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# The Job of Human Capital: What Occupational Data Reveal About Skill Sets, Economic Growth and Regional Competitiveness

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# THE JOB OF HUMAN CAPITAL:

# WHAT OCCUPATIONAL DATA REVEAL ABOUT SKILL SETS, ECONOMIC GROWTH AND REGIONAL COMPETITIVENESS

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**ABSTRACT**

A region's workforce has been described as its greatest asset. Guided by human capital theory and new growth theory, regions have pursued economic development policies to increase the number of college-educated workers and expand the pool of STEM – science, technology, engineering, and math – talent. Academic literature and policy interventions have focused on a region's human capital in terms of educational attainment instead of a more fine-grained definition of human capital based on skills and competencies. This dissertation integrates economic and business theory and combines three federal databases to explore regional human capital assets. Findings suggest that policymakers may be overestimating the importance of STEM knowledge requiring a bachelor's degree or higher and undervaluing the importance of soft skills such as communication and critical-thinking. Moreover, results indicate that regions may be best served by crafting distinct human capital interventions that reflect the particular needs of their mix of industry.

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## CHAPTER I

## INTRODUCTION

President Obama has issued an “all-hands-on-deck” alert for the critical national mission of encouraging more students to study science, technology, engineering and mathematics (STEM). The President’s 2016 proposed budget includes $3 billion – a 3.8% percent increase over the 2015 enacted spending level – in federal investments in STEM education. More broadly, President Obama has set 2020 as a deadline for the United States to once again top the world in the share of population having a college degree; a March 2015 report from the White House’s Office of Science and Technology Policy called for 1 million more college graduates earning STEM degrees within the next decade. Beyond the federal investment, state and local governments, public-private partnerships and non-profit organizations are spending billions of dollars more in efforts to improve economic competitiveness and increase the “pipeline” of highly skilled workers.

In the nearly 50 years since management guru Peter Drucker popularized the term “knowledge worker,” education, particularly advanced education, has been increasingly linked to economic needs. Higher levels of education are seen as critical not only to the individuals pursuing or possessing the advanced knowledge, but to the firms that make use of such knowledge, and the regions and nations that benefit from the new products, new firms and new technology that emerge. The presumed link between education and the economy emanates out of human capital theory, the idea that intentional investments in an individual's or nation's stock of knowledge, skills and abilities generate returns in the form of higher wages and economic growth. Further underscoring this link is new growth theory, which describes a more disembodied accumulation and flow of knowledge that leads to economic growth-sustaining new ideas, innovations and technologies. This view of increasing returns to knowledge makes human capital unique among the other factors of production – land, labor and physical capital – which ultimately reach a point of diminishing marginal returns for each incremental increase (Romer, 1990).

An extensive body of literature supports a link between higher levels of human capital, improved individual wages and increased economic output (Nelson & Phelps, 1966; Lucas, 1988 & 2009; Romer, 1990; Autor, Katz & Krueger, 1998; Quigley, 1998; Goldin & Katz, 2010). Wolfe & Gertler (2004) described the local talent pool as a region's greatest asset. Supporting that observation and helping to explain the heightened policy focus on educational attainment, Wolf-Powers (2013) found that cities with strong growth in college-educated workers had higher job growth and lower unemployment. Rapid technological change over the past several decades has driven demand for workers with higher levels of human capital, particularly those with technical capabilities (Carnevale, 2005; Cortright, 2001). These findings lie at the heart of interventions by governments and non-profit agencies to improve the educational attainment, and thus the human capital, of regions and the nation overall. However, there is evidence that such activities are poorly targeted: Half of recent college graduates in the workforce who earned science and engineering bachelor's degrees are not employed in science and engineering occupations (National Science Foundation, 2014). Regions that have grown their share of the population with a bachelor's degree have experienced mixed results in terms of economic performance and public benefit (Andreason, 2015). The skills employers say they look for in a worker are often more generic in nature (communication, critical-thinking, flexibility) than the specific ones targeted in STEM initiatives (Robles, 2012).

Many human-capital-based interventions fail to fully encompass the breadth of human capital theory. This is in part due to the fact that human capital tends to be operationalized and measured in terms of educational attainment. Yet, education is a blunt, imperfect operationalization. Having a particular degree or level of education is not necessarily the same thing as having competence in a particular set of knowledge, skills and abilities. Schultz (1961) defined human capital as both innate and acquired skills and included training and experience, along with education, as investments in human capital.

Also problematic is that much of the focus on the quality and aptitude of the supply of the workforce leaves out the equally important issue of the level and configuration of the workforce demanded. Theory connecting the quality of an area's workforce – its human capital asset – to sustained economic growth has contributed to overly simplified economic development policies that largely assume increasing the number of college degrees broadly, or STEM degrees specifically, will pay off for the nation, state or region. Policies are being enacted and considerable public resources committed to an understanding of the connection between human capital and economic growth that is both incomplete and removed. The education of a population is, at best, merely an indicator of human capital potential, not human capital deployment.

Further confounding human-capital-based economic development practiced at the local or regional level is the frequent assumption that the individual benefits of increased educational attainment roll up to the region and that the national benefits roll down. Such assumptions overlook the fact that human capital in individuals, or firms, is mobile, free to move outside the region (or state) where it was honed. Such assumptions also discount the fact that regional borders are far more porous than national ones. Human capital investments made at the regional or state level come with the very real risk that well-educated workers will migrate to other areas for higher wages and better job opportunities, undercutting or negating any return on the investment of public resources.

Human-capital-based regional economic development efforts are frequently boilerplate – more college is good; more STEM is even better – and too often fail to adequately appreciate the fact that a location's past shapes its present and future. A region's history and industrial legacy matter, giving rise to different talent pools and different ways in which human capital can support the local economy. Differences in human capital demand and deployment across regions should not invite efforts aimed at uniformity. Instead, these very differences in human capital deployment are what enable competitive and comparative advantage. As such, human-capital-based economic development efforts that are aligned to different regional industrial strengths presumably should yield the biggest return.

The accepted human capital operationalization as educational attainment used in economic development research is largely unsuitable for such a task. It fails to offer a fine-grained understanding of variation in how similar levels of human capital are applied in different settings. Moreover, it fails to connect regional human capital supply to regional human capital demand. This disconnect is particularly apparent in the context of STEM, where efforts to grow the number of college graduates in STEM fields seem more rooted in assumed future growth than determined by the quantity and level of such skills needed in the regional workforce. Such policy preoccupation with the specific, "hard," skills associated with STEM degrees also seems to diminish the importance of more generic, "soft" skills, which business leaders have described as critical to success. These challenges to policies relying too heavily on a region's share of workers with higher levels of educational attainment argue for a measure that is both finer-grained and more closely aligned to each region's level of demand.

This research makes a case for an approach to the evaluation of regional human capital that focuses on skill requirements embedded in a region's mix of occupations. Such an operationalization attempts to explore the regional human capital asset as a resource that's value extends primarily from how it is deployed in the local economy.

Chapter II explores two literature streams shaped by human capital theory emanating out of economics/economic development and business strategy/management research and gleans insights for regions where the streams converge. Chapter III details the development of an Integrated Database of Occupational Human Capital, uniting three federal databases to provide a method for matching occupational skill requirements to regional economic performance. Chapter IV analyzes the association between the skills occupations require and the wages they pay. Chapters V, VI and VII explore how regions vary in human capital – measured variously as the skill requirements of their mix of occupations – and how such variation in human capital concentrations affects regional economic wellbeing. Chapter VIII offers concluding observations, policy implications and opportunities for future research.

CHAPTER II

# THE REGIONAL HUMAN CAPITAL ASSET AS KEY TO GROWTH & ADVANTAGE: INTEGRATING TWO LITERATURE STREAMS

This exploration of the role of occupational human capital, and specifically the effect of such human capital on regional economic wellbeing, begins with an attempt to integrate two literature streams shaped by human capital theory – new growth theory out of the economics literature and resource-based theory of firm competitive advantage that developed out of the business strategy literature – specifically for their value in informing regional-level policies regarding human capital development. After providing a brief history of human capital theory. Section 2 summarizes the new growth and resource-based literature streams. Section 3 explores the challenge of education as a measure of human capital. Section 4 discusses a rising interest in the human capital embedded in occupations. Section 5 explores the regional human capital asset, reflected in its mix of occupations, as a resource for regional competitive advantage. Section 6 concludes with implications for regional economic development policy and empirical research.

Human capital theory was formalized in the mid-20$^{th}$ century, but its roots in economic theory run deep: No less than the progenitor of classical economics, Adam

Smith (1776/2008), observed the connection between "superior skill" and higher wages. Various individual attributes, according to the theory, make certain workers more productive and, thus, allow them to command a higher wage. Those individual attributes may be ones that have direct application in the workplace, such as "superior skills," innate abilities that are honed and greater knowledge, as well as less obvious productivity-enhancing attributes, such as better health, stable home environments, access to child care, and mobility to seize on opportunities. The essence of human capital theory is a broad concept encompassing anything that improves the "*quality* [italics in the original] of human effort" (Schultz, 1961).

Human capital theory assumes some level of investment, whether of money, time, psychic energy, or forgone opportunities, to acquire these quality improvements. These improvements may be higher levels of education, increased training, and years of experience, as well as learning by doing, self study or even healthier habits. These investments are expected to yield return in the form of higher wages and better job security for individuals and better economic performance for firms, regions and nations (Schultz, 1961; Arrow, 1962; Becker, 1964, 1993).

Arrow (1962) asserted that increases in per capita earnings witnessed over time could not simply be explained by the traditional economic views of changes in capital and labor. Arrow demonstrated how firms were unlikely to capture all the gains to private investment in knowledge acquisition, meaning that private investment in knowledge acquisition would be below the optimal level for society overall. Today's public sector interventions into encouraging the development of particular skills – policies aimed at growing an area's human capital – rest on this assumption of suboptimal benefit. Becker

(1962, 1993) is credited with developing a general theory explicitly linking worker skill to productivity and, thus, acknowledging human capital as a factor of production. Providing insight of particular importance in today's rapidly changing technological environment, Nelson and Phelps (1966) suggested that the return to human capital was greatest the more quickly technological changes are adopted in the market. Conversely, they theorized that the rate at which technological change is put into practice depends on a nation's level of educational attainment (its human capital). Lucas (1988) set out to explore why there has been a clear pattern of growth in per capita income across the world (particularly in industrialized nations) for centuries, which would seem to fly in the face of the economic principle of diminishing returns to ordinary production factors of land, labor and physical capital. Lucas found support for a model of human capital accumulation through on-the-job learning. However, he noted that comparative advantage, which dictates which products are made most efficiently where, would also dictate human capital accumulation, meaning that low-value products in low-cost nations would keep rates of human capital accumulation in those areas comparatively low.

Human capital accumulation has been extensively explored in the academic and policy literature (e.g., Nelson & Phelps, 1966; Autor, Katz & Krueger, 1998; Blundell, Dearden, Meghir & Sianesi, 1996; Quigley, 1998; Glaeser & Mare, 2001: Ross-Gordon, 2003; Goldin & Katz, 2010). Analysis of data on educational attainment and educational expenditures in the United States and other industrialized nations led Ehrlich (2007) to conclude that human capital investments offered the best explanation for why economic growth in the United States outpaced other industrialized nations in the years after World War II. Changes in the educational level of the U.S. workforce over the 50 years following the war were found to account for roughly a third of the observed growth in national productivity (Griliches, 1977, 1997). Similar patterns were discerned in other industrialized nations, with the fastest growth occurring in countries with the greatest expansion of higher education (Mankiw, Romer & Weil, 1992; Gemmell, 1995 & 1996). However, the positively significant findings appear to be highly dependent on how educational expansion and quality are measured (Blundell, Dearden, Meghir & Sianesi, 1996).

Although much of the early focus of human capital theory was on individual and national benefits associated with higher levels of educational attainment or expenditure, a growing body of literature supports differences in human capital accumulation as accounting for differences in economic wellbeing seen in regions across the United States. Higher levels of education in metropolitan areas were associated with higher productivity, higher future wages and higher housing prices (Glaeser & Saiz, 2004). Rauch (1991) presented evidence of a 2.8 percent increase in total factor productivity for every 1-year increase in a region's average educational level. Even controlling for city size and industrial mix, Gottlieb and Fogarty (2003) demonstrated a link between a metropolitan statistical area's (MSA) share of adults with a college degree and per capita income growth. Wolf-Powers (2013) found that cities with strong growth in college-educated workers had higher job growth and lower unemployment. Moretti (2004) demonstrated that plants in areas with large increases in the share of workers with college degrees experienced higher levels of productivity than plants in areas with less educational attainment. Better-educated communities have been shown to be more attractive to relocating businesses (Aldrich & Kusmin, 1997; Goetz, 1997; Barfield &

Beaulieu, 1999), more suited to the work of high-skilled sectors (Glaeser & Resseger, 2010), and more conducive to entrepreneurial activity (Doms, Lewis & Robb, 2009). Moreover, decisions about how much education to pursue have long-lasting effects. Simon and Nardinelli (2002) found that a metropolitan area's share of residents with college degrees in 1940 was positively related to the area's employment growth rates for the ensuing five decades.

The extensive body of research notwithstanding, human capital theory has long been met with skepticism and criticism: Blaug (1987) criticized the intangibles of learning as untestable. Moreover, a number of studies and recent criticisms have questioned the theory's value: Caselli, Esquivel, and Lefort (1996) found little support for economic growth from increasing levels of human capital. In exploring worldwide growth in schooling, Benhabib and Speigel (1994) and Islam (1995) found indications of negative economic returns to human capital accumulation in some countries. Pritchett (2001) identified a "micro-macro paradox," where human capital accumulation did result in the theorized individual gains but not in the assumed national-level returns.

Nevertheless, despite criticisms and mixed empirical results, the considerable influence of human capital theory is increasingly evident in economic development and education policy (Tan, 2014). In addition, human capital theory forms the foundation of two other influential theories emanating out of the economics/economic development and business strategy/management literature: new growth theory and resource-based theory of firm competitive advantage.

## A CONVERGENCE OF TWO LITERATURE STREAMS

New growth theory elevated human capital to a unique factor of production, not subject to the ultimately diminished returns in incremental output associated with more traditional inputs of land, labor and physical capital (Romer, 1990; Cortright, 2001; Warsh, 2006). New growth theory attributes evidence of increasing returns seen over time and across nations in the form of new technologies, new products and new processes to non-rivalrous and only partially excludable knowledge that propels economic growth (Romer, 1990; Cortright, 2001; Warsh, 2006). In other words, new growth theory elevates knowledge and technology to a near-public good. While human capital theory assumes that areas with higher levels of knowledge will experience better economic performance compared to areas with lower levels of knowledge, new growth theory suggests that, not only will the higher levels of knowledge bring about gains through greater productivity, knowledge accumulation will spur even higher levels of economic growth through new technologies and innovations (Blundell, Dearden, Menhir & Sianesi, 1999).

New growth theory is largely a virtuous cycle view of knowledge and technology begetting even more knowledge and technology. Romer (1990) and Grossman and Helpman (1994) presented models in which knowledge drives technological innovations, which, in turn, drive economic growth. Romer (1990) assumed technological advancements to be endogenous to his growth model, resulting from the deliberate profit-maximizing actions and investments of people and firms. This view was in contrast to the neoclassical treatment of technological advancement as central to long-run growth but occurring outside the economic model (Solow, 1956). Romer (1990) observed that, in developed countries, a higher total stock of human capital in countries resulted in a higher share of human capital devoted to research, which led to more knowledge, more innovation and more research.

Romer echoed Arrow (1962) in suggesting that, because firms (and individuals) cannot capture all of the gains from investing in knowledge, private investment in knowledge accumulation will be below the socially optimal level. Romer's mathematical model indicated that the fastest-growing economies are those with the greatest stock of human capital.

Economic growth and wellbeing clearly are what policymakers are hoping for when they enact human-capital based initiatives, such as those that promote college-going broadly and STEM degrees specifically. However, encouraging technology-inducing human capital as an economic development strategy can be a tricky proposition. Gains in productivity may come at the cost of jobs, at least in the near term. The literature suggests an ambiguous connection between human capital accumulation and growth in employment (Bartik, 1992; Cooper, Gimeno-Gascon & Woo, 1994; Shapiro, 2006; Holzer & Lerman, 2007; Lerman, 2008; Scott & Mantegna, 2009). The technological change that emanates from human capital investment and that drives economic growth, as described by Romer (1990), frequently leads to labor-saving devices and automations that remake work environments and eliminate jobs (Autor, Levy & Murnane, 2002 & 2003). Skill-biased technological change, where computers and automation have reshaped the nature of work, has been shown to contribute to rising income inequality (Bekman, Bound & Machin, 1998; Card & DiNardo, 2002; Autor, Katz & Kearney, 2008). There is also suggestion that human capital accumulation itself has spawned greater demand for higher skills broadly: Acemoglu (2002) identified a bias toward higher skill in the labor market, where an increase in supply of college-educated workers led to an increase in the share of employment going to college-educated workers. Exploring how technological change flows from innovators to imitators (high-tech areas to low-tech areas), Benhabib and Spiegel (1994) found that higher levels of human capital sped the flow of technological innovations from country to country but did not significantly raise per capita incomes.

The theorized connection between technology and increasing returns may lead policymakers and researchers to discount the importance of other types of human capital: Nelson and Phelps (1966) foreshadowed 50 years ago the importance of having educated scientists to keep up with change, but they noted that it was equally important to have educated managers to seize on opportunities and make decisions. Acemoglu (1998) observed that technologies and innovations don't happen out of the blue; they complement existing skills, particularly those thick in supply. Workers who are able to apply their skills to complementing the skills of other workers and the existing and emerging technology are more productive and, thus, more valuable (Lerman, 2008).

**Business Strategy/Management**

Arrow (1962) and Romer (1990) both specifically addressed human capital investments in the context of firms. Yet, unlike the focus on growth central to the economics literature, the business strategy literature provides a view of human capital as a firm resource that can be deployed for sustained competitive advantage. This view of what adds value at the firm level is a largely unexplored area in economic development policy and research. "Resource-based view of the firm" posits that competitive advantage results from the strategic management of three basic firm assets: physical capital, organizational capital and human capital (Wernerfelt, 1984; Barney, 1991). Physical capital refers to a firm's financial assets as well as its physical plant and equipment. Organizational capital encompasses a firm's management system, structure, culture and brand. Human capital reflects "such things as the skills, judgment, and intelligence of the firm's employees" (Barney & Wright, 1998, p. 32). Embedded within a firm's human capital resources and organizational structure and culture is tacit knowledge. Firm-specific tacit knowledge has the ability to impart a layer of value protection against imitators (Barney, Wright & Ketchen, 2001).

All of the economic value of human capital is translated through its application within the organization. There is variance in the extent to which firms develop human capital as a source of competitive advantage. Firms create value and competitive advantage through how they leverage their resources (Barney, 1991; Peteraf, 1993; Peteraf & Barney, 2003). As such, simply possessing a level or supply of physical, human and organizational capital is not enough to create value and generate sustained competitive advantage. Firms that succeed in the marketplace are those that manage to combine their physical, human and organizational resources into products, services or capacity that are valuable, rare, inimitable and organizationally apt (VRIO) (Barney, 1991; Amit & Schoemaker, 1993; Hitt, Bierman, Shimizu, Kochhar, 2001). The VRIO view of competitive advantage suggests dynamism, meaning that firms must continually be assessing their capacities and rethinking strategies in order to stay ahead of competitors and take advantage of market opportunities. The more a firm's products, as well as processes, can be copied, the more its competitive advantage erodes. Thus, the only true source of sustainable competitive advantage is through the human capital resources embedded within the organization.

Resource-based theory posits knowledge, particularly tacit, firm-specific knowledge, to be the most valuable asset a firm possesses (Grant, 1996; Spender; 1996; Hitt, Bierman, Shimizu & Kochhar, 2001). Tacit knowledge is more difficult to be shared and copied, affording a firm greater protection of its asset. Firm-specific knowledge is assumed to be of less value outside of the context of the firm, providing workers less of an incentive to leave and take their human capital with them. (Bailey & Helfat, 2003). Value is created in how firms are able to develop and deploy their human capital asset (Lepak & Snell, 1999; Hitt, Bierman, Shimizu & Kochhar, 2001). Human capital developed within the firm is more productive, and thus more valuable, than that acquired from outside the structure of the firm (Penrose, 1959 in Kor & Mahoney, 2004; Kor & Leblebici, 2005; Mahoney & Kor, 2015). Learning how to use knowledge and skills within the context of the firm and unlearning old ways of deploying human capital comes at considerable cost in terms of formal or informal training and lost productivity (Penrose, 1959 in Kor & Mahoney, 2004; Slater, 1980; Kogut & Zander, 1996; Kor & Leblebici, 2005). Resource-based theory assumes that a level of asymmetry of knowledge, skills and abilities accounts for differences in firm performance (Barney, 1991; Amit & Schoemaker, 1993; Peteraf, 1993; Conner & Prahalad, 1996). In addition, resource-based theory suggests that firms, the engines of economic growth, are interested in particular types of knowledge assets that fit with organizational needs or complement other organizational assets.

The message of resource-based theory from the business strategy and management literature may provide insight for the regional economic development literature. Viewing human capital as central to firm competitive advantage does not deny the importance of external market forces, transactional costs, access to financial capital and opportunistic behaviors; instead, it offers a complementary view that, within the context of these largely uncontrollable external factors, firms possessing a superior mix of knowledge, skills, experiences and insights deployed in service to the larger firm strategy should outperform firms that do not (Conner & Prahalad, 1996). Moreover, resource-based theory assumes a certain inelasticity of supply of key skills due to path dependencies, the time it takes to develop talent, a lack of clarity regarding needs and interventions, and limited infrastructure and capacity (Barney, 2001b).

A view of the regional human capital asset as a resource key to the region's competitive advantage seems largely absent from relatively standard policies that promote STEM degrees as economic development. In focusing so intently on the importance of technical knowledge to economic growth, regional human capital initiatives are pursuing strategies without regard to firm-based strategic differentiation. Human capital investments that are not aligned to strategic needs and opportunities are unlikely to build competitive advantage for a region's mix of firms and ultimately sustain the economic wellbeing of the region and its people. Aside from not improving the value proposition of the region, if human capital investments are misaligned with firm-level needs, human capital investments are apt to migrate –- as when workers educated and trained in the region find it necessary to leave the area because they cannot find work matching their level of human capital development. Helping regional firms create sustained competitive advantage may, in fact, be the more appropriate, meso-level goal of regional human capital investments, given the challenge that mobile workers, especially well-educated ones, represent. Investing in technical knowledge as a means of realizing increasing returns may be the appropriate role of national government, which has the ability to internalize migration, but regions have less influence over the macroeconomy and less ability to hold onto their talent.

