index. A high school diploma is a minimum requirement in today's workforce. Without it, people face greater employment challenges and economic hardship than those with a high school diploma or higher, and are more likely live in poverty (Bridgeland et al., 2006; Achieve, 2012; McDaniel & Kuehn, 2013). However, STEM education shows a negative interplay with a county's poverty index. There are two possible reasons for this negative interplay. First, as stated in Innovation Index 2.0, most of the STEM degrees are awarded to foreign students. Due to immigration restrictions or personal preference, many of them return to work in their home countries. Furthermore, most of the STEM degrees are awarded by universities that may locate in counties where the poverty rate is usually high, and most STEM degree graduates probably find a well-paid job at a different place after graduation. Therefore, the STEM degree creation may not really alleviate a county's poverty rate. The regional dummy variables show a different result than in Table 2. Coefficients in the Northeast and Midwest are positive, but are negative in the South and West in Table 3. This result implies that counties in the South and West regions struggle more economically.

CONCLUSION

This paper employs human capital and economic well-being data from Innovation Index 2.0, developed by the Indiana Business Research Center in the Kelley School of Business at Indiana University, to capture the nexus between human capital and economic growth in more than 3000 U.S. counties. Unlike other popularly used human capital measurements in past literature, we hypothesized that highly educated and specialized individuals in high-tech and STEM occupations are pivotal determinants of a county's economic growth. The statistical results strongly attest our hypothesis and reveal a positive and significant relationship between GDP per worker or poverty index and higher-level human capital, as expected according to the economic theory. Moreover, counties in the coastal states take more advantage of human capital assets than those in the Midwest and South.

In terms of policy implication, local governments must encourage high school graduates to attend and complete college education. Furthermore, they should welcome and create more high-tech and STEM industries and occupations. The complementary occupations within high-tech and STEM industries can provide opportunities for the regional labor force and even serve as a magnet, attracting and retaining new talent to a county. All efforts will build up a thriving and innovative community, which will benefit the long-run economic growth.

ENDNOTES

[1]Driving regional innovation: The innovation index 2.0. (2016). Retrieved from http://statsamerica.org/ii2/reports/Driving-Regional-Innovation.pdf.

[2] Note: Given that high poverty is a negative outcome, the poverty index is inverted. Thus, a higher poverty index score reflects lower poverty rates, vice versa.

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TABLE 1. SUMMARY STATISTICS

	GDP per Worker	Poverty Index	Bachelor's Degree	Edu. Att.	High-Tech Employ.	Patent Tech. Diffusion	STEM Edu.	Tech. Based Occu.
Count	3106	3106	3106	3106	3106	3106	3106	3106
Mean	105.78	114.8	108.33	110.1	104.62	83.27	80.00	109.11
Std. Dev.	36.70	42.20	43.11	26.35	38.11	59.21	31.52	40.19
Min.	51.5	50	52.5	54.8	0	0	16.7	50
Max.	200	198.7	200	190.5	200	199.9	195.1	200

TABLE 2: OLSMODELS OF GDP PER WORKER

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Bachelor's Degree	0.286					
	(19.854)***					
Education Attainment		0.368				
		(15.249)***				
High-Tech Employment			0.388			
			(24.504)***			
Patent Tech. Diffusion				0.112		
				(10.266)***		
STEM Education					0.529	
					(28.416)***	
Tech Based Occupation						0.346
						(22.807)***
Northeast						
Midwest						
South						
West						
Constant	74.833	65.292	65.232	96.433	63.476	68.041
	(44.601)***	(23.913)***	(37.035)***	(86.278)***	(39.665)***	(38.581)***
R^2	0.113	0.07	0.162	0.033	0.206	0.144
Observations	3106	3106	3106	3106	3106	3106

	Model 7	Model 8	Model 9	Model 10	Model 11
Bachelor's Degree	0.191	0.189	0.187	0.201	0.192
	(8.055)***	(7.979)***	(7.839)***	(8.496)***	(15.828)***
Education Attainment	-0.061	-0.059	-0.049	-0.124	-0.101
	(-1.602)	(-1.570)	(-1.246)	(-3.070)***	(-2.765)***
High-Tech Employment	0.138	0.139	0.139	0.134	0.134
	(5.680)***	(5.734)***	(5.720)***	(5.531)***	(5.558)***
Patent Tech. Diffusion	0.017	0.015	0.016	0.018	0.017
	(1.639)*	(1.417)*	(1.514)*	(1.756)*	(1.592)
STEM Education	0.133	0.123	0.129	0.15	0.162
	(3.202)***	(2.925)***	(3.092)***	(3.587)***	(3.880)***
Tech Based Occupation	0.164	0.168	0.165	0.162	0.161
	(7.158)***	(7.314)***	(7.223)***	(7.095)***	(7.102)***
Northeast		4.34			
		(1.864)*			
Midwest			-1.577		
			(-1.258)		
South				-5.469	
				(-4.258)***	
West					10.362
					(6.058)***
Constant	47.417	47.576	47.168	54.918	49.252
	(15.224)***	(15.275)***	(15.115)***	(15.380)***	(15.828)***
R^2	0.246	0.247	0.247	0.251	0.255
Observations	3106	3106	3106	3106	3106

Notes: *t* statistics in parentheses. * p<.1, ** p<.05, *** p<.01

TABLE 3: OLS MODELS OF POVERTY INDEX

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Bachelor's Degree	0.52					
	(34.900)***					
Education Attainment		0.86				
		(35.481)***				
High-Tech Employment			0.227			
			(11.650)***			
Patent Tech. Diffusion				0.121		
				(9.558)***		
STEM Education					0.143	
					(6.002)***	
Tech Based Occupation						0.11
						(5.875)***
Northeast						
Midwest						
South						
West						
Constant	58.547	20.081	91.124	104.789	103.364	102.819
	(33.727)***	(7.313)***	(42.072)***	(81.355)***	(50.323)***	(47.179)***
R^2	0.282	0.289	0.04	0.03	0.01	0.01
Observations	3106	3106	3106	3106	3106	3106

	Model 7	Model 8	Model 9	Model 10	Model 11
Bachelor's Degree	0.367	0.357	0.415	0.401	0.365
	(15.626)***	(15.477)***	(18.409)***	(18.119)***	(15.771)***
Education Attainment	0.617	0.623	0.459	0.373	0.682
	(16.477)***	(16.960)***	(12.466)***	(9.683)***	(18.116)***
High-Tech Employment	0.41	0.418	0.397	0.396	0.416
	(17.074)***	(17.689)***	(17.288)***	(17.200)***	(17.511)***
Patent Tech. Diffusion	0.022	0.01	0.039	0.027	0.023
	(2.154)**	(0.958)	(3.891)***	(2.705)***	(2.265)**
STEM Education	-1.09	-1.148	-1.035	-1.028	-1.131
	(-26.383)***	(-28.055)***	(-26.170)***	(-25.913)***	(-27.555)***
Tech Based Occupation	0.411	0.435	0.387	0.404	0.414
	(18.141)***	(19.472)***	(17.888)***	(18.646)***	(18.512)***
Northeast		24.286			
		(10.714)***			
Midwest			20.719		
			(17.478)***		
South				-20.827	
				(-17.071)***	
West					-15.08
					(-8.959)***
Constant	4.768	5.661	8.036	33.334	2.097
	(1.545)	(1.867)*	(2.723)***	(9.826)***	(-0.685)
R^2	0.44	0.46	0.49	0.49	0.45
Observations	3106	3106	3106	3106	3106

Notes: *t* statistics in parentheses. * p<.1, ** p<.05, *** p<.01