## CHALLENGES TO HUMAN CAPITAL-BASED POLICIES

As noted earlier, encouraging more people to pursue advanced education – whether at the national or regional level – increasingly is portrayed as an imperative for economic growth. Policies and interventions designed to increase educational investments are grounded in the promise of human capital theory. Yet, there is reason to assume that such efforts are too narrowly defined and potentially misaligned. This is due to an overreliance on and overestimation of educational attainment as an indicator of human capital in academic research and in policy development. Although human capital theory as put forth by Schultz (1961), Arrow (1962), and Becker (1962, 1964/1993) was a broad concept encompassing all manner of investments that enabled workers to be more productive, from Arrow's learning by doing (1962) to better health care, education has come to serve as the standard proxy. In large part, in public policy if not in academic research, the proxy has become the concept.

A century ago, education and economy were not so closely intertwined. The idea that workers would choose to pursue education as a means of improving their earnings potential had not become part of accepted economic theory and had not become embedded in economic development policy (Fitzsimons, 1999). Certainly, some workers were understood to be more skillful at their trades than others and that superior skill has long been assumed to have economic benefit (Smith, 1776; Babbage, 1835; Marshall, 1890). Before human capital theory was formalized, education was largely viewed as a consumption good rather than a factor of production (Schultz, 1961).

The linking of education and economy would seem an appropriate acknowledgment of observed benefits from superior skill, but it may have served to blur the lines of effective and appropriate roles of government. Friedman (1955) supported a role for government, particularly at the local level, in providing a minimum standard of knowledge and skill development for the smooth functioning of society He also conceded a role for government, most feasibly at the federal level, in providing access to professional and vocational education that would otherwise be too expensive for the socially optimal level of workers to pursue. However, investments in knowledge that would allow individual workers to command higher wages should be paid for out of those enhanced private earnings, not through public subsidy. While failing to recognize any potential spillover benefits to the larger society of education that enables new technologies, innovations and economic growth, Friedman (1955) cautioned against government subsidy of human capital investments that are ultimately claimed by individual workers or firms.

The preeminence of educational attainment, meaning the highest level of schooling completed, as the accepted measure of human capital extends from both practical and theoretical advantages. Data on education is routinely collected and readily available. Ease of access and the ability to compare different levels of attainment and expenditure across nations and regions have imparted education with a practical relevance that other potential measures of human capital, such as training and experience, may lack. Moreover, Mincer (1974) formalized the connection between higher levels of education and higher wages in his human capital earnings function. Mincer's education-based equation had profound impact in shaping subsequent empirical research because it answered early critiques suggesting that human capital was a concept too elusive to measure. Mincer's earnings equation went on to be used to assess thousands of datasets in multiple countries across various time periods, making this "workhorse" model one of the most influential in empirical economic research (Lemieux, 2003). Mincer argued that years of schooling reflected deliberate investment in skill development and, thus, could be assumed to approximate human capital.

The underlying assumption of human capital theory is that education makes workers more productive, and, subsequently, more valuable to firms. Greater productivity would justify higher wages for workers with higher levels of education. However, a counter argument is that education serves as a signal to employers that job applicants possess a set of attributes that enabled them to succeed in achieving their educational credential and that make them likely to be productive employees. Signalling theory (Spence, 1973) suggests that education doesn't improve workers' productivity; it simply reduces the risk to employers of selecting unqualified (or poor-performing or low-productivity) workers. Arrow (1973) and Stiglitz (1975) offered a different but similar view of higher education as a hiring "filter" or "screen," allowing employers to more efficiently narrow the pool of qualified job applicants. Unlike the perfect information assumed in classical economic transactions, theories on signaling and screening assume that the job market is vexed by informational asymmetries, where employers and potential employees both seek ways of facilitating good matches.

Whether it truly enhances productivity or simply signals potential (or perhaps both), education has become increasingly linked to the economy. Decades of data from the Bureau of Labor Statistics have supported human capital theory with evidence that better-educated workers, on average, earn more than less-educated ones. Moreover, better-educated workers tend to have lower rates of unemployment. As noted in the introduction, young people are increasingly viewing higher education as necessary for landing a good-paying job. Employers, too, are increasingly requiring higher education: Occupations requiring a college degree have been growing faster than occupations requiring lower levels of skill (U.S. Bureau of Labor Statistics, n.d.).

Higher education is assumed to impart or reflect the higher human capital demanded by today's rapidly changing, technologically enhanced workforce. However, there are indications that a college degree is an imperfect indicator of human capital, masking a wide range of economic return on relatively similar investments of money and time. For example, in an analysis of college majors, Carnevale, Cheah and Hanson (2015) found that majors in top-paying fields paid $3.4 million more over a lifetime than the lowest-paying majors. Entry-level workers with degrees in science, technology, engineering or mathematics – STEM – had median wages of $41,000, compared to $29,000 for workers with humanities degrees. Although a college degree typically imparts protection from unemployment, 2008 graduates with a humanities degree were far more likely to be without a job a year later than graduates with a business degree (13% to 9%, respectively) (Occupational Outlook Quarterly, 2013).

Such variation seems to undermine the usefulness of measuring human capital simply in terms of degree completion. The increasing focus, among students as well as employers and policymakers, on STEM fields is effectively an acknowledgement that certain human capital investments are more economically valuable than others in the labor market at this point in time. However, even within this subset of college majors, there is considerable variation in wages and employment outcomes. Recent graduates in engineering and computer science claimed the highest starting wages in 2012, but graduates with degrees in mathematics and hard sciences had lower entry-level wages than graduates with business and communications degrees (Carnevale, Cheah and Hanson, 2015)

Noting that human capital theory fails to provide guidance as to which types of skills are most highly valued at a given time in the economy, Lerman (2008) warned of relying too heavily on educational attainment or even skill levels alone. Workers who are able to apply their skills toward complementing existing skill sets and industrial demands, as well as adapt and support emerging ones, will be more productive and, thus, more valuable (Lerman, 2008). This suggests that the value of human capital is not only in its development but in its deployment. This is an important understanding of human capital prevalent in resource-based theory of the firm but largely absent from economic development literature and practice.

Another challenge to human capital-based policies enacted at the regional level involves assumptions about the ability to realize gains from human capital investments. As noted earlier, Pritchett (2001) identified a “micro-macro paradox,” where human capital accumulation led to private returns to the individual but not the expected public national-level gains. Regions that have launched initiatives to increase college-going, especially in STEM fields, as a path toward economic growth may find themselves caught in a *micro-macro-meso paradox,* where individuals capture gains from human capital development, the nation experiences growth due to expanding technical knowledge, but the region realizes limited return on its human capital investments, especially if the "talent" educated locally migrates to another region.

Human capital theory largely views investments as individual-based: Workers who are more skilled are more productive, which is assumed to allow them to command higher wages and contribute to growth in the larger economy. Pritchett (2001), among others, indicated that the assumed "win-win" outcome is frequently not realized. Initiatives to increase the number of workers with STEM knowledge seem largely motivated by the promise of increasing returns from higher levels of technical knowledge, as posited in new growth theory. However, the technical knowledge of new growth theory is a largely disembodied asset engendering future returns. Individuals may not capture the full value of their human capital as diffuse technology enables new products and innovations, which sustains growth in the larger economy. At the regional level, the public return to human capital development may be even more elusive due to its inability to contain its investments. Human capital embedded in individuals can easily leave the region for better opportunities; disembodied technology can easily permeate regional boundaries. Either way, human capital-based interventions and initiatives at the regional level are at risk of leaking out, especially if they are not aligned to the specific current needs and opportunities of the region. This suggests regions may be better served by approaching human capital-based initiatives through a resource-based perspective: The regional human capital asset is what enables sustained regional competitive advantage, which is responsible for regional economic wellbeing.

## HUMAN CAPITAL REFLECTED IN OCCUPATIONAL REQUIREMENTS

Better aligning regional human capital-based interventions to fit existing and emerging opportunities for regional competitive advantage requires a different understanding of the regional human capital asset than is typical of policies and programs aimed at growing the supply of college graduates and STEM workers. Such policies have largely been shaped by new growth theory's emphasis on knowledge and technology as central to sustained economic growth. Resource-based theory suggests that the value of the regional human capital asset is in how it can be applied in the specific context of the regional economy.

Periodic claims of "shortages" of certain skill sets, often in nursing, engineering or mechanical fields, get the attention of regional policymakers, and a decade of attention has been directed toward attracting and supporting "creative'' workers (e.g., Florida, 2002a, 2002b; Markusen, 2006) as a means of improving regional wellbeing. Both could be considered resource-based human capital interventions, but neither offers a comprehensive understanding of a region's human capital asset.

In addition, boilerplate policies promoting higher education, or STEM degrees specifically, as a path toward regional economic growth largely disregard the literature on comparative advantage and uneven return (Lucas, 1988; Grossman & Helpman, 1994). Instead of the equalizing force suggested by Goldin & Katz (2010), regions that have lower levels of educational attainment and presumably lower levels of human capital demanded in their economies will theoretically see a lower rate of return on their human capital investments because they start from so far behind. They are more likely to find themselves in the role of technological imitators instead of innovators (Benhabib & Spiegel, 2005). Signs of imitation instead of innovation are plentiful in economic development practice: Dozens of U.S. regions, for example, have adopted hopeful "me-too" monikers – from Silicon Desert to Silicon Bayou – attaching themselves to the technological transformations emanating out of San Francisco, San Jose and other communities of Silicon Valley.

The regional human capital asset would best be captured at the level of a region's collection of jobs. More specifically, thinking of jobs as a bundle of knowledge, skills, abilities, educational requirements and experiences (Bacolod, Blum & Strange, 2010) would more closely align to the broad concept of human capital and would provide insight into each region's particular alchemy of attributes. Human capital required of jobs would best explain how each region's unique human capital asset is deployed and valued in the larger economy. Human capital required of jobs also reflects insight into a region's rare, inimitable and aligned resources that form the basis of sustained competitive advantage (Barney, 1991).

However, human capital measured at the individual job level would be too unwieldy and singular to provide generalizable understanding. The unique qualities of each region's human capital resource may be the "secret sauce" behind variation in regional economic performance, but singularity is not the realm of public policy. Economic development interventions are assumed to have broader applications than supporting or promoting human capital necessary for one job in one region.

Over the past decade, a growing body of literature has focused on the different human capital requirements associated with regions' differing mixes of occupations (Autor, Levy & Murnane 2003; Feser, 2003; Koo, 2005; Ingram & Neumann, 2006; Markusen, 2006; Maxwell, 2008; Scott, 2009; Bacolod, Blum & Strange, 2010; Yakusheva, 2010; Nolan, Morrison, Kumar, Galloway & Cordes, 2011; Gabe & Abel, 2012; Chrisinger, Fowler & Kleit, 2012; Florida, Mellander, Stolarick & Ross, 2012; Wolf-Powers, 2013; Rothwell, 2013; Wan, Kim & Hewings, 2013; Yamaguchi, 2013). This potentially "just right" measure of regional human capital – neither overly broad, nor overly narrow – has been facilitated by the development of a federally sponsored database that is both in-depth and iterative in its detailing of individual skills, abilities and knowledge areas required of occupations, as well as most frequent educational, experience and training levels. The dataset, the Occupational Information Network (O*NET), is enabling an exploration of human capital that is more reflective of the broad definition of the concept but that, like educational attainment, is also available and accessible.

Using the O*NET database, Scott (2009) and Florida et al. (2012) found that employment in occupations requiring cognitive skills has increased across metropolitan areas, while employment requiring physical abilities has declined. This fits the broad "knowledge economy" narrative of "brains" supplanting "brawn." However, somewhat counter to the view that bigger cities attract better-educated workers (e.g., Glaeser & Resseger, 2010), Scott (2009) found that smaller regions had grown their employment in occupations requiring higher cognitive abilities, while employment requiring physical skills had increased most in larger cities, indicating growth in population-serving activities. Koo (2005) drew on O*NET data to explore the usefulness of occupational cluster analysis as a tool in understanding regional economies. Again focusing on differences in regional size, Gabe and Abel (2012) demonstrated that larger cities attracted more scientists, engineers and executives and, thus, had greater need of problem-solving and resource-management skills.

Even within this body of work, which explores human capital in terms of occupational requirements, a gap in the literature is apparent: Little attention has been paid to aligning research to political rhetoric and economic development policy objectives regarding STEM skills. Rothwell (2013) revealed that occupations demanding high- as well as mid-level STEM knowledge varied across regions and both contributed significantly to the local economy. However, his approach was somewhat unusual in directly addressing a perceived high-skill bias in STEM policies. Despite the intense focus in policy, and the connection theorized in the new growth literature, much of the discussion of STEM skills specifically is found in the education literature. Largely, this research appears to take three forms: growing the pipeline of students pursuing science, technology, engineering and math; calling for (or countering calls for) reforms to address the underperformance of U.S. students in science and math compared to world competitors; and assessing the underrepresentation of certain groups (namely, women, minorities and the disabled) in STEM (Bybee, & Fuchs, 2006; Bagiati, Yoon, Evangelou, & Ngambeki, 2010; DeJarnette, 2012). Yet, there is a rising contrarian view in the educational literature seeking to de-STEM. Metcalf (2010) argued for shutting off the "pipeline" metaphor as it relates to education's role in producing STEM workers. Teitelbaum (2014) and Stevenson (2014) challenged the narrative of a STEM worker shortage that has its roots in the Cold War and continues to be perpetuated by business organizations, government agencies and advocacy groups. “Part of the confusion regarding today’s STEM-qualified worker shortage narrative is that there is not one acceptable standard as to what constitutes a STEM job” (Stevenson, 2014, p. 138).

Adding to the confusion is what constitutes STEM skills. Policy and media accounts seem largely to focus on technical and scientific expertise. More recently, “problem-solving” and “critical-thinking” have been added to the mix, as President Obama did in proposing $2.9 billion for STEM education in his 2015 budget. Yet, many occupations outside of STEM fields require high levels of problem-solving and critical-thinking. Moreover, in addition to problem-solving and critical-thinking, “21$^{st}$ century skills” frequently encompass more generic, “soft” skills such as creativity, collaboration, communication, leadership, initiative and flexibility. According to the Glossary of Education Reform, “21$^{st}$ century skills” is, in fact, a broadly accepted but largely “amorphous” set of competencies, ranging from reasoning, comprehension and creativity to public speaking, listening and collaboration. Many of these “21$^{st}$ century skills” are those employers say they value in employees (Robles, 2012).

Certainly, the economic development policy focus on STEM emanates out of new growth theory, with its assertion regarding the importance of non-rivalrous technology. However, the disembodied knowledge new growth theory posits as necessary to sustained economic growth will not fit into all regional occupational configurations. Goodness of fit, how the human capital asset aligns to organizational structure and can be managed to advantage, is an important concept in the business strategy literature (Argote, McEvily & Reagans, 2003; Das, 2003; Sorenson, 2003).

New growth theory suggests that greater technical knowledge fuels growth;

resource-based theory suggests that policies enacted to grow a region's level of STEM human capital will be ineffective if they do not align with opportunities to apply and deploy such skills in the region. This underscores the particular challenge of regional economic development – operating within a larger national or global economy but supporting the specific strengths and needs of a regional economy. New growth theory asserts that private investment in knowledge will always be below the optimal level for maximum social benefit because of the nature of knowledge and technology as non-rivalrous, only partially excludable resources (Romer, 1990, Cortright, 2001; Warsh, 2006). This represents a classic market failure justification in neoclassical economics for government intervention into encouraging higher levels of human capital.

However, there are clear difficulties in adhering to such a view in regional economic development policy. Guided by new growth theory, regions – and states – have adopted largely supply-side initiatives with limited regard to how increasing human capital truly fits within the demand of their mix of firms and industries. Although globalization has untethered production from location to some extent, geography still matters (Cortright, 2001). Regions have differing levels of human capital on which to build. If technology diffuses more rapidly in areas with higher levels of human capital to start with (Benhabib & Spiegel, 1994), particularly complementary human capital (Acemoglu, 1998; Lerman, 2008), regions with a smaller share of human capital, particularly human capital not aligned to technological advances, will likely see lower returns on their human capital investments despite enacting near-identical new growth-influenced policies. Cortright (2001) asserts that the increasing returns stemming from a region's advantage in technical knowledge encourage areas over time to "lock in" to particular industries and technologies. However, this also means that the regional human capital resource may itself be locked in to these industries and technologies, leaving the region vulnerable to disruptions and declines. In addition, the diffuse quality of knowledge and technology theorized to be of critical importance to economic growth makes policies and strategies designed to grow a region's share of human capital somewhat risky bets if those policies and strategies are not aligned to how human capital is deployed and demanded within the region. Regional (or state) investments in human capital development may not bring about the expected return if workers educated through public subsidy migrate out of the region (or state) because they cannot find jobs matching their level of skill and expertise. Or, the higher level of regional (or state) human capital may go unused even if workers remain in the region but accept jobs below their level of human capital.

## OCCUPATION-BASED HUMAN CAPITAL AS A REGIONAL RESOURCE

Given the term "human capital," it's not surprising that so much policy attention is on a region's people. Yet, each region's human capital asset in actuality arises out of two distinct but intertwined pools of potential inputs: its people and its firms. The channel through which a region's raw human capital is deployed as a regional human capital asset is through its collection of jobs.

As noted earlier, the assumption of new growth theory is that human capital lies at the heart of technological change, which drives increasing returns and leads to sustained economic growth (Lucas, 1988; Romer, 1990; Warsh, 2006). Yet, not all potential human capital is harnessed by the market. As a factor of production, even one viewed as functioning unique to other ordinary inputs, human capital derives its direct economic value from how it contributes to the local economy. Certainly, regions enjoy other benefits from higher human capital quality – people with higher levels of educational attainment, for example, tend to be healthier (Grossman & Kaestner, 1997), vote more (Hillygus, 2005), and maintain more stable family structures (Maynard & McGrath, 1997) – but these are not the focus of this research. Human capital as a factor of production within a region is bounded by the jobs available in the region. More specifically, the deployable regional human capital asset is bounded by the knowledge, skills and abilities required of the available jobs.

It is not unreasonable to assume that individuals may have knowledge, skills and abilities that are not realized within the confines of their employment. Numerous articles in the popular press (and in the academic literature) have sounded the alarm about the recent high level of underemployment, as well as unemployment. Workers who have been displaced or forced to take jobs below their skill levels are themselves not capturing the benefits of their human capital investments. A difficult job market is only one reason that workers fail to maximize return on their human capital investments; personal preferences, locational choices, health issues and family demands are others. Consider the mid-level business manager who chooses to opt out of the job market to care for an aging family member. Or the singer who tires of a peripatetic lifestyle and takes a job in customer service. Or the downsized technical support specialist who would relocate if only he could sell his house. Or the nurse who opts for a less physically and emotionally demanding job. Or the travel agent whose occupation is effectively made obsolete by technology. All of these represent regional human capital potential that is not, or is alternately, deployed in the local economy.

These representations illustrate the challenge to using such a blunt measure as educational attainment. It is worth remembering that, before the formalization of human capital theory, education was typically assumed to be a function of consumption, not production (Schultz, 1961). Education certainly has elements of both. People choose to pursue education because of the future return it promises in the form of higher wages and better jobs (investment in production), but they also choose to pursue education for such reasons as status, family expectations, personal preference, work avoidance and even entertainment (consumption factors). Perhaps education's duality of function – both a productive and consumptive good – helps explain the frequently mixed results from higher and increasing educational attainment apparent in the literature (e.g., Benhabib & Spiegel, 1994; Blundell, Dearden, Meghir & Sianesi, 1996; Cooper, 2004; Shapiro, 2006; Holzer & Lerman, 2007; Lerman, 2008; Scott & Mantegna, 2009; Andreason, 2015).

Measuring the educational level of the worker misses much of what human capital does for regional growth. The common proxy variable does exhibit some of theorized effect because it correlates with the multiple attributes of human capital, but it does not offer policy makers insight on which aspects of human capital to support. Moreover, the pervasive analytical use of this measure has led to assumptions – evident both in policy and the literature – that the educational level of workers *is* what sparks growth. The proxy has become the phenomenon. Yet, education fails to capture many other methods for developing human capital, such as experience, training and learning by doing (Schultz, 1961; Arrow, 1962). Good health (Schultz, 1961; Knowles & Owen, 1995; Bloom, Canning & Sevilla, 2004; Howitt, 2005) and family structure (Becker, 1993) also can be considered forms of human capital.

Measuring a region's human capital based on the educational attainment of its population also fails to account for human capital embedded in its mix of firms (Barney, 1991; Ployhart & Moliterno, 2011). In advocating a new approach to the conceptualization of human capital, Ployhart and Moliterno (2011) described the knowledge, skills and abilities of individuals as the basic inputs; the human capital resource arises when these inputs are shaped by firm processes and strategies. This conceptualization out of the business management literature would seem to offer insight for human-capital-based regional economic development activities.

Overreliance on education attainment as a measure of a region's human capital asset may lead to inefficient allocations of limited resources, labor market distortions and missed opportunities for meaningful policy interventions. A region's human capital asset is not found in the educational attainment, or even the knowledge, skills and abilities, of its residents. Nor can it even be inferred from clusters of activities in technology or "creative" industries. A region's human capital asset is in how these individual talents interface with its firm capacity and are deployed through the region's particular mix of jobs.

Resource-based theory of firm competitive advantage indicates that sustained firm growth emanates from the development and deployment of resources to strategic, competitive advantage (Penrose, 1959, Barney, 1991; Peteraf, 1993; Kor & Leblebici, 2005). Competitive advantage is not achieved simply through differences in resources but in their efficient allocation, their strategic deployment and their enabling of innovation

(Penrose, 1959; Mahoney, 1995; Kor & Leblebici, 2005). This would suggest that human capital-inspired economic development policies will not achieve the desired boost in economic wellbeing unless they are aligned to the particular needs and strengths of the region.

Assuming jobs to be a bundle of knowledge, skills, abilities and experiences (Bacolod, Blum & Strange, 2010), each region's particular mix of job demands collectively represents the valued and unique human capital asset that resource-based theory places at the heart of competitive advantage. Although the human capital required of each individual job would be the most fine-grained measure of the regional asset — and the best test of the model — collecting such data for all firms across an entire region would be an onerous task. Moreover, that onerous task would only yield insight into the human capital asset of one region, not offer a model for understanding the effects of human capital concentrations on economic performance across regions. Testing the usefulness of a generalizable resource-based model of the regional human capital asset will require a measurement concession. This is not an unreasonable expectation; educational attainment, after all, is used throughout the human capital literature as a proxy for the difficult-to-measure human capital characteristics of knowledge, skills, abilities and more. A growing body of research provides theoretical grounding and empirical guidance for a more demand-focused, job-based view of human capital measured at the occupation level. This would move exploration of regional human capital closer to its deployment mechanism. In advocating for an alternate or additional focus of economic development efforts directed at industry, Markusen (2004) identified occupations as a “fundamental mesoeconomic unit” (p. 253), better suited for detecting entrepreneurship, productivity enhancements and equity opportunities.

The resource-based literature suggests that a region’s economic wellbeing arises out of how valuable, rare, inimitable and apropos its regional human capital asset is within the context of its mix of industries. Although much of the discussion of regional human capital in the economic development literature focuses on individual human capital, frequently educational attainment levels, a region’s human capital asset also includes firm human capital, which includes embedded, tacit knowledge; organizational structure and internal processes; and management capacity, as discussed in the business strategy literature. These individual and firm human capital characteristics come together in the mix of regional jobs and forms the foundation for the regional human capital asset. Other individual characteristics, such as family structure and health, contribute to the regional human capital asset. Other firm characteristics, such as intellectual property and branding, also may serve to enhance the regional human capital asset if the region is able to capture some of this largely disembodied firm knowledge asset. In addition, the *consumption* choices regarding education can even be thought of as human capital contributions to the local economy through increased demand. However, most of a region’s firm-level and individual-level capacity that affects regional economic performance is deployed through jobs. This view of the regional human capital asset as a job-level, or, as demonstrated throughout this project, an occupation-based measure, reflects an integration of the two complementary literature streams and forms the basis of this research. It’s important to acknowledge, although the point is typically ignored in the literature, that not all human capital capacity is channeled into the regional human capital asset. Individuals may have human capital, as measured in educational attainment, that they cannot or choose not to use in the context of the local economy. Firms may have human capital, such as ideas for new products of which there is no viable market, that does not contribute to the local economy.

## CONCLUSION & IMPLICATIONS

Integrating theories on human capital that are found in the economics and business literature streams leads to a recognition that human capital is embedded in firms as well as individuals. Not only does focusing so intently on the educational level of workers fail to capture the multidimensional quality of human capital in individuals (Bacolod, Blum & Strange, 2010), using educational level as a proxy for the human capital asset of a region, as occurs in both research and policy, would seem to be an even more distorted view of the relationship between a region's human capital asset and its economic performance. A region's individual-level human capital capacity includes educational attainment, certainly, but also skills developed through training, practice or self-study; it includes experience, migration, and even health. A region's firm-level human capital capacity includes firm-specific practices and processes, intellectual property, branding, as well as organizational systems and structures. Both individual- and firm-level human capital have value in their own right, but they are the building blocks from which the regional human capital asset emerges. As resource-based theory makes clear, human capital alone doesn't lead to competitive advantage. Human capital must be allocated and deployed in a way that adds value and fits within the broader capacity and strategy of a firm or a region. This is particularly instructive for research and practice regarding regional economic development. Efforts that focus on regional human capital capacity instead of regional human capital deployment are likely to lead to distortions in the supply and demand equilibrium and miss opportunities to facilitate fit. The way in which individual-level and firm-level human capital come together and are deployed is through jobs. As such, the human capital demanded of jobs making up the regional economy should offer the most appropriate measure for assessing regional competitive advantage and economic development.

Workers vary in not only their level of human capital but in how they are able to apply it in ways that affect firm performance and, ultimately, economic development. In other words, their occupations both frame the context of their human capital value and directly connect it to performance of the firm and the larger economy. Economic development policy and practice have taken, largely, a supply-side view of human capital, assuming that increasing the educational levels of the population, especially increasing the share of workers with expertise in science, technology, engineering and math, will be rewarded with economic growth. Such policies and practices are guided by the theorized special property of knowledge and technology that is set forth in new growth theory. However, such a view neglects the importance of demand, goodness of fit and strategic deployment in transforming the regional human capital asset into a component of regional economic wellbeing.

The two literature streams suggest the following overarching research question that will be explored in subsequent chapters:

**RQ:** What is the relationship between regional human capital assets reflected in the knowledge, skills and abilities required of its mix of occupations and regional economic performance?

# CHAPTER III

# STEMMING THE TIDE: A METHOD FOR DEVELOPING AN INTEGRATED DATABASE OF OCCUPATIONAL HUMAN CAPITAL

This chapter explores an alternate method of operationalizing human capital that more explicitly captures the knowledge, skills and abilities required of occupations. Focusing on the human capital requirements of occupations represents a closer reflection of the market-based mechanism by which knowledge and skills of individual workers affect the economic wellbeing of regions. Educational level or expenditure have typically been used to measure human capital because such information is readily available and accessible (Borghans, 2001). Data on education attainment or years of schooling have long been mandated and captured by the federal government. This chapter details the development of a database to enable an alternate approach to the study of human capital, which focuses on occupational skill requirements. The Occupational Information Network (O*NET), a database sponsored by the U.S. Department of Labor/Employment and Training Administration, measures specific characteristics of individual occupations. This extensive occupational mapping allows for a finer-grained understanding of human capital – the stock of knowledge, skills and abilities – associated with economic gain, both for individual workers and for regions.

The O*NET database has been used in economic development research to assess the benefit of occupations requiring high- and mid-level STEM knowledge to regional vitality (Rothwell, 2013). Scott (2009) and Florida et al. (2012) used O*NET data to demonstrate an increase in occupations requiring cognitive skill and decrease in employment requiring physical skill. Koo (2005) explored O*NET to show the importance of occupational clusters to regional performance. Yakusheva (2010) demonstrated the college wage premium to be a function of the goodness of fit between field of study and occupation, and Maxwell (2008) drew on the O*NET database to identify skills that command higher wages among lower educated workers. The O*NET database has also attracted the attention of researchers in the areas of psychology, human resources, career guidance, and family relations. However, aside from Rothwell (2013) and an article highlighting O*NET's value in assessing students' vocational interest (Toker & Ackerman, 2012), research on human capital has rarely drawn on the O*NET database for its value in understanding occupational STEM requirements.

The purpose of this chapter is to present the steps involved in creating an Integrated Database of Occupational Human Capital (IDOHC), linking information available from three federal databases. That process will be explored after a brief overview of the three primary databases used to build the IDOHC. Linking fine-grained O*NET data with other datasets will allow more fine-grained evaluation of differences in regional human capital concentration and deployment. Multiple operational definitions of human capital are explored in this chapter based on different levels of analysis. Thus, the combination of the O*NET database with other economic data on occupations and economic wellbeing provides new insights and new research opportunities. One research opportunity of particular relevance is the ability to examine occupational human capital requirements within the current policy focus on high-STEM fields. Such research will address what has been described as a lack of definition regarding STEM fields and occupations (Teitelbaum, 2014).

The methodology is guided by a foundational research question central to understanding whether focusing on how knowledge, skills and abilities are deployed, instead of levels of education attained, better captures variation in regional human capital. Policy and the literature drive the following research question:

**RQ:** How well does a method of measuring the regional human capital asset reflected in the knowledge, skills and abilities required of regional occupational mixes explain differences in regional economic performance?

## OVERVIEW OF 3 FEDERAL DATABASES USED TO CREATE THE IDOHC

This study uses cross-sectional archival data collected primarily by U.S. government resources. The sources of archival data are:

1. The Occupational Information Network (O*NET) database, which presents a fine-grained assessment of roughly 950 occupations nationwide;
2. Occupational Employment Statistics (OES), which annually provides employment and wage data for occupations at the national, state and regional level;

3. The American Community Survey (ACS), which presents demographic and socioeconomic data in 1-year, 3-year and 5-year samples.

Understanding the value of an occupation-based method for exploring regional human capital requires a method for concatenating three separate federal databases: Two – O*NET and OES – are maintained or supported by the U.S. Department of Labor. The ACS is annually released by the U.S. Census Bureau. Similar coding systems regarding occupations and locations make it possible to extract data from the three separate datasets and connect them in a database of occupational skill concentrations by geographic area, employment and wage metrics, and then link those characteristics to regional demographic and economic indicators. The 2010 Standard Occupational Classification system serves as the foundation for both the O*NET and OES databases, allowing details on occupational skill sets in the O*NET to be matched to occupations in the OES. Because the OES provides data on the distribution and wages of occupations, the SOC linkage allows those occupations also to be examined by their competencies and can be used to indicate the extent of human capital in a geographic area based on skill sets. Adherence to the delineation of metropolitan statistical areas (MSAs), defined by the Office of Management and Budget (OMB) and used by the OES and ACS databases, allows concentrations of regional skill sets to be linked to indicators of regional economic performance. Integration of these three data sources allows an exploration of the value of an occupation-based and skill-based alternative to the use of educational attainment as a proxy for regional human capital.

Although shared classification systems make it possible to connect the three federal databases, matching occupational skill sets to regional occupational concentrations to regional well-being, the method is by no means straightforward.

**O*NET Overview**

The O*NET database was developed to supplant the Dictionary of Occupational Titles. With a stated goal of serving as “the nation’s primary source of occupational information” (O*NET website), the O*NET database has been regularly updated and expanded since 2003. This research draws on Version 19.0, which was released in July 2014. Version 19.0 provides a detailed mapping of 942 occupations, including comprehensive updating of 126 of the 942 occupations. The O*NET method and analysis has received endorsements from hundreds of industry organizations and associations. The endorsements reflect the success of O*NET’s mission of presenting what amounts to a time lapse rendering of the U.S. work environment and developing a “national labor exchange system” with participating establishments both informing and drawing from the database of occupational requirements and expectations (O*NET website).

The foundational framework for O*NET is its Content Model, described as a “theoretically and empirically sound” system for guiding the collection and integration of information to develop a deep understanding of each occupation’s mix of attributes. The Content Model divides six major informational domains into worker-oriented and job-oriented characteristics, as well as cross-occupation and occupation-specific ones. The six domains are: worker characteristics, worker requirements, experience requirements, occupation-specific information, workforce characteristics, and occupational requirements.

**O*NET Data Sample**

The O*NET database has been continually and regularly updated since its first release in 2003. This has the effect of refining data collection, improving reliability, and identifying occupations that are emerging or evolving. A two-stage process is used to identify the data sample for each update: First, a random sample of businesses assumed to employ workers in the occupations of interest is selected; then, a random sample of workers in the occupations of interest within those select businesses is identified. Typically, two to three dozen workers in each occupation are surveyed about their day-to-day tasks and are asked to provide demographic information, meaning that the database collects information from between 22,000 and 33,000 unique contributors across all 942 occupations. The 24 to 36 workers surveyed for each occupation are assumed to represent all workers in the same occupation nationwide. Given that answering hundreds of corresponding questions would be burdensome for participating establishments and workers, the sampled job incumbents are randomly assigned one of three standardized questionnaires. Each questionnaire is designed to require only about 30 minutes to complete.

**O*NET Data Collection**

The O*NET Data Collection Program surveys incumbent workers in the sample of occupations to gather information on the knowledge, skills, abilities, educational, experience and job training requirements of their jobs, as well as their work styles and interests. Occupational experts drawn from trade or industry associations are asked to complete questionnaires for occupations that pose difficulty in identifying incumbent workers, due to small employment numbers or remote employment locations. Occupational analysts, typically eight of them, then review information from the surveyed workers and occupational experts to rate the skills and abilities required to perform each occupation. Supplemental information, such as labor market trends data, is also drawn from other federal agencies.

Although the O*NET questionnaires collect information from representative workers regarding daily tasks, preferred work styles and personal interests, the integrated database of occupational human capital (IDOHC) focuses exclusively on the knowledge, skill and ability attributes, which fall within the worker requirements and worker characteristics domains of the O*NET Content Model. The decision to limit the focus was guided by the career advising and human resources literature, as well as general practice; job descriptions are often built – and job applicants evaluated – based on key knowledge, skill and ability (KSAs) requirements. Information on each occupation's average level of education, experience and training – drawn from the worker requirements and experience requirements domains – was also incorporated into the IDOHC.

The O*NET questionnaires collect data on 120 KSAs – 33 knowledge domains, 35 individual skills, and 52 abilities. Although surveyed workers are asked to rate each of the 120 KSA attributes separately, there is a level of overlap, especially among the skill and ability attributes. For example, workers are asked to assess the mathematics knowledge, the mathematical skill and the mathematical reasoning ability necessary to perform their job. In the O*NET Content Model, skill is conceptualized as a developed capacity, whereas ability is more an innate characteristic. Worker skills can be thought of as being built on individual abilities. For example, mathematical reasoning ability underlies mathematical skill.

Each KSA attribute is assessed on two dimensions. Surveyed workers are first asked to assess the **importance** of a specific attribute to their job performance on a scale of 1 to 5, with 1 equaling "not important" and 5 being "extremely important." For KSAs that rate a 2 or higher, meaning the attribute is at least "somewhat important," surveyed workers are then asked to rate, on a scale of 1 to 7, the **level** of the attribute necessary to perform their job. Workers completing the questionnaire are provided attribute-specific anchors to guide their rating. For example, workers who indicate that oral comprehension is an ability at least "somewhat important" to performing their job are then asked what level of oral comprehension their job requires, with 2 indicating a level sufficient to "understand a television commercial," 4 indicating a level equal to understanding "a coach's oral instructions for a sport," and 6 equaling the level of oral comprehension necessary to "understand a lecture on advanced physics."

Occupational analysts, typically eight of them, review information from the surveyed workers and occupational experts to rate the skills and abilities required to perform each occupation. Trained analysts are assumed to possess a better understanding of often relatively abstract skill and ability constructs and lack any temptation workers may feel to inflate work requirements in an effort to increase compensation levels and job status (Morgeson, Delaney-Klinger, Mayfield, Ferrara, & Campion, 2004; Lievens & Sahchez, 2007; Tsacoumis, 2007). For the most recent O*NET assessment, interrater reliability among the eight occupational analysts exceeded the .80 threshold both in terms of the relative value of each individual skill and ability construct across all occupations and within the mix of attributes making up each occupation. This suggests strong agreement among the analysts (Reeder & Tsacoumis, 2014a, 2014b). For many of the 35 skill and 52 ability attributes, agreement among the analysts exceeded .90. Agreement among the occupational analysts has tended to increase as the O*NET database has been updated and refined (Tsacoumis, 2007; Reeder & Tsacoumis, 2014a, 2014b).

**OES Overview**

The Occupational Employment Statistics (OES) is a federal-state collaboration between the DOL's Bureau of Labor Statistics and State Workforce Agencies. The OES provides estimates of employment and wages at the national, state and MSA levels for roughly 800 occupations. The OES, a semiannual mail survey, is considered the most accurate and comprehensive source for cross-sectional wage and employment data.

**OES Data Sample**

The OES surveys 200,000 establishments every six months over a 3-year cycle, meaning each release draws estimates from a sample of 1.2 million establishments. Full- and part-time hourly and salaried workers in non-farm industries are included in the sample; self-employed workers, partners in unincorporated firms, and household workers are not.

## OES Data Collection

Across the six survey panels over the 3-year cycle, the OES is able to obtain occupational wage and employment data reflecting roughly 57% of total national employment. Occupations are identified by SOC codes; wage and employment data are provided at the national, state and regional geographic levels. May and November form the reference periods. Data for the IDOHC come from the May 2014 release, which includes wage and employment from November 2011.

## ACS Overview

The ACS is an annual survey conducted by the U.S. Census Bureau that randomly samples a percentage of addresses in every state on a rotating basis; participation is mandatory. The ACS collects data on a broad swath of demographic and economic topics, including questions on educational attainment, family status, labor force participation, household income, and house price. Information collected is used by policymakers to guide interventions and target federal and state funds. The ACS includes geographic identifiers so that data can be examined at the state and regional levels.

## ACS Data Sample

The 2013 ACS had a sample size of roughly 3.54 million residential addresses nationwide, covering 98.8% of housing units.

## ACS Data Collection

The ACS provides 1-year, 3-year and 5-year estimates. The 1-year estimate offers the most current data but includes information only for areas with populations greater than 65,000. The 5-year estimate has the largest sample size and is, thus, the most reliable but the least current of the ACS estimates. The 5-year estimate provides data for all geographic categories regardless of size. Data from small areas, such as census tracts and block groups, which used to be available only through the decennial census, are collected via a series of monthly samples; these samples provide the means for an annual updating of estimates. Due to a mismatch in adoption of new MSA delineations between the OES and the ACS, the IDOHC used county-level data collected as part of the 5-year ACS estimates to build MSAs that matched the OES regional definitions. This study draws primarily on data available in the 2013 5-year estimate; data were collected over a 60-month period between January 1, 2009, and December 31, 2013. The data elements for the IDOHC drawn from the ACS included regional population, share of change in population due to net migration, labor force participation, share of regional employment in manufacturing, share of regional population with a bachelor's degree or higher, regional per capita income, and the share of each region's population below the poverty line.

In addition to data from the three federal databases, the IDOHC also extracted information on two key economic indicators from Moody's Analytics, a private-sector provider of national and regional economic data, analysis and forecasting. As with the ACS data, a mismatch in adoption of new MSA delineations required the IDOHC to use county-level data collected by Moody's Analytics to build MSAs that matched the OES regional definitions. The data elements for the IDOHC drawn from Moody's Analytics were gross regional product for 2009 and 2013 and regional employment in 2013.

## AN INTEGRATED DATABASE OF OCCUPATIONAL HUMAN CAPITAL

The first element of the IDOHC was created by extracting and summarizing data from O*NET to more clearly distinguish the human capital associated with each occupation. The academic literature includes analyses of O*NET data that have used only the importance (Maxwell, 2008; Scott, 2009; Scott & Mantegna, 2009; Yakusheva, 2010) or the level (Rothwell, 2013) score to describe a particular attribute's contribution to occupational performance. However, in developing the IDOHC, both O*NET dimensions were used to fully understand how each KSA contributes to the performance of each specific occupation. For example, the skill active listening is assessed as very important (4.12 on a 5-point scale) for occupation 11-1011.00 (chief executives), but the level of active listening chief executives need to perform their job is little more than average (4.88), a little higher than what is necessary to "answer inquiries regarding credit references." Occupations 29-2052.00 (pharmacy technicians), 39-5092 (manicurists and pedicurists) and 39-9011 (child care workers) rate inductive reasoning as "important" (3) to their jobs, but the manicurists and pedicurists rated the level of the skill needed as 2.38, a little more than the level necessary to "decide what to wear based on the weather report," pharmacy technicians rated the level of skill needed as a 3, and child care workers needed the most inductive reasoning of the three occupations (3.25). Occupation 19-1031.03 (conservation scientists) rate the level of inductive reasoning needed to perform their job the same as pharmacy technicians, but they indicate that the ability is more important (3.63) to their work. Occupation 13-1011 (agents and business managers of artists, performers and athletes) rate the importance of inductive reasoning the same as conservation scientists, but the level required to perform the job is somewhat higher (3.88), a little less than what's needed to "determine the prime suspect based on crime scene evidence."

Using only one dimension of the occupational assessment (as done in Maxwell, 2008; Scott, 2009; Scott & Mantegna, 2009; Yakusheva, 2010; Rothwell, 2013) loses some of the detail in understanding variation in how knowledge, skills and abilities are deployed throughout occupations. For the IDOHC, the O*NET importance score and level score for each occupational attribute were multiplied together (as demonstrated in Hadden, Kravets, and Muntaner, 2004; Reiter-Palmon, Brown, Sandall, Buboltz, & Nimps, 2006; Abel & Gabe, 2008; Florida et al., 2012) to derive a single score reflecting the intensity of each KSA for each occupation. The intensity score for each KSA in the IDOHC ranges from a minimum of 0 to a maximum of 35.

**KSA Intensity Across Occupations**

KSAs reflecting communication and understanding have the highest mean scores across all 942 O*NET occupations. However, "thinking skills," such as problem-solving and deductive reasoning, also have high mean scores, suggesting a relatively high intensity across occupations. Altogether, 92 occupations had oral comprehension scores of 20.0 or higher. Only nine occupations had mathematical reasoning scores of 20 or greater. Conversely, 759 occupations had mathematical reasoning scores of less than 10.

Sixteen occupations have critical thinking scores of 20 or higher; 261 occupations had critical-thinking scores below 10, suggesting that the vast majority of occupations require a moderate level of critical-thinking skills.

Rounding out the top 10% of KSAs is near vision (12.98), an ability linked to the importance of reading and writing skills, as well as likely reflecting the increasing reliance on computers and other technological devices in the workplace. Mathematics knowledge has the highest mean score among obviously “STEM” KSAs, at 11.03. Knowledge of computers and electronics is close behind at 10.47. Not surprisingly, science- and engineering-related knowledge and skills have relatively low mean scores, reflecting the fact that only a limited number of occupations require them at any level of importance, as compared to a oral comprehension and expression, which are abilities required across a broad swath of occupations.

Also not surprising is the fact that STEM-related knowledge has some of the highest standard deviations among the 120 KSAs, indicating a wider gap in what occupations require. For example, engineering and technology knowledge has a standard deviation across the 942 occupations of 6.93; close behind are medicine and dentistry (6.54), psychology (6.53), biology (6.40), computers and electronics (6.30), and mathematics (6.0). Knowledge of physics and chemistry and skills in science are slightly lower. Interestingly, other KSAs with presumably broader application across the occupations also have high standard deviations, such as customer and personal service (6.71) and English language (5.91). Mechanical knowledge has the highest standard deviation among the 120 KSAs at (7.00). On the other hand, critical thinking, a skill employers often describe as needed but lacking in employees, and originality, an ability presumably necessary for the innovation seen as an economic imperative, have much lower standard deviations (3.60 and 3.56, respectively), indicating a much narrower range of scores across all occupations. Surprisingly, programming and technology design skills have even less variation (and far lower mean scores) across the occupations, with standard deviations of 2.54 and 2.21, respectively. In general, knowledge scores tend to have the highest standard deviations, reflecting variation in occupational requirements of specific knowledge sets. With some exceptions, skills and abilities tend to have broader application and, thus, lower standard deviations. For example, oral expression had one of the highest mean scores across all occupations with a relatively low standard deviation of 3.99.

**Identifying STEM and Soft KSA Bundles**

The O*NET Content Model sorts abilities into categories of cognitive, psychomotor, physical, and sensory. It divides skills into categories described as basic, described as "capacities that facilitate learning or the more rapid acquisition of knowledge," cross-functional, which is defined as "capacities that facilitate performance of activities that occur across jobs," and technical, defined as "capacities used to design, set-up, operate, and correct malfunctions involving application of machines or technological systems." Technical skills, complex problem-solving and resource management activities fall within the cross-functional domain. Knowledge is divided into 10 domains: business and management activities, manufacturing and production, engineering and technology, mathematics and science, health services, education and training, arts and humanities, law and public safety, communications, and transportation.

Given O*NET's explicit description of categories, it is possible to extract those KSAs that could be assumed to reflect what is meant in the policy realm by STEM – science, technology, engineering and mathematics, as well as medicine – and those that could reasonably be assumed to be generic "soft" skills. Business executives describe attributes such as communication, social skills, courtesy, responsibility, teamwork and flexibility as critical worker attributes in today's work environment (Robles, 2012). In a review of empirical work on communication skills, Brink and Costigan (2015) find listening to be a critical but often underappreciated ability. Business articles in the mainstream press, when they are not highlighting a lack of STEM KSAs, often suggest that new college graduates are lacking in "basic skills, particularly problem solving, decision making, and the ability to prioritize tasks" (Selingo, 2015, online). Borghans, ter Weel, and Weinberg (2014) demonstrate that sweeping technological and organizational change over the past few decades has made "people skills" – that is, the ability effectively to interact, communicate, care for, and motivate others – increasingly important in the labor market, even though such skills are more likely to receive attention in the psychology literature than in the economics literature.

Due to the importance of STEM, evident in both public policy and economic development literature, the IDOHC includes an identifier to distinguish occupations that emphasize STEM KSAs from those that do not. The IDOHC also includes an identifier to differentiate occupations that require a high degree of so-called "soft" skills from those that do not. To be able to differentiate STEM occupation from non-STEM occupation, it is first necessary to determine which KSAs could logically be identified as STEM competence. To differentiate occupations requiring a higher level of Soft competence from those that do not, it is necessary to determine which KSAs could logically be identified as Soft competence. Although what exactly is included under the STEM heading is often ill-defined, policy, the media, interest groups, educators and research often belie an assumption that STEM jobs require higher levels of skills and higher levels of educational attainment (Rothwell, 2013, Teitelbaum, 2014). Yet, occupations such as engineering technicians (17-3029), computer user support specialists (15-1151), surveying and mapping technicians (17-3031) and embalmers (39-4011) may require above-average STEM skills despite having educational requirements below a bachelor's degree. Engineering technicians, for example, tend to have higher than average skills in math and monitoring, as well as well-above-average skills in active learning and complex problem-solving despite having relatively low educational attainment. Although the focus of much policy and media attention has been on the critical importance of STEM skills, employers asked to list critical skills often cite ones that are softer and more general, such as critical thinking, problem-solving and communication.

Extracting only the KSAs that O*NET defines as involving science, technology, engineering, mathematics or medicine should reveal the understanding and capabilities that employers, the popular media and political leaders mean when they advocate for "STEM skills." Based on O*NET definitions, 35 of the total 120 assessed KSAs can be classified as "STEM skills" – 13 skills, ranging from the obvious (math and science) to the less so (quality control analysis and troubleshooting); 17 knowledge domains (including social sciences, which the National Science Foundation counts among STEM college majors); and 4 abilities (all having to do with numeracy and spatial facility). The highest mean scores across all occupations are found in the knowledge areas of mathematics (11.03) and computers and technology (10.47). The lowest mean scores among the STEM KSAs are for installation skill (0.84), food production knowledge (1.20), programming skill (1.64) and spatial orientation ability (1.82).

Removing these STEM KSAs, as well as those measures defined by O*NET as reflecting psychomotor, physical and sensory capabilities, left a collection of understanding and capabilities that reasonably can be thought of as what is meant by the rather nebulous concept of "soft skills." In this manner, 50 of the total 120 KSA variables were sorted into a "soft skills" grouping – 19 skills, which encompass active listening as well as time management; 14 knowledge domains, including language and philosophy; and 17 abilities, such as oral expression and problem sensitivity. Oral comprehension (15.0) and oral expression (14.70) had the highest mean "soft skills" scores across all occupations, an observation that seems to support and perhaps inform repeated references in the business literature and media regarding the importance of "communication skills." This residual grouping does include some KSAs that may be thought of as more specific, or "harder," than the relationship and cognitive abilities typically identified as "soft skills." Underscoring the more generic, transferable nature of "soft skills," the included knowledge domains tend to have the lowest mean scores among the 50 attributes, reflecting either a lower general intensity or less applicability across occupations, or both. Knowledge of fine arts (1.43), history and archeology (1.87), and foreign language (1.88) had the lowest mean scores across all occupations. The knowledge domains with the highest mean scores – customer and personal service (13.81), English language (13.79), and education and training (11.00) – can be classified as facilitating relationships and understanding. Although school curricula often interpret "communication skills" as written expression, the mean scores suggest that listening and speaking may have even higher and broader value. The business literature and educational policies tout the importance of thinking critically and solving problems, but occupational requirements indicate a demand for workers who are able to recognize problems, prioritize information, and make decisions, as well.

Table 1 provides a list of the 35 STEM and 50 soft KSAs and their mean scores (importance score multiplied by level score) across all O*NET-assessed occupations. As can be seen in the table, included in the list are a number of professional knowledge domains. As noted earlier, many of the social sciences are included in the list of STEM KSAs based on O*NET and NSF definitions. The list of Soft KSAs includes knowledge domains such as history, philosophy and economics. Although these specific disciplines may fall outside broad generalizability typically associated with “soft skills,” such knowledge domains tend to be classified as part of the humanities. Given that many of the soft skills deal with human interactions, disciplines that focus on the study of human culture and condition would seem to be acceptably labeled “soft.” The limitations of two broad KSA dimensions, and the choices to include all skills and abilities not defined by O*NET as physical or psychomotor and to include all knowledge domains drove these groupings.

**Table 1. Mean Scores for 35 STEM and 50 Soft KSAs**

| STEM KSAs | Mean | SD | CV | Soft KSAs | Mean | SD | CV |
|---|---|---|---|---|---|---|---|
| Mathematics(s) | 6.94 | 4.06 | 0.59 | Reading Comprehension(s) | 12.87 | 4.67 | 0.36 |
| Science(s) | 4.35 | 5.25 | 1.21 | Active Listening(s) | 12.87 | 3.67 | 0.28 |
| Operations Analysis(s) | 4.60 | 3.83 | 0.83 | Writing(s) | 10.80 | 4.51 | 0.42 |
| Technology Design(s) | 1.99 | 2.21 | 1.11 | Speaking(s) | 12.40 | 3.99 | 0.32 |
| Equipment Selection(s) | 2.64 | 3.03 | 1.15 | Critical Thinking(s) | 12.77 | 3.60 | 0.28 |
| Installation(s) | 0.84 | 2.10 | 2.49 | Active Learning(s) | 10.11 | 3.84 | 0.38 |
| Programming(s) | 1.64 | 2.54 | 1.55 | Learning Strategies(s) | 8.08 | 3.73 | 0.46 |
| Operation Monitoring(s) | 6.64 | 4.22 | 0.64 | Monitoring(s) | 11.34 | 2.99 | 0.26 |
| Operation and Control(s) | 5.03 | 4.39 | 0.87 | Social Perceptiveness(s) | 10.10 | 3.53 | 0.35 |
| Equipment Maintenance(s) | 2.87 | 3.95 | 1.38 | Coordination(s) | 10.18 | 2.74 | 0.27 |
| Troubleshooting(s) | 4.11 | 3.89 | 0.95 | Persuasion(s) | 8.06 | 3.18 | 0.39 |
| Repairing(s) | 2.78 | 4.03 | 1.45 | Negotiation(s) | 7.10 | 3.02 | 0.43 |
| Quality Control Analysis(s) | 6.02 | 3.81 | 0.63 | Instructing(s) | 8.64 | 3.73 | 0.43 |
| Production and Processing(k) | 6.26 | 4.99 | 0.80 | Service Orientation(s) | 8.63 | 3.22 | 0.37 |
| Food Production(k) | 1.20 | 2.88 | 2.40 | Complex Problem Solving(s) | 10.33 | 3.42 | 0.33 |
| Computers and Electronics(k) | 10.47 | 6.30 | 0.60 | Judgment and Decision Making(s) | 10.68 | 3.41 | 0.32 |
| Engineering and Technology(k) | 6.51 | 6.93 | 1.07 | Time Management(s) | 9.72 | 2.56 | 0.26 |
| Design(k) | 5.66 | 6.29 | 1.11 | Management of Personnel Resources(s) | 7.35 | 3.21 | 0.44 |
| Building and Construction(k) | 3.74 | 5.42 | 1.45 | English Language(k) | 13.79 | 5.91 | 0.43 |
| Mechanical(k) | 7.25 | 6.99 | 0.96 | Foreign Language(k) | 1.88 | 2.29 | 1.22 |
| Mathematics(k) | 11.03 | 5.96 | 0.54 | Fine Arts(k) | 1.43 | 3.97 | 2.78 |
| Physics(k) | 4.41 | 5.30 | 1.20 | History and Archeology(k) | 1.87 | 3.38 | 1.81 |
| Chemistry(k) | 5.02 | 5.22 | 1.04 | Philosophy and Theology(k) | 2.68 | 3.47 | 1.29 |
| Biology(k) | 4.00 | 6.40 | 1.60 | Communications and Media(k) | 5.55 | 4.44 | 0.80 |
| Psychology(k) | 7.10 | 6.53 | 0.92 | Oral Comprehension(a) | 15.00 | 3.63 | 0.24 |
| Sociology and Anthropology(k) | 3.94 | 4.82 | 1.22 | Written Comprehension(a) | 13.21 | 4.51 | 0.34 |
| Geography(k) | 3.91 | 4.92 | 1.26 | Oral Expression(a) | 14.70 | 3.99 | 0.27 |
| Medicine and Dentistry(k) | 3.60 | 6.54 | 1.82 | Written Expression(a) | 11.63 | 4.77 | 0.41 |
| Therapy and Counseling(k) | 3.62 | 5.95 | 1.65 | Fluency of Ideas(a) | 8.63 | 3.49 | 0.40 |
| Telecommunications(k) | 3.47 | 3.41 | 0.98 | Originality(a) | 8.40 | 3.56 | 0.42 |
| Mathematical Reasoning(a) | 7.02 | 4.26 | 0.61 | Problem Sensitivity(a) | 13.09 | 3.66 | 0.28 |
| Number Facility(a) | 6.83 | 3.62 | 0.53 | Deductive Reasoning(a) | 12.64 | 3.76 | 0.30 |
| Spatial Orientation(a) | 1.82 | 2.57 | 1.41 | Inductive Reasoning(a) | 12.07 | 4.00 | 0.33 |
| Visualization(a) | 8.23 | 3.37 | 0.41 | Information Ordering(a) | 11.35 | 2.53 | 0.22 |
| Systems Analysis(s) | 7.38 | 3.72 | 0.50 | Category Flexibility(a) | 10.16 | 2.51 | 0.25 |
| | | | | Memorization(a) | 5.78 | 2.15 | 0.37 |
| | | | | Speed of Closure(a) | 6.19 | 2.35 | 0.38 |
| | | | | Flexibility of Closure(a) | 8.59 | 2.72 | 0.32 |
| | | | | Perceptual Speed(a) | 7.85 | 2.40 | 0.31 |
| | | | | Selective Attention(a) | 9.29 | 1.83 | 0.20 |
| | | | | Time Sharing(a) | 6.76 | 1.86 | 0.28 |
| | | | | Systems Evaluation(s) | 7.22 | 3.76 | 0.52 |
| | | | | Administration and Management(k) | 9.63 | 4.53 | 0.47 |
| | | | | Clerical(k) | 8.52 | 5.22 | 0.61 |
| | | | | Economics and Accounting(k) | 4.31 | 4.24 | 0.98 |
| | | | | Sales and Marketing(k) | 5.32 | 4.79 | 0.90 |
| | | | | Customer and Personal Service(k) | 13.81 | 6.71 | 0.49 |
| | | | | Personnel and Human Resources(k) | 5.91 | 4.13 | 0.70 |
| | | | | Education and Training(k) | 11.00 | 6.13 | 0.56 |
| | | | | Law and Government(k) | 6.48 | 5.04 | 0.78 |

N=942

a=Ability; s=Skill; k=Knowledge

**Using STEM & Soft KSA Bundles to Categorize Occupations by Skill**

As noted earlier, a bias toward "high" skills, especially in terms of STEM activities, is discernible in policy, practice and the popular press (Rothwell, 2013; Teitelbaum, 2014). High skills, both STEM and non-STEM, are assumed to be in greater demand by employers, return greater reward to individual workers, and create greater economic prosperity for cities, regions and nations. "Low" skills, conversely, are assumed to be in need of upgrading in order to access the in-demand higher-skilled jobs and bring economic benefit to individuals, firms and regions. This methodology attempts to explore the KSAs of occupations within this high-low rhetoric. The academic literature, mainstream media and policy arena have also focused to some extent on the importance of "middle skills" in today's economy, but that will be the topic of Chapters VI and VII.

The first step in sorting occupations based on their human capital requirements involved assessing their skill intensity requirements on all 35 KSAs making up the STEM bundle. The mean scores across all 942 O*NET occupations were calculated for each of the 35 STEM KSAs. Occupations that were above the mean score for each STEM KSA were classified as "high" on that particular descriptor and those below the mean were classified as "low." Thus, each of 942 occupations was classified as either high or low on each of the 35 different STEM KSA descriptors. Multiplying the number of "high" KSAs by 2 and each "low" descriptor by 1 allowed for calculating a total STEM score across all 35 KSAs for each occupation. Calculating the mean STEM score across all 942 occupations allowed for categorizing occupations with above-average STEM scores as "high" and those with below-average STEM scores as "low."

Each occupation's STEM label could have been derived by totaling the 35 KSA skill intensity scores and then using that total number to calculate a mean for all 942 occupations. The intermediary step of labeling each occupation as "high" or "low" on each of the 35 STEM KSAs could have been eliminated. However, the intermediary step had the effect of giving more weight to those occupations with a higher number of above-average STEM KSAs than those that may have a fewer number of STEM KSAs with very high mean scores. This reflects an assumption that occupations require a "skill set," not simply one or two high-level competencies. In actuality, either method revealed very similar results in terms of labeling occupations as high or low. Only 78 occupations – 8.28% of the total O*NET sample of occupations – were sorted into different categories based on which approach was used. Main differences were in which occupations topped the list. Somewhat surprisingly, First-line Supervisors of Fire-fighting and Prevention Workers (33-1021.01) required the most above-average STEM KSAs (33), followed by Industrial Production Managers (11-3051.02) and Health and Safety Engineers, Except Mining Safety Engineers and Inspectors (17-2111.01), which both had 32. Based on total score across all KSAs, Engineers, All Others (17-2199.08) topped the list, a finding more in keeping with the STEM skills debate. In fact, the top 14 occupations measured by total score across the 35 STEM KSA descriptors were in engineering. However, Engineers, All Others (17-2199.08) had above-average capability requirements on only 23 of the STEM KSAs. Of the 942 O*NET occupations, 461 were classified as "high STEM" and 481 "low STEM" using the intermediary step.

The same process was used with the bundle of 50 Soft KSAs to again label each of the 942 occupations as either "High Soft" or "Low Soft." This yielded 472 "High Soft" and 470 “Low Soft” occupations. Three occupations required above-average capabilities on all 50 Soft KSAs: Lodging Managers (11-9081.00), Instructional Coordinators (25-9031.00), and Obstetricians and Gynecologists (29-1064.00). Another 10 occupations were above average on 49 Soft KSAs. Conversely, 37 occupations were below average on all 50 KSAs.

Combining the STEM and Soft labels revealed that 28.98% of O*NET occupations (273) require both above-average STEM KSAs and above-average Soft KSAs; 19.96% (188) require High STEM but Low Soft KSAs; 21.02% (198) require Low STEM but High Soft KSAs; and 29.94% (282) require both below-average STEM and Soft KSAs.

**Linking Occupational Skill Sets to Occupational Wage & Employment Data**

Exploring the value of an occupation-based operationalization and measure of human capital requires linking the occupational skill categories derived from O*NET data to occupational wage and employment data available from the OES. For the most part, this was a straightforward process for national level occupational data, given that both O*NET and OES are based on the BLS Standard Occupational Classification (SOC) system. However, there were a number of mismatches between the databases that needed to be addressed. The O*NET system classifies occupations at an 8-digit level, whereas OES categorizes occupations at a 6-digit level. Despite the finer-grained approach, ONET reported only a single series of KSA, education, experience and training data for the vast majority of occupations. Most 8-digit O*NET occupations ended in the suffix .00, but some others had a different suffix (i.e., .01, .02, etc.). However, regardless of suffix, if only one series of data was reported by O*NET, the 8-digit O*NET occupational codes were matched to the 6-digit OES codes. For 65 occupations at the 6-digit OES level, the 8-digit ONET database reported KSA, educational, experience, and training data for two or more distinct occupational subsets. To arrive at a single occupational designation that could be matched to the 6-digit OES occupational code, the mode KSA category, and education, experience and training level was selected. For the few codes with only two occupational subsets or where no mode could be determined, the level for the 8-digit subset ending in .01 was assumed to be most reflective of the 6-digit level code.

A number of occupations in the O*NET database had no corresponding OES data on wages and employment. For seven occupations (29-1022.00 – Oral and Maxillofacial Surgeons; 29-1023.00 – Orthodontists; 29-1061.00 – Anesthesiologists; 29-1063.00 – Internists, General; 29-1064.00 – Obstetricians and Gynecologists; 29-1067.00 – Surgeons; and 29-1069.01 – Physicians and Surgeons, All Other), the OES reported data on wages only for the bottom 10% or 25% of earners. Given that even below-average earners in these extremely high-wage medical fields earned substantially more than average earners for most of the other occupations and given that the purpose of this study is to explore the connection between occupational KSA requirements and wages as an alternative measure to individual educational attainment, the highest wage level reported for these high-wage occupations was substituted for the median wage to allow them to be included in the analysis.

Ultimately, the O*NET occupational data on KSA intensity, as well as education, experience and training expectations, were matched to 2014 OES national wage and employment data for 764 occupations. Roughly 45.8% of these occupations (350) were categorized as requiring above-average STEM KSAs; 44.1% required above-average Soft skills. Examining occupations on both dimensions revealed that 23.8% required above-average STEM and Soft skills; 22.0% required High STEM but below-average Soft KSAs; 20.3% required Low STEM but above-average Soft skills; and 33.9% of the 764 matched occupations required both below-average STEM and soft skills.

**Putting Occupational Skills Sets in Regional Context**

To explore how skill sets vary across regions and how such variation may affect regional economic vitality, the next step in building out the IDOHC was to move beyond the national level to match O*NET data on occupational KSAs to OES data on employment and wages for 403 individual metropolitan statistical areas (MSAs) and New England City and Town Area (NECTA) divisions. It's important to note that not all occupations were represented – or represented in sufficient numbers to be counted – in all MSAs. For a number of MSA-level occupations, the OES database included MSA-specific information on employment but did not provide information on wages. For these occupations, the national median wage was entered as a proxy for the MSA wage. Given that no MSA had more than 25 occupations (out of a possible 764) with missing median wage values and that the occupations were a mix of high and lower wage activities (there were a fair number of higher wage occupations such as anesthesiologists, surgeons and chief executives but also lower wage occupations such as hair stylists and shoe leather workers), inserting the national median wage for these missing values would not seem to add any significant skew.

**Matching Occupational Data to Regional Indicators of Economic Wellbeing**

Previous articles exploring the O*NET data set for its value in understanding the human capital of regions have tended to use wages or employment as dependent variables (Koo, 2005; Maxwell, 2008; Scott, 2009; Yakusheva, 2010; Florida et al., 2012; Rothwell, 2013). Control variables are often similar to those used in other analyses of regional economic growth: MSA population, educational attainment, median household value, labor force participation, share of manufacturing and migration. Higher skills have been shown to gravitate toward or be required more in larger cities (Rauch,1993; Glaeser & Maré, 2001; Glaeser & Saiz, 2003; Moretti, 2004; Gould, 2007; Combes, Duranton,, Gobillon, Puga & Roux, 2008; Elvery; 2010). Human capital theory has served as the foundation for various articles demonstrating – to varying success – that areas with better-educated residents tend to experience better economic performance (Nelson & Phelps, 1966; Lucas, 1988 & 2009; Romer, 1990; Rauch, 1993; Benhabib & Spiegel, 1994; Feser & Bergman, 2000; Feser, 2003; Glaeser & Saiz, 2003; Gottlieb & Fogarty, 2003; Moretti, 2004; Wolfe & Gertler, 2004; Ehrlich, 2007; Holzer, 2008; Goldin & Katz, 2010) Better-educated areas tend to grow faster, attracting both domestic and international migration (Greenwood, 1981; Bartik, 1993; Glaeser, 1994; Simon, 1998; Black & Henderson, 1999; Simon & Nardinelli, 2002; Partridge & Rickman, 2003) Median owner-occupied house value helps control for regions experiencing higher wages, higher growth and often higher costs of living (Capozza, Hendershott, Mack &

Mayer, 2002; Glaeser and Saiz, 2003). Areas where a larger share of working-age adults are actually working should see greater economic performance than those regions where higher shares of eligible workers are idle (Glaeser and Saiz, 2003; Kodrzycki & Muñoz, 2013). Share of manufacturing helps control for the effects of industry mix on economic performance (Glaeser and Saiz, 2003; Blumenthal, Wolman & Hill, 2009; Kodrzycki & Muñoz, 2013).

In addition to median wages, a number of other measures have been used to reflect the economic health of regions. This study explores the effects of an occupation-based measure of regional human capital on five common measures of economic wellbeing: median wage (Feser & Bergman 2000; Feser, 2003; Florida et al., 2012;); percent change in GRP (Quigley, 1998; Cortright, 2001; Gottlieb & Fogarty, 2003; Wolfe & Gertler, 2004; Blumenthal , Wolman & Hill, 2009; Goldin & Katz, 2010); total factor productivity (Rauch, 1991; Moretti, 2004; Ehrlich, 2007; Lerman, 2008); per capita income (Benhabib & Spiegel, 1994; Gottlieb and Fogarty, 2003; Ehrlich, 2007; Baum & Ma, 2007; Lerman, 2008); and poverty (Holzer, 2008; Chrisinger, Fowler & Kleit, 2012).

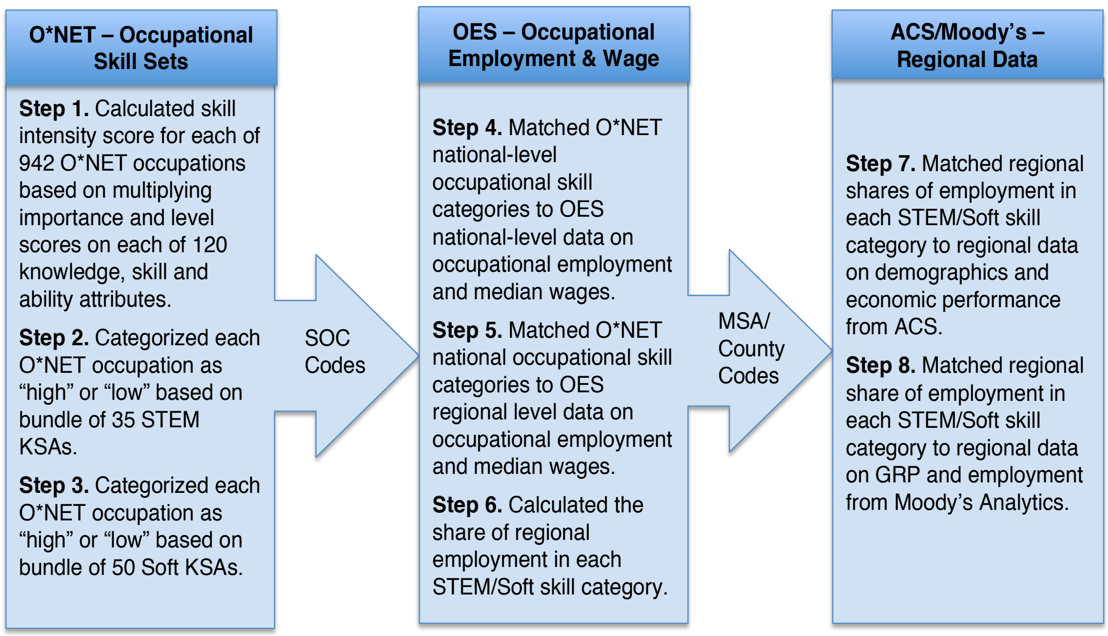
Regional wages were easily gathered from the OES data at the MSA and NECTA levels, as described earlier. Data on GRP and total factor productivity (GRP divided by employment) were drawn from Moody's Analytics, a private-sector provider of national and regional economic data and forecasting models. For the remainder of this work, total factor productivity will be referred to simply as productivity. The Census Bureau's ACS provides data on MSA population, educational attainment, labor force participation, poverty rate, household income and median home value.

Matching the ACS and Moody's data to the OES and O*NET region-level data should have been a straightforward process. The ACS, Moody's and OES all provide data at the MSA level and adhere to the Office of Management and Budget's Standards for Delineating Metropolitan and Micropolitan Statistical Areas and its 5-digit coding system. However, the OES MSA definitions, which reflected the OMB's 2009 MSA definitions, did not match the ACS and Moody's delineations, which reflected the 2013 OMB update. Moreover, the OES data subdivided10 large MSAs into 28 metropolitan divisions, and Boston-Cambridge-Nashua, Mass.-N.H. was divided into 10 New England City and Town Area divisions. These subdivisions did not correspond to the MSA-level data provided by the ACS and Moody's. To address these MSA definitional mismatches, county-level data available from the ACS and Moody's were aggregated to correspond with the OES MSA, metropolitan division and NECTA delineations. However, GRP and employment data were not available for 34 counties – all in Virginia. Therefore, the corresponding MSAs were omitted from the analysis of GRP and productivity.

Ultimately, O*NET and OES data were matched to ACS data for 396 regions.

The following figure summarizes the steps taken in creating the Integrated Database of Occupational Human Capital:

**Figure 1. Summary of Sources & Process in Creating Integrated Database of Occupational Human Capital**




**OPERATIONALIZING OCCUPATION-BASED HUMAN CAPITAL**

The IDOHC enabled different operational definitions of human capital based on different levels of analysis. Chapter IV operationalizes individual-level human capital as the STEM and Soft KSAs required of occupations. Chapter IV explores the private return to occupation-based human capital. The direct way individuals are theorized to benefit from human capital development is through wages. Chapters V, VI and VII operationalize the regional human capital asset as the concentration of regional employment by occupational skill requirements. By matching O*NET data regarding

KSA requirements to each occupation's level of regional employment, a region's human capital asset can be operationalized as the rolled up share of MSA employment in the STEM and Soft skill categories.

## MEASURING & TESTING OCCUPATION-BASED HUMAN CAPITAL

### Independent Variables

**Occupation-based human capital** was measured for Chapter IV as two dummy variables and one categorical variable reflecting occupational STEM and Soft KSA intensity. One dummy variable indicated whether each occupation required above- or below-average STEM KSAs; the other indicated an occupation's below or above-average Soft skill requirements. In addition, the two dimensions were combined to label each occupation as one of four possible STEM/Soft skill categories. The independent variables of interest for the regression analysis described and discussed in Chapter IV were coded as follows:

High STEM – occupations with above-average STEM KSA requirements were coded as 1; those below average were coded as 0.

High Soft – occupations with above-average SOFT KSA requirements were coded as 1; those below average were coded as 0.

High STEM/High Soft – occupations with above-average STEM and above-average Soft KSA requirements were coded as 1; all other categories were coded as 0.

High STEM/Low Soft – occupations with above-average STEM but below-average Soft KSA requirements were coded as 1; all other skill categories were coded as 0.

Low STEM/High Soft – occupations with below-average STEM but above-average Soft KSA requirements were coded as 1; all other skill categories were coded as 0.

**Regional human capital** was measured for the series of regression analyses discussed in Chapter V as six different independent variables reflecting the share of total regional employment various skill categories. The independent variables of interest were:

High STEM – share of 2014 total regional employment in occupations requiring above-average STEM KSAs.

High Soft – share of 2014 total regional employment in occupations requiring above-average SOFT KSAs.

High STEM/High Soft – share of 2014 total regional employment in occupations requiring above-average STEM KSAs and above-average Soft KSAs.

High STEM/Low Soft – share of 2014 total regional employment in occupations requiring above-average STEM KSAs but below-average Soft KSAs.

Low STEM/High Soft – share of 2014 total regional employment in occupations requiring below-average STEM KSAs but above-average Soft KSAs.

Low STEM/Low Soft – share of 2014 total regional employment in occupations requiring below-average STEM KSAs and below-average Soft KSAs.

Although dividing a region's share of employment into four quadrants indicating occupational skill requirements could be expected to introduce collinearity into the model, the four categories do not total to 100% of regional employment. This may be due to the fact that not all occupations have been mapped by O*NET, the OES survey does not include self-employed workers; federal, state and local government workers are not included in this analysis; and the OES suppresses data at the detailed occupational level if inclusion of the data may reveal specific establishments in an MSA. Although the four quadrants did capture greater than 95% of regional employment for some MSAs, they captured little more than two-thirds in others. The average share of regional employment accounted for by the four skill categories was 86.9%.

Regional human capital was also the subject of Chapters VI and VII, but the concept was measured slightly differently. These two chapters attempt to address a debate found in the literature regarding the prevalence and value of “middle skill” jobs. This debate on how exactly to define “middle” continues here, although this research focuses on occupational skill requirements, whereas the literature largely uses educational levels or wages to define jobs in the middle.

Developing the human capital measures for Chapters VI and VII followed similar steps as described for Chapters IV and V. However, for Chapter VI, instead of giving each occupation a label for each of the 35 STEM KSAs and 50 Soft KSAs indicating whether it was above or below the mean and then using those labels to tally a label for the occupation overall as to whether it was High or Low STEM and High or Low Soft, the individual KSAs in the two skill groupings were tallied for each occupation. Occupations for which the total score on the STEM KSAs was 1 standard deviation or more above the mean were labeled “High STEM.” Those occupations that were 1 standard deviation or more below the mean were labeled “Low STEM.” The remaining occupations were labeled “Mid STEM.” The method was repeated for the group of 50 Soft KSAs. The occupational labels on the two skill dimensions were then used to sort the occupations into STEM/Soft categories. No occupation was sorted into the High STEM/Low Soft category, and only three occupations were sorted into the Low STEM/High Soft category. Given the small number of occupations and employment, these two categories were eliminated from the analysis for Chapter 6. The skill variables are more explicitly discussed in Chapter VI.

The methodology explored in Chapter VII mirrored the steps followed for Chapter V. However, instead of giving each occupation a label for each of the 35 STEM KSAs and 50 Soft KSAs indicating whether it was above or below the mean and then using those labels to tally a label for the occupation overall as to whether it was High or Low STEM and High or Low Soft, the individual KSAs were grouped by thirds. Occupations that had scores that were equal to or less than the bottom 33$^{rd}$ percentile on each of the 35 STEM KSAs or 50 Soft KSAs were labeled Low. Occupations with skill requirement scores that were greater than or equal to the 67$^{th}$ percentile for each of the 35 STEM and 50 Soft KSAs were categorized as High. The remaining occupations were assumed to require a Mid level for the individual KSAs of interest. These labels for each relevant KSA were then used to calculate a score reflecting each occupation's overall STEM and Soft skill intensity. Scores in the bottom third across all occupations was labeled as Low STEM or Low Soft. Scores in the top third among all occupation were labeled as High STEM or High Soft. The remaining occupations were labeled as Mid Stem or Mid Soft. Combining the dimensions for each occupation resulted in nine regional human capital variables:

High STEM/High Soft – share of 2014 total regional employment in occupations requiring top-third STEM KSAs and top-third Soft KSAs.

High STEM/Mid Soft – share of 2014 total regional employment in occupations requiring top-third STEM KSAs but middle-third Soft KSAs.

High STEM/Low Soft – share of 2014 total regional employment in occupations requiring top-third STEM KSAs but bottom-third Soft KSAs.

Mid STEM/High Soft – share of 2014 total regional employment in occupations requiring middle-third STEM KSAs and top-third Soft KSAs.

Mid STEM/Mid Soft – share of 2014 total regional employment in occupations requiring middle-third STEM KSAs but middle-third Soft KSAs.

Mid STEM/Low Soft – share of 2014 total regional employment in occupations requiring middle-third STEM KSAs but bottom-third Soft KSAs.

Low STEM/High Soft – share of 2014 total regional employment in occupations requiring bottom-third STEM KSAs and top-third Soft KSAs.

Low STEM/Mid Soft – share of 2014 total regional employment in occupations requiring bottom-third STEM KSAs but middle-third Soft KSAs.

Low STEM/Low Soft – share of 2014 total regional employment in occupations requiring bottom-third STEM KSAs but bottom-third Soft KSAs.

**Dependent Variables**

The impact of occupation-based human capital (the subject of Chapter IV) was measured as:

Median Wage – 2014 OES national median wage for each occupation.

The economics and economic development literature includes various measures of regional economic wellbeing (explored in Chapters V, VI and VII). These range from indicators of economic activity (such as change in GRP and total factor productivity) to indicators of resident welfare (such as per capita income and poverty rate). Andreason (2015) observed that human capital, measured as change in the share of residents with college degrees, may have different effect on different measures. In other words, higher levels of human capital may be association with higher productivity levels but also higher levels of poverty. Higher levels of human capital may increase regional wages but lead to sluggish GRP growth. As such, five separate dependent variables capturing different measures of regional wellbeing were explored in analyses discussed in Chapters V, VI and VII:

Median Wage – median regional wage averaged over 3-year period ending May 2014

% Change in GRP – percent change in GRP from 2009 to 2013

Total Factor Productivity – GRP divided by regional employment in 2013

Per Capita Income – per capita income in 2013

Poverty – share of region population below the poverty threshold in 2013

**Control Variables**

Control measures for Chapter IV, which tests the predictive ability of above-average STEM or above-average Soft KSAs on median occupational wage were:

Education – dummy variable indicating whether the occupation requires a bachelor's degree or higher.

Experience – dummy variable where occupations requiring more than 1 year of experience were coded as 1; occupations requiring less experience were coded as 0.

OJT – dummy variable where occupations requiring more than 3 months on-the-job training were coded as 1; occupations requiring less training were coded as 0.

Six control variables were developed for use in regression models discussed in Chapters V. Two variables were measured as natural logs after a skewness check of normality revealed distributions skewed beyond an acceptable threshold of absolute value of 2:

BA and Above – share of the 2013 regional population age 25 or older with a bachelor's degree or higher.

LN_2013 Pop. – the natural log of regional population in 2013

LN_Net Migration – the natural log of the share of population change from 2009 to 2013 due to net migration (as opposed to births and deaths). (This is measured alternatively for Chapters VI and VII as the ratio of the share of regional population change due to net migration compared to the share of U.S. population change due to net migration.)

Labor Force Participation – the share of the region's population 16 and over in the labor force in 2013

Manufacturing Employment – the share of the region's employment engaged in manufacturing in 2013

Regional to U.S. Median House Value – owner-occupied median house value (which is how the ACS reports the data) for the MSA divided by the U.S. median house value in 2013. This measure helps to control for regions experiencing higher costs of living. However, the direction of the relationship is somewhat ambiguous: Workers earning higher wages may drive up housing costs, but higher housing costs may lead workers to demand higher wages.

Although, guided by the literature, this methodology assumed use of all six control variables, the regression models revealed levels of multicollinearity that exceeded a Variance Inflation Factor threshold of 2.5 for several of the control variables. To address this potentially confounding correlation, only four variables were ultimately used as controls in Chapters VI and VII. Chapter V demonstrates that removal of the variables did not substantially alter the results.

There was one other change in control variables made in the regression analyses discussed in Chapters VI and VII. For these, the logged migration variable was recalculated as a ratio of the share of regional population change due to net migration compared to the U.S. population change due to migration. This change was to facilitate interpretability.

## LIMITS OF USING O*NET TO MEASURE REGIONAL HUMAN CAPITAL

The O*NET database is by no means a perfect tool for exploring the unique blend of talents and expertise contained in individual workers or the specific mix of talents and expertise exhibited in the jobs of each individual region. It is reasonable to question whether the survey responses of relatively few workers can be generalized to represent the knowledge, skills and abilities associated with their occupation nationwide. It is reasonable to question whether such a small number of occupational analysts (8) reviewing the responses of incumbent workers' and, where workers are difficult to survey, the judgment of occupational experts can accurately rate the importance and levels of KSAs across such a broad range of activities.

It is also reasonable to question whether a national database can be assumed to reflect regional workplace dynamics. It is certainly possible, and perhaps likely, that different regions have different skill requirements for occupations. For example, a Machinist (51.4041) job in Birmingham may require a lower set of skills than a Machinist job in Cleveland; a Web Developer (15-1134) working in San Francisco may need to be higher skilled than one working in Austin due to differences in the nature of each region's industrial activity. Yet, as extensive as O*NET's database is, it does not make such regional distinctions; it assumes that a Machinist's or Web Developer's job is largely the same regardless of location. This may not be a wholly accurate assumption regarding regional occupation and industry mixes, but, as noted earlier, the O*NET database aims to serve as "the nation's primary source of occupational information." In other words, part of O*NET's function in delineating occupations is also to standardize them across regions. Therefore, given that O*NET's one KSA level per occupation is all that is available and given that the O*NET database is a tool human resource personnel in Birmingham, Cleveland, San Francisco, Austin and regions throughout the nation can access to help in developing job descriptions, it seems reasonable to assume the O*NET score for each occupation can be used across all regions as a means of calculating skill level.

The annual updates and repeated tweaks make assessments across a number of years challenging. All of these are challenges to the validity of the O*NET database as a tool for regional human capital assessment. However, O*NET's endorsement by hundreds of national trade and professional associations and its mission of serving as the "nation's primary source of occupational information," as the federally sponsored program notes on its website, suggests that the O*NET database may be helping to standardize occupational criteria as information is both pulled out of the marketplace and pushed into the marketplace through resources targeted at helping human resource personnel develop jobs descriptions. The potential weakness of having only eight analysts rate responsible for assessing what is now roughly 1,000 detailed occupations can also be viewed as a strength given that the level of agreement among individual raters has tended to increase with each database iteration. The O*NET provides a counter to what is likely a bias toward, or even self-interest in, educational attainment as a proxy measurement of human capital among academic researchers, ignoring other methods of human capital development and assuming, perhaps wrongly, that classroom learning easily transitions to the workplace. Moreover, similar questions of generalizability could be leveled at the reliance on bachelor's degrees or other measures of educational attainment, given that educational quality, rigor and expectations varies across institutions and fields of study.

With the above cautions in mind, analysis of the O*NET database provides insight into the modern American labor market that should be useful in shaping the current policy focus on increasing the share of the working-age population with advanced education and, specifically, STEM degrees.

Perhaps most importantly, it allows for a shifting of the largely supply-side approach of human capital research, which tends to focus on the educational attainment and skills of individuals, toward a more demand-driven view of human capital revealed through the knowledge, skills and abilities requirements of occupations. Such a shift in understanding has a number of primary advantages:

1.It better reflects the supply-and-demand mechanism of markets.

2. It more accurately captures how human capital of an individual, region, state or nation is deployed directly through jobs in a way that returns economic value, instead of the current more indirect indicator of human capital potential, as indicated by the educational degree of an area's population.

3. It helps return the concept of human capital from the current relatively narrow focus on educational attainment to a broader appreciation of skills sets and understanding however they are obtained, whether through years of experience, practice, self-study or Arrow's learning-by-doing (1962).

# CHAPTER IV

# A STEM TO STERN ASSESSMENT OF OCCUPATIONAL SKILL SETS & WORKER WAGES

In the domain of political speeches, popular media and human capital literature, desirable skill sets are those that are – or are assumed to be – "high," especially in terms of STEM skills (Rothwell, 2013; Teitelbaum, 2014). High skills, both STEM and non-STEM, are assumed to be in greater demand by employers, return greater reward to individual workers, and create greater economic prosperity for cities, regions and nations. "Low" skills, conversely, are assumed to be in need of upgrading in order to access the in-demand higher-skilled jobs and bring economic benefit to individuals, firms and regions. This methodology attempts to explore the KSAs of occupations within this binary high-low structure.

Higher education is assumed to impart or reflect the higher human capital demanded by today's rapidly changing, technologically enhanced workforce. However, there are indications that the heightened policy focus on college degrees masks a wide range of economic return on similar investments of money and time. For example, in an analysis of college majors, Carnevale, Cheah and Hanson (2015) found that top-paying fields paid $3.4 million more over a lifetime than the lowest-paying majors. Entry-level workers with degrees in science, technology, engineering or mathematics – STEM – had median wages of $41,000, compared to $29,000 for workers with humanities degrees. Although a college degree typically imparts protection from unemployment, 2008 graduates with a humanities degree were far more likely to be without a job a year later than graduates with a business degree (13% to 9%, respectively) (Occupational Outlook Quarterly, 2013).

Such variation seems to undermine the usefulness of measuring human capital simply in terms of degree completion. The increasing focus, among students as well as employers and policymakers, on STEM fields is effectively an acknowledgement that certain human capital investments are more economically valuable than others in the labor market. However, even within this subset of college majors, there is considerable variation in wages and employment outcomes. Recent graduates in engineering and computer science claimed the highest starting wages in 2012, but graduates with degrees in mathematics and hard sciences had lower entry-level wages than graduates with business and communications degrees.

Noting that human capital theory fails to provide guidance as to which types of skills are most highly valued at a given time in the economy, Lerman (2008) warned of relying too heavily on educational attainment or even skill levels alone. Workers who are able to apply their skills toward complementing existing skill sets and industrial demands, as well as adapt and support emerging ones, will be more productive and, thus, more valuable (Lerman, 2008). This suggests that the value of human capital is not only in its development but in its deployment.

Occupations are the primary means by which human capital potential of individuals is deployed in the economy. Although Borghans (2001) highlighted the challenges of accurately measuring skill in the workplace, a growing body of literature has attempted specifically to assess differences in the human capital required of occupations (Autor, Levy & Murnane 2003; Feser, 2003; Koo, 2005; Ingram & Neumann, 2006; Markusen, 2006; Maxwell, 2008; Scott, 2009; Bacolod, Blum & Strange, 2010; Yakusheva, 2010; Nolan, Morrison, Kumar, Galloway & Cordes, 2011; Gabe & Abel, 2011; Chrisinger, Fowler & Kleit, 2012; Florida, 2012; Wolf-Powers, 2012; Rothwell, 2013; Wan, Kim & Hewings, 2013; Yamaguchi, 2013). Human capital requirements and wages vary considerably by occupation (e.g., Carnevale, Cheah & Hanson, 2015).

Given the importance of human capital "fit" to return on human capital investment (Yakusheva, 2010), as well as the cost and "friction" (Acemoglu, 1996,1998) associated with acquiring human capital, educational attainment alone seems an insufficient measure for the task. A growing number of studies have set out to explore the heterogeneity of demand for human capital by exploring the bundle of knowledge, skills, abilities (KSAs) and other attributes required within and across occupations. However, there has been very little in the economic development literature that has attempted to explore the effects of STEM skills specifically on regional economic wellbeing. There has been little attempt to match the literature to key human capital policy interventions. Rothwell (2013) was an exception, using knowledge requirements to explore a perceived "high STEM" bias.

There is also evidence in the popular press and in the business literature that the intense policy focus on STEM may be misplaced. Business executives describe attributes such as communication, social skills, courtesy, responsibility, teamwork and flexibility as critical worker attributes in today's work environment (Robles, 2012). Robles concluded that employers place a higher value on soft skills (personal attributes) than hard (technical) skills, but soft skills are often ignored in university curricula and the academic literature. In a review of empirical work on communication skills, Brink and Costigan (2015) found listening to be a critical but often underappreciated ability. Borghans, ter Weel, and Weinberg (2014) demonstrated that sweeping technological and organizational change over the past few decades has made "people skills" – that is, the ability effectively to interact, communicate, care for, and motivate others – increasingly important in the labor market, even though such skills are more likely to receive attention in the psychology literature than in the economics literature. General skills (i.e., communication and problem-solving) and occupation-specific skills have been found to be as important as the overriding focus on technical and "academic skills" (Lerman, 2008). In addition, Gibbons and Waldman (2004) highlighted the importance of task-specific skills to labor demand, particularly job ladders and mobility.

The dearth of literature directly testing the value of STEM skills, especially related to regional economic wellbeing, despite their prominence in policy indicates a significant gap in the literature. Moreover, the policy focus on "hard" or "specific" STEM skills – despite literature indicating the importance of "generic" or "soft" skills – suggests another gap in understanding what human capital investments are rewarded. However, the existing literature does indicate testable hypotheses:

**H1.** Occupations requiring above-average STEM and above-average Soft KSAs pay higher wages than occupations requiring other skill combinations.

**H2.** Occupations requiring above-average STEM but below-average Soft KSAs pay higher wages than occupations with low skill requirements but lower wages than occupations with the highest skill requirements.

**H3.** Occupations requiring below-average STEM KSAs but above-average Soft skills pay higher wages than occupations with low skill requirements but lower wages than occupations with the highest skill requirements.

**H4.** Occupations requiring below-average STEM and below-average Soft skills are hypothesized to pay less than occupations requiring higher levels of skill.

The following table summarizes the hypothesized relationship between occupational skill sets and median wage:

**Table 2. Hypothesized Relationship Between Occupational Skill Sets and Median Wage**

| | Low STEM | High STEM |
|---|---|---|
| **High Soft** | **H3** | **H1** |
| **Low Soft** | **H4** | **H2** |

**METHODOLOGY**

As Borghans (2001) observed, part of the reason some measure of education has become the common proxy for human capital is the availability of data. The U.S. government, as well as other national governments, has long collected data on years of schooling and educational expenditures. However, a federally sponsored database now makes it possible to test an alternative proxy for human capital, one measured at the occupational level.

This chapter builds on the methodology for developing an Integrated Database of Occupational Human Capital (IDOHC), which was described in Chapter III. This chapter focuses exclusively on data available as part of two ongoing projects coordinated or sponsored by the Department of Labor. Data from the Occupational Information Network (O*NET) serves as the foundation for this analysis. O*NET data on occupational knowledge, skill and abilities (KSA) requirements were matched to information on occupational employment and wages available in the Occupational Employment Statistics.

Chapter III provides a detailed description of the process involved in categorizing each occupation on its STEM intensity and on its Soft skill, as well as the specific 35 KSAs making up the STEM group and the 50 KSAs grouped as Soft.

In order to test the groupings through regression analysis, the two STEM and Soft KSA bundles were coded as dummy variables, with 1 indicating “high” and 0, “low.” Given that occupations classified as high STEM may also require a high level of soft KSAs, the occupations were further sorted into four categorical measures: “High STEM/High Soft,” “High STEM/Low Soft,” “Low STEM/High Soft,” and “Low STEM/Low Soft.” In order to enter these categories directly into a regression model, the four categories were recoded into three dichotomous variables, omitting the Low STEM/Low Soft category.

In addition to the skill variables, data on education, experience and training were extracted from the O*NET database to serve as control variables. O*NET's 1-12 coding scheme that ranged from "less than high school" to "post-doctoral" was recoded into a dummy variable with 1 indicating bachelor's degree or higher and 0 indicating less than a bachelor's degree. The 1-12 coding scheme for experience was recoded into a dummy variable with 1 indicating more than a year of experience required and 0 indicating a year or less. O*NET's 1-9 coding scheme for on-the-job training was recoded into a dummy variable with 1 indicating more than 3 months of training required and 0 indicating 3 months or less.

Assessing the usefulness of the four STEM/Soft independent variables as a measure of human capital operationalized at the occupation level required connecting the O*NET data to median occupational wage through the OES database. The human capital literature frequently uses median wage as the dependent variable indicating the effects of educational attainment and other measures of human capital (e.g., Feser & Bergman 2000; Feser, 2003; Carnevale, Smith & Strohl, 2010; Florida, 2012). The OES, a semiannual mail survey, is considered the most accurate and comprehensive source for cross-sectional wage and employment data. Table 3 summarizes the independent, dependent and control variables used in the regression analysis explored in this chapter.

**Table 3. How Variables Were Defined & Calculated for Occupational Human Capital Analysis**

| Variable | Definition | Source |
|---|---|---|
| ***Dependent Variables*** | | |
| Median Wage | Occupational median wage | OES, May 2014 |
| ***Independent Variables*** | | |
| High STEM | Dummy variable where occupations requiring above-average STEM skills = 1; below-average STEM skills = 0 | Calculated using O*NET 19.0 |
| High Soft | Dummy variable where occupations requiring above-average Soft skills = 1; below-average Soft skills = 0. | Calculated using O*NET 19.0 |
| High STEM/High Soft | Dummy variable where occupations requiring above-average STEM skills and above-average Soft skills = 1; any other skill combination = 0. | Calculated using O*NET 19.0 |
| High STEM/Low Soft | Dummy variable where occupations requiring above-average STEM skills but below-average Soft skills = 1; any other skill combination = 0. | Calculated using O*NET 19.0 |
| Low STEM/High Soft | Dummy variable where occupations requiring below-average STEM skills but above-average Soft skills = 1; any other skill combination = 0. | Calculated using O*NET 19.0 |
| ***Control Variables*** | | |
| Education | Dummy variable where occupations requiring BA or higher are coded as 1; occupations requiring less than BA = 0. | Calculated using O*NET 19.0 |
| Experience | Dummy variable where occupations requiring more than 1 year of experience are coded as 1; occupations requiring a year or less experience = 0. | Calculated using O*NET 19.0 |
| OJT | Dummy variable where occupations requiring more than 3 months of on-the-job training are coded as 1; occupations requiring 3 months or less training = 0. | Calculated using O*NET 19.0 |

## RESULTS & DISCUSSION

Table 4 provides frequency statistics for the six KSA variables of interest, as well as the number of occupations requiring a bachelor's degree or higher, and the number of occupations in the two experience and two training categories. It is interesting to note that a slightly higher share of occupations is categorized as High STEM than High Soft. This would seem to reflect the ascendency of technology, engineering and medical activities in the modern economy. Although mean scores for both the bundle of STEM KSAs and the bundle of Soft KSAs were used to sort the occupations, in each case the number of occupations categorized as high make up less than 50% of the total occupations. This suggests that some particularly high scores skewed the mean. When the occupations are further sorted on both skill dimensions, three of the categories capture relatively similar shares of the total number of occupations. However, one category – Low STEM/Low Soft – stands out, capturing nearly 34% of all occupations.

**Table 4. Occupational Skill Categories & Education, Experience & Training Requirements**

| | No. of OCCs | Percent |
|---|---|---|
| **Label Based on 35 STEM KSAs** | | |
| **High** | 350 | 45.8% |
| **Low** | 414 | 54.2% |
| **Label Based on 50 Soft KSAs** | | |
| | **No. of OCCs** | **Percent** |
| **High** | 337 | 44.1% |
| **Low** | 427 | 55.9% |
| **Label Based on STEM & Soft KSAs** | | |
| | **No. of OCCs** | **Percent** |
| **High STEM/High Soft** | 181 | 23.7% |
| **High STEM/Low Soft** | 168 | 22.0% |
| **Low STEM/High Soft** | 155 | 20.3% |
| **Low STEM/Low Soft** | 259 | 33.9% |
| **Education** | | |
| | **No. of OCCs** | **Percent** |
| **BA or Above** | 265 | 34.7% |
| **Less than BA** | 499 | 65.3% |
| **Experience** | | |
| | **No. of OCCs** | **Percent** |
| **1 Year or Less** | 321 | 42.2% |
| **More Than 1 Year** | 439 | 57.8% |
| **On-the-Job Training** | | |
| | **No. of OCCs** | **Percent** |
| **3 Months or Less** | 374 | 49.2% |
| **More Than 3 Months** | 386 | 50.8% |

*N*=764

Although the number of occupations sorted into the skill categories may be relatively similar, there is considerable difference in employment. U.S. employment totaled 131.8 million in 2014, according to the OES data. Of that number, 35.9% (47.4 million workers) were in occupations requiring above-average Soft skills, while only 36.7 million workers (27.8% of all U.S. workers) had jobs requiring High STEM KSAs. Despite the considerable policy and media focus on STEM jobs and degrees, 95.2 million workers nationwide were employed in occupations requiring below-average STEM skills.

Even more concerning, 69.2 million workers (52.5% of all U.S. workers) were employed in jobs requiring below-average STEM and below-average Soft skills.

Table 5 provides the U.S. employment for each of the four KSA categories. Although 27 more occupations were categorized as requiring High STEM and High Soft skills than Low STEM/High Soft skills, Low STEM/High Soft occupations employed 21.6% more workers than High STEM/High Soft occupations. Occupations requiring High STEM but Low Soft KSAs accounted for the smallest share of employment by far, employing only 11.6% of the total U.S. workforce. It's important to note that although only 27.8% of all employment in this two-dimensional way of categorizing occupations was in jobs requiring above-average STEM skills, this is a liberal interpretation of STEM compared to the occupations the BLS identifies as STEM. For this analysis, occupations classified as High STEM may be those that require above-average technical and mechanical KSAs, as well as occupations that require above-average knowledge of social science domains. This inclusion of the social sciences is consistent with the National Science Foundation's definition of STEM. The BLS does not include such occupations. As noted earlier, the BLS estimated employment in 96 identified STEM jobs to be 7.9 million in 2012, projected to grow to 9 million by 2022 (Vilorio, 2014).

**Table 5. U.S. Employment by STEM/Soft Category**

| | Low STEM | High STEM | Total |
|---|---|---|---|
| **High Soft** | 25,990,470<br>*19.7%*<br>(*N*=155) | 21,366,660<br>*16.2%*<br>(*N*=182) | 47,357,130<br>35.9%<br>(*N*=337) |
| **Low Soft** | 69,157,630<br>*52.5%*<br>(*N*=259) | 15,298,390<br>*11.6%*<br>(*N*=168) | 84,456,020<br>64.1%<br>(*N*=427) |
| **Total** | 95,148,100<br>72.2%<br>(*N*=414) | 36,665,050<br>27.8%<br>(*N*=350) | 131,813,150<br>100%<br>(*N*=764) |

The 350 occupations requiring above-average STEM KSAs paid a median wage of $53,775. The 337 occupations requiring above-average Soft KSAs paid a median wage more than $10,000 higher ($64,570). The wage for the High Soft occupations was similar to, but slightly less than, the $67,790 median wage for the 265 occupations requiring a bachelor's degree or higher. Table 6 displays median wages for the four STEM/Soft categories, without controlling for differences in education, experience and training requirements. As can be seen in the table, occupations requiring above-average STEM and above-average Soft skills paid the highest median wages, higher even than the median wage for the occupations requiring at least a 4-year college degree. Moreover, Low STEM/High Soft occupations paid 38.9% more than occupations requiring above-average STEM but below-average Soft skills ($57,360 vs. $41,300).

**Table 6. Occupational Median Wage by STEM/Soft Category**

| | Low STEM | High STEM |
|---|---|---|
| **High Soft** | $57,360 (*N*=155) | $72,220 (*N*=182) |
| **Low Soft** | $29,500 (*N*=259) | $41,300 (*N*=168) |

Median wage was positively correlated with both High STEM (0.32) and High Soft (0.63) KSAs, as well as higher educational requirement (0.62), experience (0.46), and on-the-job training (0.14). (In the case of a dichotomous and a continuous variable, the coefficients produced in SPSS reflect point-biserial correlation.) The correlation provides support for the use of higher education as a proxy for high skill in studies of human capital development. High Soft KSAs were even more correlated with the dummy variable indicating a higher education occupational requirement (0.70). Given the difficulty in measuring qualities such as critical thinking and problem solving, it is understandable that researchers, as well as employers, have come to rely on higher education as an indication of higher levels of human capital. The STEM measure had a positive but weak correlation with the higher education indicator (0.12), suggesting that the STEM variable is capturing occupations that have lower educational requirements.

Table 7 provides the share of occupations in the four STEM/Soft categories that require a bachelor's degree or higher. Supporting the view of higher education as a proxy for higher skill, nearly three-quarters of occupations with the highest skill requirements also required a bachelor's degree or higher. A similar share of occupations requiring below-average STEM but above-average Soft skills also required a 4-year college degree or more. However, less than 7% of occupations in the High STEM/Low Soft category required a bachelor's degree or higher. This would seem to suggest a closer relationship between higher education and above-average Soft skills than above-average STEM ones. It may also indicate that, for many employers, a bachelor's degree helps signal the presence of hard-to-assess Soft skills. What is also interesting is the difference in employment between the High STEM/High Soft and Low STEM/High Soft categories. Clearly, occupations requiring a higher level of education related to STEM employ far fewer workers than those requiring a higher level of education related to Soft skills. This may indicate differences in the nature of work, where technology-intensive activities likely require fewer workers than people-intensive ones.

**Table 7. Share of Occupations by Skill Category Requiring Bachelor's Degree or Higher**

| Skill Category | No. of OCCs BA+ | Share of OCCs BA+ | Share of Employment BA+ |
|---|---|---|---|
| High STEM/High Soft | 132 | 72.5% | 49.5% |
| High STEM/Low Soft | 11 | 6.6% | 9.6% |
| Low STEM/High Soft | 112 | 72.3% | 60.6% |
| Low STEM/Low Soft | 8 | 3.1% | 3.0% |

A linear regression analysis was conducted to test the explanatory power of the KSA variables in predicting median wage, controlling for variables related to education, experience and training requirements. Given that exploring an alternative measure of human capital that is both finer-grained and broader-based than the common proxy of educational attainment is one goal of this research, a two-stage hierarchical model was used to see whether the STEM/Soft variables added explanatory power beyond the dummy variable indicating whether an occupation required a bachelor's degree or higher. The two STEM and Soft KSA dummy variables were entered in Model 2 and then replaced in Model 3 by three dummy variables representing the four possible STEM/Soft categories. As can be seen in Table 8, the High STEM and High Soft variables were both statistically significant, even after controlling for education, experience and training requirements. The two models adding KSA variables to the education, experience and training variables increased explanatory power over the control variables alone, both increasing $R^2$ by 0.08. All three models were significant at the $p < 0.001$ level. The training variable was not significant in any of the models; all other variables in all three models were significant at the $p < 0.001$ level.

As Table 8 indicates, High STEM occupations paid a median wage $10,589 higher than Low STEM occupations, even after controlling for education, experience, training and High Soft occupational requirements. High Soft occupations paid a median wage that was $16,303 higher than occupations requiring Low Soft skills. Although a similar share of occupations required above-average Soft skills (44.1%) compared to occupations requiring above-average STEM skills (45.7%), the wage premium of working in a High Soft occupation was 54% greater than for High STEM. Occupations requiring a bachelor's degree or higher had a median wage $18,054 higher than occupations with lower educational requirements, controlling for skill, experience and training requirements. The large change in *t*-statistic for the OCC BA+ variable suggests collinearity between it and the skill variables. The education variable and High Soft variable were moderately correlated (0.71), but no variable exceeded the 2.5 variance inflation factor threshold suggesting instability in the model (Allison, 2012).

**Table 8. Regression Analysis Models of Relationship Between Occupational Skill Sets And Median Wage**

| | Model 1 | | Model 2 | | Model 3 | |
|---|---|---|---|---|---|---|
| **Variables** | **Coefficient** | ***t*** | **Coefficient** | ***t*** | **Coefficient** | ***t*** |
| Intercept | 33093.91 | 27.07*** | 29255.64 | 24.71*** | 29675.01 | 24.00*** |
| OCC BA+ | 29300.63 | 17.70*** | 18054.19 | 8.96*** | 18041.84 | 8.95*** |
| Experience | 12272.32 | 7.31*** | 7425.48 | 4.60*** | 7749.03 | 4.74*** |
| On-the-Job Training | 1974.29 | 1.31 | -1090.84 | -0.75 | -898.39 | -0.61 |
| High STEM | -- | -- | 10589.67 | 7.30*** | -- | -- |
| High Soft | -- | -- | 16303.87 | 8.41*** | -- | -- |
| High STEM/High Soft | -- | -- | -- | -- | 26864.99 | 11.23*** |
| High STEM/Low Soft | -- | -- | -- | -- | 8977.27 | 4.49*** |
| Low STEM/High Soft | -- | -- | -- | -- | 14643.37 | 6.10*** |
| | $R^2$ = 0.44<br>Adj. $R^2$ = 0.44<br>$F$ (df) = 200.26 (3, 756)*** | | $R^2$ = 0.52<br>Adj. $R^2$ = 0.52<br>$F$ (df) = 165.48 (5, 754)***<br>$R^2$ change = 0.08<br>$F$-change = 63.58*** | | $R^2$ = 0.52<br>Adj. $R^2$ = 0.52<br>$F$ (df) = 200.26 (6, 753)***<br>$R^2$ change = 0.08<br>$F$-change = 138.20*** | |

$N$ = 763
*$p \leq$ .05 level; **$p \leq$ .01 level; ***$p \leq$ .001 level

Model 3 demonstrates how much more occupations requiring some higher level of skill pay over those requiring below-average STEM and below-average soft skills. After controlling for differences in educational, experience and training, occupations requiring High STEM and High Soft skills paid $26,865 more than occupations requiring below-average STEM and below-average Soft skills. Occupations requiring Low STEM but High Soft skills paid $14,643 more, and occupations requiring above-average STEM but below-average Soft skills paid $8,977 more than occupations with the lowest skill requirements, controlling for education, experience and training. All three skill categories were significant at the $p < 0.001$ level. These results suggest that occupation-based human capital, measured as above- and below-average STEM and Soft KSAs, is a useful measure in predicting median wage. As hypothesized, the highest wages were in occupations requiring both above-average STEM and above-average soft skills. The fact that Model 2, with the two dummy categories, explained as much of the variation in occupational wage as the three dummy variables reflecting the four categories of STEM and Soft occupational requirements explored in Model 3 is interesting. This finding suggests that, at least in terms of occupational median wages, the effects of the Soft and STEM variables are additive rather than multiplicative.

The regression analysis largely confirms the four hypothesized relationships between occupational skill requirements and median wages.

**H1.** Occupations requiring above-average STEM and above-average Soft KSAs pay higher wages than occupations requiring other skill combinations. This category paid the highest wages among the four occupational categories, confirming the hypothesis.

**H2.** Occupations requiring above-average STEM but below-average Soft KSAs pay higher wages than occupations with low skill requirements but lower wages than occupations with the highest skill requirements. This category of employment paid the third-highest wages among the four occupational categories. This confirms the hypothesis that such employment would pay more than occupations requiring the least skill and less than occupations requiring the most skill.

**H3.** Occupations requiring below-average STEM KSAs but above-average Soft skills pay higher wages than occupations with low skill requirements but lower wages than occupations with the highest skill requirements. This category of employment paid the second-highest wages among the four occupational categories. This confirms the hypothesis that such employment would pay more than occupations requiring the least skill and less than occupations requiring the most skill. This finding indicates that employers do desire workers with higher Soft skills, as indicated in the business literature, and are willing to pay higher wages for them.

**H4.** Occupations requiring below-average STEM and below-average Soft skills are hypothesized to pay less than occupations requiring higher levels of skill. This category paid the lowest wages among the four occupational categories, confirming the hypothesis.

Given that High Soft occupations accounted for a substantially larger share of employment (35.9%) than did High STEM occupations (27.8%) and given that High Soft/Low STEM occupations paid considerably more than High STEM/Low Soft occupations, these findings suggest that individual workers may be better served by efforts to improve their Soft skills instead of getting too caught up in the current focus on STEM. The findings also indicate the outsized impact of low-skill occupations. Low STEM/Low Soft occupations accounted for only about a third of all occupations but 52.5% of all U.S. employment. The high-skill jobs may command much higher wages, but they also demand far fewer workers.

# CHAPTER V

## LOVELY, LOUSY & LEGACY JOBS: REGIONAL ECONOMIC WELLBEING STEMS FROM HUMAN CAPITAL EMBEDDED IN ITS MIX OF OCCUPATIONS

Policymakers and policies increasingly reflect a view of a region's workforce as its most valuable asset for economic growth. Initiatives to grow educational attainment and increase the quantity of workers with science, technology, engineering and mathematics – STEM – skills represent widespread acceptance of human capital theory, the notion that investments in acquiring knowledge, skills and abilities (KSAs) bring economic reward.

The use of the term "workforce" is important here. It assumes that a region's human capital is somehow engaged in contributing to the local economy and that this important resource is constrained by the human capital requirements of workers' jobs. Given the term, it's not surprising that human capital-derived policies, initiatives and research tend to focus on the attributes of a region's people. Specifically, the educational level of individuals dominates as the measurement of choice, whether exploring differences among workers' wages, firm performance or regional economic growth.

Yet, it is not unreasonable to assume that individuals may have knowledge, skills and abilities that are not realized within the confines of their employment. Numerous articles in the popular press and in the academic literature have sounded the alarm about the recent high level of underemployment, as well as unemployment. Early employment opportunities, or lack thereof, have been shown to have lasting impact on wages and career paths (Oreopoulos, von Wachter & Heisz, 2006). Workers who cannot find work or who are forced to accept jobs below their level of expertise are not capturing the benefits of their human capital investments. Moreover, public resources committed toward human capital investment in workers whose skills do not fit available job opportunities fail to achieve the presumed economic return when these workers leave the region or accept jobs in the region below their level of education or skill.

Guided by theory that largely uses educational attainment to operationalize human capital and that posits technical knowledge as critical to economic growth, regions are adopting somewhat "me-too" policies and initiatives to increase the level of college-going broadly and raise the number of STEM workers specifically. Such policies may serve to elevate a region's human capital capacity, but do little to understand how human capital is deployed throughout a region's economy. Such policies fail to account for differences in industrial presence and heritage that account for regional differences in human capital accumulation and deployment.

Feser (2003) advocated for greater focus on "what regions do rather than make," suggesting that occupational clusters based on human capital requirements may offer important insight into regional economic performance. This research tends to support Feser's observation about the largely underexplored contribution of occupation-based human capital in understanding regional differences. However, findings presented here can more accurately be summarized as what regions do reflects what they make. This simple observation offers important insight for policy and offers some possible explanation for why regional investments in human capital development, measured in terms of educational attainment broadly, may not yield expected returns (Andreason, 2015).

This chapter presents analysis of a measure of the regional human capital asset based on occupational KSA (interchangeably referred to as skill throughout the remainder of this discussion) requirements. An occupation-based measure of human capital has the advantage being a more fine-grained reflection of how human capital is deployed throughout regions than typical educational attainment proxies afford. Moreover, operationalizing regional human capital as a product of a region's mix of occupational requirements allows for better alignment to the current policy focus on STEM skills.

As discussed in previous chapters, higher wages associated with certain occupations in STEM fields, as well as the importance of technical knowledge to economic growth asserted in new growth theory, has led to considerable interest among regional policymakers in "STEM skills." Although the perceived importance of STEM skills are revealed throughout education, economic development and workforce development initiatives – President Obama dubbed expanding the nation's pool of STEM talent an economic imperative – STEM capacity tends not to be specifically addressed in the human capital literature, even in articles addressing specific skills. Rothwell (2013) was an exception, using knowledge requirements to explore a perceived "high STEM" bias.

In addition, business executives describe attributes such as communication, social skills, courtesy, responsibility, teamwork and flexibility as critical worker attributes in today's work environment (Robles, 2012). In a review of empirical work on communication skills, Brink and Costigan (2015) found listening to be a critical but often underappreciated ability. Borghans, ter Weel, and Weinberg (2014) demonstrated that sweeping technological and organizational change over the past few decades has made "people skills" – that is, the ability effectively to interact, communicate, care for, and motivate others – increasingly important in the labor market, even though such skills are more likely to receive attention in the psychology literature than in the economics literature. Resource-based theory would suggest that the interest of the business community results from the importance of these skills in developing an inimitable competitive advantage.

This chapter explores how the regional human capital asset, defined as the mix of occupations STEM and skill requirements, affects regional economic wellbeing. Despite countless initiatives at the regional and state level to upgrade STEM skills in the workforce, little in the economic development literature has attempted to explore, or even define, the importance of STEM skills directly. The assumed "economic imperative" of STEM skills and the importance of Soft skills indicated in the business literature and popular press invite a test of how regional human capital assets contribute to economic growth and other measures of regional wellbeing. As Rothwell (2015) noted, much of the policy focus is preoccupied with the need for "high" skills (i.e., those associated with a bachelor's degree or higher). The clear assumption is that regions with a higher share of workers with high skills (or a higher share of workers with advanced degrees) will have higher economic wellbeing, however measured. Certainly, workers who have managed to graduate college with a degree in one of the STEM fields also likely possess skills, such as reading comprehension, active learning, and reasoning that fall into the Soft skill grouping. This intermingling of skills is reflected in President Obama's inclusion of critical thinking and problem solving in his proposed $2.9 billion 2015 STEM education budget (White House Office of Science & Technology Policy, 2014). The White House synopsis of proposed increased funding for STEM as important for preparing students with 21st century skills demonstrates the need to think about occupations as a mix of skill sets. "21st century skills" are frequently described as involving critical thinking, communication and collaboration, attributes that seem more in line with "generic" Soft skills than more "specific" STEM ones.

Complicating this "fuzzy," to use Markusen's (2003) term, conceptualizing of skills and policies designed to support them is the assumption that regional economies function as national ones do, simply on a smaller scale. Underlying many human capital-shaped initiatives enacted at the regional level is the assumption that upgrading the skill sets of workers will yield economic benefit to the region. How such skills are demanded in the regional economy seems often little appreciated and little explored. This suggests a potentially rich vein of research. Guided by the new growth theory and resource-based theory this chapter will explore the following general hypotheses:

**H1.** A higher share of regional employment in high human capital occupations, measured as above-average STEM skill requirements and above-average Soft KSA requirements, should lead to greater regional economic wellbeing.

New growth theory's modeling of technical knowledge as a driver of economic growth suggests:

**H2.** Regions with a larger share of employment in occupations requiring above-average STEM skills despite below-average Soft skill requirements will also see greater economic benefit.

The business literature and the RBV of the firm suggest that Soft skills are of particular value to employers; as such:

**H3.** Regions with greater shares of employment in occupations requiring above-average Soft skills but below-average STEM KSAs are hypothesized to see economic benefit, although less than regions with a greater share of employment in high-STEM occupations.

**H4.** Regions with a larger share of employment in occupations requiring neither above-average STEM nor above-average Soft skills will be more likely to face threats to their economic wellbeing.

Economic wellbeing can be measured in many ways. Commonly, median wage or employment growth is used to indicate economic health, but, as Andreason (2015) demonstrated, there are many ways of measuring regional economic wellbeing and sometimes these may be in conflict. Regions with a larger share of employment in occupations requiring above-average STEM and soft KSAs are hypothesized to pay higher wages, see greater economic growth, have higher productivity, enjoy higher per capita incomes and experience lower rates of poverty. Table 9 summarizes the hypothesized relationship between regional human capital deployment and regional economic wellbeing. The hypotheses are numbered in order of expected contribution to regional economic wellbeing for each of the five measures of interest.

**Table 9. Hypothesized Effects of Occupation-Based Human Capital on 5 Measures of Regional Economic Health**

**Median Wage, % Change in GRP, Total Factor Productivity & Per Capita Income**

| | **Low STEM** | **High STEM** |
|---|---|---|
| **High Soft** | + (H3) | +++ (H1) |
| **Low Soft** | - (H4) | ++ (H2) |

**Regional Poverty Rate**

| | **Low STEM** | **High STEM** |
|---|---|---|
| **High Soft** | - (H3) | --- (H1) |
| **Low Soft** | + (H4) | -- (H2) |

## METHODOLOGY

This chapter builds on the methodology for developing an Integrated Database of Occupational Human Capital (IDOHC), which was described in Chapter III. The IDOHC concatenated data collected or supported by three federal databases, as well information from the private provider of data analysis, modeling and forecasting, Moody's Analytics. Data from the Occupational Information Network (O*NET) serves as the foundation for this analysis. O*NET data on occupational knowledge, skill and abilities (KSA) requirements were matched to information on occupational employment and wages available in the Department of Labor's Occupational Employment Statistics, as well as demographic and economic data available from the U.S. Census Bureau's 5-year American Community Survey. Moody's Analytics data on gross regional product (GRP) and employment were obtained for the years 2009 and 2013 from Cleveland State University's Center for Economic Development.

Chapter III provides a detailed description of the process involved in categorizing each occupation on its STEM intensity and on its Soft skill intensity based on O*NET data on occupational KSA requirements. From these two skill dimensions, the 942 O*NET occupations were sorted into four categories of primary interest: High STEM/High Soft, High STEM/Low Soft, Low STEM/High Soft and Low STEM/Low Soft. Using Standard Occupational Classification codes shared across the O*NET and OES databases, these occupational skill labels could be matched to employment and wage data at the national and regional levels.

It is important to remember that the O*NET data are collected at the national level. There is no assessment of regional differences in occupational skill requirements. It is certainly possible, and perhaps likely, that different regions have different skill requirements for occupations. For example, a Machinist (51.4041) job in Birmingham may require a lower set of skills than a Machinist job in Cleveland; a Web Developer (15-1134) working in San Francisco may need to be more highly skilled than one working in Austin due to differences in the nature of each region’s industrial activity. Yet, as extensive as ONET’s database is, it does not make such regional distinctions; it assumes that a Machinist’s or Web Developer’s job is largely the same regardless of location. This may not be a wholly accurate assumption regarding regional occupation and industry mixes, but, as noted earlier, the O*NET database aims to serve as “the nation’s primary source of occupational information.” In other words, part of O*NET’s function in delineating occupations is also to standardize them across regions. Therefore, given that O*NET’s one KSA level per occupation is all that is available and given that the O*NET database is a tool human resource personnel in Birmingham, Cleveland, San

Francisco, Austin and regions throughout the nation can access to for help in developing job descriptions, it seems reasonable to assume the O*NET STEM and Soft label for each occupation can be assumed to relatively fairly represent KSA requirements regardless of location. Educational attainment is usually interpreted in much the same way. Although there are likely differences in the what college graduates learned depending on which school they attended, typical measure of human capital – whether years of schooling or possessing a bachelor's degree – is assumed to represent a fairly uniform level of human capital.

Although the O*NET data is not fine-grained enough to assess variation in regional human capital on the basis of potentially different skill requirements for the same occupation in different regions, it is possible to explore variation in regional human capital on the basis of differences in employment concentration of skill sets (for a theoretical discussion of regionally different occupational mixes, see Markusen, 2008.) In this manner, the share of employment requiring above-average STEM or above-average Soft KSAs could be calculated for each MSA. Each region's share of employment in the four combined categories of interest (e.g., High STEM/High Soft) could also be calculated. These derived skill-based measures of regional employment enabled testing of the relationship between occupation-based measures of regional human capital and regional economic performance through a series of regression analyses.

Previous articles exploring the O*NET data set for its value in understanding the human capital of regions have tended to use wages or employment as dependent variables (Koo, 2005; Maxwell, 2008; Scott, 2009; Yakusheva, 2010; Florida, 2012; Rothwell, 2013). However, there are many measures of regional economic wellbeing. In addition to median wage, change in GRP, productivity, per capita income, poverty, change in employment, and income inequality are all measures found in the economics and economic development literature. Although the literature largely suggests an across-the-board positive benefit to greater levels of human capital, Andreason (2015) presented a more nuanced view, where increases in human capital, measured as the share of population with a bachelor's degree or higher, improved some regional economic indicators but had no effect on or worsened others. Given such mixed results, this research analyzed the effects of regional human capital variation on five separate measures of regional economic wellbeing: median wage, percent change in GRP, productivity, per capita income and poverty.

Control variables were pulled from other analyses of regional economic growth: MSA population, educational attainment, median household value, labor force participation, share of manufacturing and migration. Higher skills have been shown to gravitate toward or be required more in larger cities (Rauch,1993; Glaeser and Maré, 1994 & 2001; Glaeser & Saiz, 2003; Moretti, 2004; Gould, 2007; Combes, Duranton, & Gobillon 2008; Elvery; 2010). Human capital theory has served as the foundation for various articles demonstrating – to varying success – that areas with better-educated residents tend to experience better economic performance (Nelson & Phelps, 1966; Lucas, 1988 & 2009; Romer, 1990; Rauch, 1991; Benhabib & Spiegel, 1994; Feser & Bergman 2000; Feser, 2003; Glaeser and Saiz, 2003; Gottlieb and Fogarty, 2003; Swenson & Eathington, 2003; Wolfe & Gertler, 2004; Moretti, 2004; Baum & Ma, 2007; Ehrlich, 2007; Holzer, 2008; Lerman, 2008; Markusen, 2008; Borbely, 2009; Goldin & Katz, 2010) Better-educated areas tend to grow faster, attracting both domestic and international migration (Greenwood, 1981; Bartik, 1993; Glaeser, 1994; Simon, 1998; Black & Henderson, 1999; Nardinelli and Simon, 1996, 2002; Partridge & Rickman, 2003; Yeo & Holland, 2004) Median house value helps control for regions experiencing higher wages, higher growth and often higher costs of living (Capozza, Hendershott, Mack & Mayer, 2002; Glaeser and Saiz, 2003). Areas where a larger share of working-age adults are actually working should see greater economic performance than those regions where higher shares of eligible workers are idle (Glaeser and Saiz, 2003; Kodrzycki & Muñoz, 2013). Share of manufacturing helps control for the effects of industry mix on economic performance (Glaeser and Saiz, 2003; Blumenthal, Wolman & Hill, 2009; Kodrzycki & Muñoz, 2009 & 2013; Friedhoff, Wial, & Wolman, 2010). In addition to median wages, a number of other measures have been used to reflect the economic health of regions. This study explores the effects of an occupation-based measure of regional human capital on five common measures of economic wellbeing: median wage (Feser & Bergman 2000; Feser, 2003; Swenson & Eathington, 2003; Borbely, 2009; Florida, 2012;); percent change in GRP (Quigley, 1998; Cortright, 2001; Gottlieb & Fogarty, 2003; Wolfe & Gertler, 2004; Blumenthal , Wolman & Hill, 2009; Goldin & Katz, 2010); productivity (Rauch, 1991; Moretti, 2004; Ehrlich, 2007; Lerman, 2008); per capita income (Benhabib & Spiegel, 1994; Sanchez & Laanan, 1998; Grubb, 2002; Gottlieb & Fogarty, 2003; Ehrlich, 2007; Baum & Ma, 2007; Lerman, 2008); and poverty (Holzer, 2008; Chrisinger, Fowler & Kleit, 2012).

A check of skewness to test for normality revealed that three control variables had distributions that were skewed beyond an acceptable threshold of an absolute value of 2. These variables included ones where skewed distribution was expected – 2013 estimated population (4.57), share of population change due to net migration (-18.330), and median owner-occupied house value, 2013. The natural log of the population and migration variables was taken to address the skewed distribution. To facilitate interpretability, the skewed median house value measure was recalculated as the ratio of regional median house value to U.S. median house value. Table 10 lists the variables, their definitions and sources.

**Table 10. How Variables Were Defined and Calculated for Regional Human Capital Analysis**

| Variable | Definition | Source |
|---|---|---|
| *Dependent Variables* | | |
| Median Wage | MSA median wage for all occupations | OES, May 2014 |
| % Chg in GRP | Percent change in gross regional product, 2009-2013 | Calculated using Moody's Analytics |
| Productivity | MSA GRP divided by total MSA employment | Calculated using Moody's Analytics |
| Per Capita Income | MSA per capita income for the previous 12 months in 2013 dollars | ACS 5-year estimate, 2013 |
| Poverty Rate | Share of MSA population below the poverty line | ACS 5-year estimate, 2013 |
| *Independent Variables* | | |
| High STEM Employment | Share of MSA employment in occupations requiring above-average STEM skills | Calculated using O*NET 19.0 and OES, May 2014 |
| High SOFT Employment | Share of MSA employment in occupations requiring above-average SOFT skills | Calculated using O*NET 19.0 and OES, May 2014 |
| High STEM/High Soft EMP | Share of MSA employment in occupations requiring both above-average STEM and above-average SOFT skills | Calculated using O*NET 19.0 and OES, May 2014 |
| High STEM/Low Soft EMP | Share of MSA employment in occupations requiring above-average STEM but below-average SOFT skills | Calculated using O*NET 19.0 and OES, May 2014 |
| Low STEM/High SOFT EMP | Share of MSA employment in occupations requiring below-average STEM but above-average SOFT skills | Calculated using O*NET 19.0 and OES, May 2014 |
| Low STEM/Low SOFT EMP | Share of MSA employment in occupations requiring both below-average STEM and below-average SOFT skills | Calculated using O*NET 19.0 and OES, May 2014 |
| *Control Variables* | | |
| Population | Natural log of MSA population, 2013 | Calculated using ACS 5-year estimate, 2013 |
| Migration Share | Natural log of the share of MSA population change due to net migration, 2009-2013 | Calculated using ACS 5-year estimate, 2009 & 2013 |
| Labor Force Participation | Share of the MSA population age 16 and over in the labor force, 2013 | Calculated using ACS 5-year estimate, 2013 |
| Manufacturing Employment | Share of the MSA total employment in manufacturing | Calculated using ACS 5-year estimate, 2013 |
| Region to U.S. Median House Value | Ratio of MSA owner-occupied median house value to U.S. median of $160,000. | Calculated using ACS 5-year estimate, 2013 |
| % Population With BA or Higher | Share of the MSA population age 25 and over with a BA degree or higher, 2013 | Calculated using ACS 5-year estimate, 2013 |

## RESULTS

Table 11 provides the mean, standard deviation, coefficient of variation, minimum and maximum for the variables. Prior to the regression analyses, the natural logs of the three variables with skewed distributions – 2013 population, population change due to migration, and median house value – were calculated and all variables were standardized for ease of interpretation due to different units of measurement. However, the descriptive statistics reflect each variable's measurement before transformation for ease of discussion.

**Table 11. Descriptive Statistics of the Variables[a]**

| Variable | Mean | Std. Dev. | CV | Minimum | Maximum |
|---|---|---|---|---|---|
| % High STEM Employment | 22.6% | 4.1% | 0.18 | 11.5% | 37.0% |
| % High SOFT Employment | 29.0% | 5.6% | 0.19 | 15.9% | 48.1% |
| % High STEM-High Soft Employment | 13.1% | 3.1% | 0.23 | 5.0% | 25.4% |
| % High STEM-Low Soft Employment | 9.5% | 2.6% | 0.27 | 4.1% | 25.1% |
| % Low STEM-High SOFT Employment | 15.9% | 3.1% | 0.20 | 8.1% | 26.2% |
| % Low STEM-Low SOFT Employment | 48.4% | 4.3% | 0.09 | 34.9% | 62.3% |
| 2013 Population | 739,794 | 1,242,150 | 1.68 | 54,061 | 11,926,639 |
| %Population Change due to Migration | 32.1% | 211.7% | 6.60 | -1225.4% | 1551.4% |
| % Labor Force Participation | 63.7% | 4.9% | 0.08 | 44.1% | 75.3% |
| % Employment in Manufacturing | 11.1% | 5.3% | 0.48 | 2.1% | 36.5% |
| Region to U.S. Median House Value | 1.1 | 0.6 | 0.50 | 0.5 | 4.6 |
| % Population with BA or higher | 26.9% | 8.4% | 0.31 | 11.9% | 58.3% |
| Median Wage ($) | $33,644 | $4,713 | 0.14 | $22,780 | $57,430 |
| % Chg in GRP | 6.5% | 8.9% | 1.37 | -9.2% | 70.0% |
| Productivity ($) | $99,552 | $22,579 | 0.23 | $63,244 | $199,263 |
| Per Capita Income ($) | $41,761 | $8,547 | 0.20 | $23,073 | $87,897 |
| % Population Below Poverty Line | 15.8% | 4.4% | 0.28 | 5.5% | 34.8% |

N = 390, except for per capita income (389) GRP and Productivity (379)

a. Descriptives are in raw data for ease of understanding; for the analysis, population, migration and house value variables were logged and all variables were standardized.

The data show a wide variation among the regions, both in terms of economic performance and in terms of human capital, whether measured as advanced education or high or low skills:

- The gap between the regions with the highest and the lowest median wages was nearly $35,000.
- Per capita incomes in the lowest-performing regions were little more than one-quarter that of per capita incomes in the highest-performing regions.
- Although the regions, on average, experienced tepid, but positive, 5-year growth in GRP, some regions saw their economies shrink while others surged.
- GRP to employment was little more than $102,000 across all regions in the sample, but the highest-performing region had total factor productivity that was nearly 3.5 times that of the lowest-performing MSA.
- Poverty in the worst-performing region was nearly double the average for all regions.
- Although the average share of employment in occupations requiring High Soft KSAs was 29%, the region with the highest share had nearly half of all workers employed in such occupations.
- The gulf in terms of High STEM employment was not quite so wide, ranging from 11% to 37% of all regional employment.
- Among three of the four STEM/Soft categories, regions with the highest share had nearly 3 to 5 times the concentration of such employment as regions with the least.

- Little less than half of employment across regions, on average, was in Low STEM/Low Soft occupations, but some regions had as many as 6 out of 10 workers in low-skill jobs.
- As wide as these occupational skill gaps were, they were not as great as for the divide regarding educational attainment: Although, on average, little more than a quarter of each region's population age 25 or over had a bachelor's degree or higher, the gap between the regions with the highest and lowest share was 46 percentage points.

Although dividing a region's share of employment into four quadrants indicating occupational skill requirements could be expected to introduce collinearity into the model, the four categories do not total to 100% of regional employment. This may be due to the fact that not all occupations have been mapped by O*NET, the OES survey does not include self-employed workers; federal, state and local government workers are not included in this analysis; and the OES suppresses data at the detailed occupational level if inclusion of the data may reveal specific establishments in an MSA. Although the four quadrants did capture greater than 95% of regional employment for some MSAs, they captured little more than two-thirds in others. The average share of regional employment accounted for by the four skill categories was 86.9%.

### Testing the STEM/Soft Occupation-Based Measures

Whether the wide variations in regional human capital, measured as occupation-based skill sets, help to explain the wide variation in observed regional economic wellbeing was tested through a series of five regression analyses. As noted earlier, human capital theory and endogenous growth theory posit that areas with greater levels of human capital – whether defined as educational attainment or occupational skill – will see greater economic benefit than regions with lower levels of human capital.

One goal of this research was to explore occupational skill sets matched to political and mainstream rhetoric as a measure of regional human capital. Another goal was to test whether such a measure would have greater explanatory power than the commonly used human capital measure – share of a region's population with a bachelor's degree or higher. As such, a multiple-model approach, allowing each set of variables of interest to enter separately, was adopted to explore whether the occupation-based skill set variables improved explanatory power. For each dependent variable, Model 1 shows results for five control variables: population change due to migration, labor force participation, median house value, manufacturing employment, and 2013 population. Model 2 adds the share of population with a bachelor's degree of higher to the set of control variables. Model 3 provides results for entering the two independent variables measuring the share of regional employment in High STEM occupations and the share of regional employment in High Soft occupations. Model 4 substitutes the share of employment in occupations in the four STEM/Soft categories for the two variables indicating High STEM or High Soft employment separately. The use of educational attainment as the typical proxy measure for regional human capital by definition would be assumed to be related to a region's stock of knowledge, skills and abilities. Not surprisingly, tests of multicollinearity revealed variance inflation factor scores that exceeded the acceptable threshold of 2.5. However, education was not the only variable in the models for which collinearity was a potential problem. The population variable also had a VIF that exceeded the acceptable threshold. As such, those two variables were removed from the regression equation in Model 5. This allowed a tighter focus on the variables of interest.

**Occupation Human Capital Variables Explain Nearly 80% of Wage Variation**

Table 12, below, presents the results of the five linear regression models of independent variables on the dependent variable median wage. The primary focus of this research is on the four variables indicating the share of regional employment in the four STEM/Soft categories, examined in Models 4 and 5. In brief, Model 1 demonstrates that the five control variables, all positively significant, explained more than half of variation in regional median wage, Adj. $R^2$ = .61. Model 2 demonstrates that adding the commonly employed education-based human capital variable, share of population with a bachelor's degree or higher, significantly, but only modestly, improved explanatory power, Adj. $R^2$ = .62. As theory predicts, the education variable was positively associated ($b$ = .18) with regional median wage, as were the five control variables. Model 3 adds the two skill variables indicating the share of regional employment in High STEM occupations and the share of employment in High Soft occupations. Model 3 significantly improved explanatory power, Adj. $R^2$ = .71. The two occupation-based variables were both positively significant at $p < .001$. However, the variable indicating share of the population with a bachelor's degree was no longer significant. Also, the population variable changed signs, indicating a significant negative association. This may be due to instability in the model from multicollinearity among the variables. As can be seen in Model 4, substituting the four STEM/Soft variables significantly improved explanatory power of the model, Adj. $R^2 = .80$. Two of the four STEM/Soft variables were significant, but the education variable changed signs, suggesting instability due to multicollinearity. Model 5 demonstrates that, even after removing two correlated variables, the four control variables and four independent variables of interest explained a significant proportion of variance in median wage, Adj. $R^2 = .79$. All four of the STEM/Soft KSA variables had a statistically significant ($p < .001$) relationship with median wage. The share of regional employment in High STEM/High Soft occupations was positively associated with median wage ($b = .22$), as were the share of High STEM/Low Soft employment ($b = .06$) and the share of Low STEM/High Soft employment ($b = .18$). The share of regional employment in Low STEM/Low Soft occupations was negatively related to regional median wage ($b = -.29$). Employment in Low STEM/Low Soft occupations had a larger effect on regional wage than did the share of employment in High STEM/High Soft occupations. The effect of the share of regional employment in High STEM/High Soft occupations and Low STEM/High Soft occupations were relatively similar. However, the greatest indicator of regional median wage was median owner-occupied house value ($b = .49$).

**Table 12. Regression Analysis Models of Relationship Between Occupational Skill Sets And Regional Median Wage**

| | Model 1 | | Model 2 | | Model 3 | | Model 4 | | Model 5 | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Variables** | **Coefficient** | ***t*** | **Coefficient** | ***t*** | **Coefficient** | ***t*** | **Coefficient** | ***t*** | **Coefficient** | ***t*** |
| Intercept | 0.06 | 2.12* | 0.06 | 2.14* | 0.05 | 1.86 | 0.06 | 2.79** | 0.06 | 2.61** |
| LN_Pop. Change Due to Net Migration | 0.14 | 4.15*** | 0.11 | 2.96** | 0.05 | 1.48 | 0.08 | 2.89** | 0.03 | 1.22 |
| Labor Force Participation | 0.24 | 7.46*** | 0.17 | 4.66*** | 0.11 | 3.24*** | 0.13 | 4.53*** | 0.10 | 4.02*** |
| Region to U.S. Median House Value | 0.53 | 14.75*** | 0.46 | 11.29*** | 0.51 | 14.26*** | 0.49 | 16.54*** | 0.49 | 17.95*** |
| Manufacturing Employment | 0.06 | 2.02* | 0.09 | 2.92** | 0.12 | 4.26*** | 0.10 | 4.21*** | 0.12 | 5.13*** |
| LN_MSA Population | 0.22 | 5.96*** | 0.19 | 4.95*** | -0.11 | -2.49** | 0.17 | 3.736*** | -- | -- |
| Share of Pop. With BA or Higher | -- | -- | 0.18 | 3.82*** | 0.04 | 0.88 | -0.06 | -1.49 | -- | -- |
| High STEM Employment | -- | -- | -- | -- | 0.20 | 5.30*** | -- | -- | -- | -- |
| High Soft Employment | -- | -- | -- | -- | 0.33 | 5.88*** | -- | -- | -- | -- |
| High STEM/High Soft Employment | -- | -- | -- | -- | -- | -- | 0.21 | 5.65*** | 0.22 | 6.69*** |
| High STEM/Low Soft Employment | -- | -- | -- | -- | -- | -- | 0.02 | 0.73 | 0.06 | 2.59** |
| Low STEM/High Soft Employment | -- | -- | -- | -- | -- | -- | 0.08 | 1.81 | 0.18 | 5.22*** |
| Low STEM/Low Soft Employment | -- | -- | -- | -- | -- | -- | -0.33 | -12.55*** | -0.29 | -11.89*** |
| | $R^2$ = 0.61<br>Adj. $R^2$ = 0.61<br>$F$ (df) = 120.42 (5, 383)*** | | $R^2$ = 0.63<br>Adj. $R^2$ = 0.620<br>$F$ (df) = 106.33 (6, 382)***<br>$R^2$ change = 0.01<br>$F$-change = 14.56*** | | $R^2$ = 0.72<br>Adj. $R^2$ = 0.71<br>$F$ (df) = 121.60 (8, 380)***<br>$R^2$ change = 0.09<br>$F$-change = 63.33*** | | $R^2$ = 0.80<br>Adj. $R^2$ = 0.80<br>$F$ (df) = 153.85 (10, 378)***<br>$R^2$ change = 0.18<br>$F$-change = 84.94*** | | $R^2$ = 0.80<br>Adj. $R^2$ = 0.79<br>$F$ (df) = 184.06 (8, 380)*** | |

$N$ = 388 MSAs and NECTAs

*p ≤ .05 level; **p ≤ .01 level; ***p ≤ .001 level

## Higher Employment in High STEM/Low Soft Occupations Linked to GRP Growth

Table 13, below, presents the results of the five linear regression models of independent variables on the dependent variable percent change in GRP, 2009-2013. Model 1 demonstrates that only three of the five control variables were significant, with labor force participation positively associated with percent change in GRP but net migration and median house value negatively associated. The model was significant but explained little of regional variation in percent change in GRP, Adj. $R^2$ = .08. Model 2 demonstrates that adding share of population with a bachelor's degree or higher did not improve explanatory power, Adj. $R^2$ = .08. The education variable was not significant. Model 3, which adds the two skill variables indicating the share of regional employment in High STEM occupations and the share of employment in High Soft occupations, significantly improved explanatory power, Adj. $R^2$ = .27. The two occupation-based variables were both positively significant at $p < .001$. However, the High STEM variable was positively associated with change in GRP, but the High Soft variable was negatively associated. As can be seen in Model 4, substituting the four STEM/Soft variables significantly improved explanatory power, but the model of control and human capital independent variables accounted for less than a third of the variation in GRP, Adj. $R^2$ = .30. Three of the four occupation-based variables were significant, but only the share of regional employment in High STEM/Low Soft occupations was positively associated with percent change in GRP. Model 5, with the two collinear measures removed, still more than tripled the explanatory power of the control variables and the education human capital measure alone and had no loss of power compared to Model 4, Adj. $R^2$ = .30. Two of the STEM/Soft KSA variables had a statistically significant relationship with change in GRP. This finding is somewhat surprising in that it would seem to undercut the theorized relationship between higher concentrations of human capital and regional economic growth. Instead, human capital's effect at the regional level may, at least in part, be due to how it fits industrial demand. The share of regional employment in High STEM/Low Soft occupations was positively associated with change in GRP ($b$ = .43), but the share of employment in Low STEM/Low Soft occupations ($b$ = -.17) was a drag on regional change in GRP. However, High STEM/Low Soft employment had a much greater effect on GRP, based on the coefficients for the standardized variables. Labor force participation ($b$ = .21) had a positive effect on regional GRP growth, while migration had a negative effect ($b$ = -.11), but neither had as large an impact as High STEM/Low Soft employment.

**Table 13. Regression Analysis Models of Relationship Between Occupational Skill Sets And Percent Change in GRP, 2009-2013**

| | Model 1 | | Model 2 | | Model 3 | | Model 4 | | Model 5 | |
|---|---|---|---|---|---|---|---|---|---|---|
| Variables | Coefficient | *t* | Coefficient | *t* | Coefficient | *t* | Coefficient | *t* | Coefficient | *t* |
| Intercept | 0.00 | -0.03 | 0.00 | -0.03 | -0.01 | -0.31 | 0.00 | -0.07 | -0.01 | -0.11 |
| LN_Pop. Change Due to Net Migration | -0.13 | -2.22* | -0.11 | -1.80 | -0.11 | -1.92 | -0.12 | -2.13* | -0.11 | -2.30* |
| Labor Force Participation | 0.28 | 5.11*** | 0.31 | 4.96*** | 0.21 | 3.55*** | 0.16 | 2.71** | 0.21 | 4.07*** |
| Region to U.S. Median House Value | -0.10 | -1.62 | -0.06 | -0.89 | 0.01 | 0.20 | -0.01 | -0.12 | 0.04 | 0.79 |
| Manufacturing Employment | 0.11 | 2.03* | 0.09 | 1.71 | 0.01 | 0.10 | 0.04 | 0.71 | 0.02 | 0.51 |
| LN_MSA Population | -0.11 | -1.71 | -0.09 | -1.37 | 0.03 | 0.44 | 0.06 | 0.60 | -- | -- |
| Share of Pop. With BA or Higher | -- | -- | -0.09 | -1.11 | 0.09 | 1.13 | 0.14 | 1.74 | -- | -- |
| High STEM Employment | -- | -- | -- | -- | 0.61 | 9.46*** | -- | -- | -- | -- |
| High Soft Employment | -- | -- | -- | -- | -0.65 | -6.56*** | -- | -- | -- | -- |
| High STEM/High Soft Employment | -- | -- | -- | -- | -- | -- | -0.18 | -2.35* | -0.11 | -1.66 |
| High STEM/Low Soft Employment | -- | -- | -- | -- | -- | -- | 0.45 | 8.37*** | 0.43 | 9.00*** |
| Low STEM/High Soft Employment | -- | -- | -- | -- | -- | -- | -0.16 | -1.86 | -0.13 | -1.84 |
| Low STEM/Low Soft Employment | -- | -- | -- | -- | -- | -- | -0.18 | -3.25*** | -0.17 | -3.52*** |
| | $R^2$ = 0.09 | | $R^2$ = 0.10 | | $R^2$ = 0.28 | | $R^2$ = 0.32 | | $R^2$ = 0.31 | |
| | Adj. $R^2$ = 0.08 | | Adj. $R^2$ = 0.08 | | Adj. $R^2$ = 0.27 | | Adj. $R^2$ = 0.30 | | Adj. $R^2$ = 0.30 | |
| | *F* (df) = 7.76 (5, 372)*** | | *F* (df) = 6.68 (6, 371)*** | | *F* (df) = 17.96 (8, 369)*** | | *F* (df) = 17.21 (10, 367)*** | | *F* (df) = 20.96 (8, 369)*** | |
| | | | $R^2$ change = .00 | | $R^2$ change = 0.18 | | $R^2$ change = 0.22 | | | |
| | | | *F*-change = 1.23 | | *F*-change = 46.87*** | | *F*-change = 29.89*** | | | |

*N* = 377 MSAs and NECTAs
*p ≤ .05 level; **p ≤ .01 level; ***p ≤ .001 level

## All Occupation Human Capital Variables Affect Regional Variation in Productivity

Table 14, below, presents the results of the five linear regression models of independent variables on the dependent variable 2013 productivity. Model 1 demonstrates that only three of the five control variables – labor force participation, median house value and 2013 population – were significant, all positively associated with regional productivity (Adj. $R^2$ = .44) Model 2 demonstrates that adding share of population with a bachelor's degree or higher did not improve explanatory power, Adj. $R^2$ = .44. The education variable was not significant. Model 3, which adds the two skill variables indicating the share of regional employment in High STEM occupations and the share of employment in High Soft occupations, significantly improved explanatory power, Adj. $R^2$ = .59. The High STEM variable was positively associated with regional productivity ($b$ = .55), but the High Soft variable was negatively associated ($b$ = -.23). As can be seen in Model 4, adding the four STEM/Soft variables significantly increased the explanatory power of the regression equation, Adj. $R^2$ = .65. Removing the two collinear measures (Model 5) did reduce the explanatory power of the regression equation, but the truncated model still explained more than the control variables and education measure, Adj. $R^2$ = .61. All four of the STEM/Soft KSA variables had a statistically significant relationship with productivity in Model 5. The share of regional employment in High STEM/Low Soft occupations ($b$ = .41), the share of regional employment in Low STEM/High Soft ($b$ = .17), and the share of regional employment in High STEM/High Soft occupations ($b$ = .13) were positively associated with productivity. The share of employment in Low STEM/Low Soft occupations ($b$ = -.19) was negatively associated with regional productivity. Median house value ($b$ = .44) was positively related to productivity, while the share of population change due to migration had a smaller effect in the opposite direction ($b$ = -.12).

**Table 14. Regression Analysis Models of Relationship Between Occupational Skill Sets and Regional Total Factor Productivity, 2013**

| | Model 1 | | Model 2 | | Model 3 | | Model 4 | | Model 5 | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Variables** | **Coefficient** | ***t*** | **Coefficient** | ***t*** | **Coefficient** | ***t*** | **Coefficient** | ***t*** | **Coefficient** | ***t*** |
| Intercept | 0.01 | 0.14 | 0.01 | 0.14 | -0.01 | -0.36 | 0.00 | 0.07 | -0.01 | -0.15 |
| LN_Pop. Change Due to Net Migration | 0.00 | 0.08 | 0.02 | 0.45 | -0.01 | -0.31 | 0.00 | 0.11 | -0.12 | -3.27*** |
| Labor Force Participation | 0.18 | 4.31*** | 0.22 | 4.37*** | 0.10 | 2.29* | 0.09 | 2.24* | 0.04 | 1.05 |
| Region to U.S. Median House Value | 0.33 | 6.99*** | 0.36 | 6.75*** | 0.44 | 9.66*** | 0.43 | 10.07*** | 0.44 | 10.83*** |
| Manufacturing Employment | 0.02 | 0.58 | 0.01 | 0.26 | -0.03 | -0.90 | -0.03 | -0.91 | 0.02 | 0.48 |
| LN_MSA Population | 0.36 | 7.38*** | 0.37 | 7.47*** | 0.27 | 4.61*** | 0.47 | 7.18*** | -- | -- |
| Share of Pop. With BA or Higher | -- | -- | -0.08 | -1.28 | -0.05 | -0.83 | -0.09 | -1.53 | -- | -- |
| High STEM Employment | -- | -- | -- | -- | 0.55 | 11.50*** | -- | -- | -- | -- |
| High Soft Employment | -- | -- | -- | -- | -0.23 | -3.15** | -- | -- | -- | -- |
| High STEM/High Soft Employment | -- | -- | -- | -- | -- | -- | 0.07 | 1.25 | 0.13 | 2.71** |
| High STEM/Low Soft Employment | -- | -- | -- | -- | -- | -- | 0.31 | 8.10*** | 0.41 | 11.35*** |
| Low STEM/High Soft Employment | -- | -- | -- | -- | -- | -- | -0.10 | -1.67 | 0.17 | 3.36*** |
| Low STEM/Low Soft Employment | -- | -- | -- | -- | -- | -- | -0.31 | -8.16*** | -0.19 | -5.18*** |
| | $R^2$ = 0.45<br>Adj. $R^2$ = 0.44<br>$F$ (df) = 59.58 (5, 372)*** | | $R^2$ = 0.45<br>Adj. $R^2$ = 0.44<br>$F$ (df) = 50.01 (6, 371)***<br>$R^2$ change = 0.00<br>$F$-change = 1.64 | | $R^2$ = 0.60<br>Adj. $R^2$ = 0.59<br>$F$ (df) = 69.36 (8, 369)***<br>$R^2$ change = 0.15<br>$F$-change = 70.88*** | | $R^2$ = 0.66<br>Adj. $R^2$ = 0.65<br>$F$ (df) = 72.33 (10, 367)***<br>$R^2$ change = 0.22<br>$F$-change = 58.95*** | | $R^2$ = 0.62<br>Adj. $R^2$ = 0.61<br>$F$ (df) = 73.91 (8, 363)*** | |

*N* = 377 MSAs and NECTAs
*p ≤ .05 level; **p ≤ .01 level; ***p ≤ .001 level

## High STEM/Low Soft & Low STEM/High Soft Skills Raise Per Capita Incomes

Table 15, below, presents the results of the five linear regression models of independent variables on per capita income. Model 1 shows that all but one of the five control variables – share of regional employment in manufacturing – were significant, all positively associated with regional per capita income. The model was significant (Adj. $R^2$

= .64). Model 2 demonstrates that adding share of population with a bachelor's degree or higher did not improve explanatory power, Adj. $R^2$ = .64. The education variable was not significant. Model 3, which adds the two skill variables indicating the share of regional employment in High STEM occupations and the share of employment in High Soft occupations, significantly, but very modestly, improved explanatory power, Adj. $R^2$ = .66. The High STEM variable was positively associated with regional per capita income ($b$ = .21), but the High Soft variable was not significant. As can be seen in Model 4, adding the four STEM/Soft variables increased the explanatory power of the regression equation but again very modestly, Adj. $R^2$ = .67. Removing the two collinear measures in Model 5 only negligibly reduced the explanatory power of the regression equation, Adj. $R^2$ = .66. Three of the STEM/Soft KSA variables had a statistically significant relationship with per capita income. The share of regional employment in High STEM/Low Soft occupations ($b$ = .18) and the share of employment in Low STEM/High Soft occupations ($b$ = .17) were positively associated with per capita income. The share of employment in Low STEM/Low Soft occupations ($b$ = -.07) was negatively associated with regional per capita income. Three of the four control variables in Model 5 were positively related to per capita income: net migration ($b$ = .18), labor force participation ($b$ = .21), and median house value ($b$ = .63).

**Table 15. Regression Analysis Models of Relationship Between Occupational Skill Sets and Regional Per Capita Income, 2013**

| | Model 1 | | Model 2 | | Model 3 | | Model 4 | | Model 5 | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Variables** | **Coefficient** | ***t*** | **Coefficient** | ***t*** | **Coefficient** | ***t*** | **Coefficient** | ***t*** | **Coefficient** | ***t*** |
| Intercept | 0.00 | 0.05 | 0.00 | 0.04 | -0.01 | -0.19 | 0.00 | -0.02 | 0.00 | -0.15 |
| LN_Pop. Change Due to Net Migration | 0.25 | 6.84*** | 0.23 | 6.14*** | 0.22 | 5.86*** | 0.21 | 5.77*** | 0.18 | 5.41*** |
| Labor Force Participation | 0.28 | 8.26*** | 0.25 | 6.41*** | 0.21 | 5.29*** | 0.18 | 4.60*** | 0.21 | 6.03*** |
| Region to U.S. Median House Value | 0.59 | 15.80*** | 0.56 | 13.12*** | 0.59 | 14.09*** | 0.58 | 14.03*** | 0.63 | 16.75*** |
| Manufacturing Employment | -0.05 | -1.43 | -0.03 | -1.03 | -0.05 | -1.51 | -0.04 | -1.05 | -0.03 | -0.91 |
| LN_MSA Population | 0.23 | 5.93*** | 0.21 | 5.39*** | 0.17 | 3.29*** | 0.20 | 3.13** | -- | -- |
| Share of Pop. With BA or Higher | -- | -- | 0.07 | 1.51 | 0.08 | 1.63 | 0.11 | 1.97* | -- | -- |
| High STEM Employment | -- | -- | -- | -- | 0.21 | 4.78*** | -- | -- | -- | -- |
| High Soft Employment | -- | -- | -- | -- | -0.09 | -1.34 | -- | -- | -- | -- |
| High STEM/High Soft Employment | -- | -- | -- | -- | -- | -- | -0.04 | -0.83 | 0.04 | 0.90 |
| High STEM/Low Soft Employment | -- | -- | -- | -- | -- | -- | 0.17 | 4.54*** | 0.18 | 5.35*** |
| Low STEM/High Soft Employment | -- | -- | -- | -- | -- | -- | 0.05 | 0.88 | 0.17 | 3.66*** |
| Low STEM/Low Soft Employment | -- | -- | -- | -- | -- | -- | -0.11 | -3.01** | -0.07 | -2.06* |
| | $R^2$ = 0.64 | | $R^2$ = 0.64 | | $R^2$ = 0.67 | | $R^2$ = 0.68 | | $R^2$ = 0.67 | |
| | Adj. $R^2$ = 0.64 | | Adj. $R^2$ = 0.64 | | Adj. $R^2$ = 0.66 | | Adj. $R^2$ = 0.67 | | Adj. $R^2$ = 0.66 | |
| | $F$ (df) = 136.99 (5, 383)*** | | $F$ (df) = 114.91 (6, 382)*** | | $F$ (df) = 94.29 (8, 380)*** | | $F$ (df) = 79.66 (10, 378)*** | | $F$ (df) = 94.37 (8, 380)*** | |
| | | | $R^2$ change = 0.00 | | $R^2$ change = 0.02 | | $R^2$ change = 0.04 | | | |
| | | | $F$-change = 2.28 | | $F$-change = 12.20*** | | $F$-change = 10.19*** | | | |

$N$ = 388 MSAs and NECTAs
*p ≤ .05 level; **p ≤ .01 level; ***p ≤ .001 level

## High STEM/Low Soft Employment Linked to Lower Regional Rates of Poverty

Table 16, below, presents the results of the five linear regression models of independent variables on the share of regional population living below the poverty line. Model 1 shows that all five control variables were significant, all negatively associated with regional poverty. The model was significant and explained about half of regional variation in poverty rates, Adj. $R^2$ = .51. Model 2 demonstrates that adding share of population with a bachelor's degree or higher very slightly improved explanatory power, Adj. $R^2$ = .52. The education variable was positively significant ($b$ = .17), a somewhat unexpected sign because it suggests higher levels of college completion is associated with higher rates of regional poverty. Although this result does not fit the typically rosy picture of increased economic benefit from increased human capital investment, it does support findings in the literature that have associated larger concentrations of higher education with increased regional income inequality (e.g., Andreason, 2015). This may be due to better-educated regions attracting lower skilled migrants who hope to find work in population-serving jobs. Another possible explanation is that labor-saving technological advancements may create greater demand for better educated workers but lead to fewer workers being employed in the region overall. Model 3, which adds the two skill variables indicating the share of regional employment in High STEM occupations and the share of employment in High Soft occupations, significantly, but very slightly, improved explanatory power, Adj. $R^2$ = .53. The High STEM variable was negatively associated with regional poverty rate (*b* = -.15), but the High Soft variable was not significant. As can be seen in Model 4, adding the four STEM/Soft variables slightly increased the explanatory power of the regression equation over what was achieved by simply adding the education variable to the control variables, but the four STEM/Soft variables had no more explanatory power than the two skill variables, Adj. $R^2$ = .53. Removing the two collinear measures in Model 5 actually had showed no loss in explanatory power compared to Model 4, Adj. $R^2$ = .53. Only one of the four skill variables was significant: The share of regional employment in High STEM/Low Soft occupations was negatively associated with poverty level (*b* = -.18), meaning that as the share of such employment went up in a region, the poverty rate went down. All four control variables in Model 5 were also negatively related to poverty: net migration (*b* = -.33), labor force participation (*b* = -.40), median house value (*b* = -.49), and manufacturing employment, (*b* = -.11).

**Table 16. Regression Analysis Models of Relationship Between Occupational Skill Sets And Regional Poverty Rates, 2013**

| | Model 1 | | Model 2 | | Model 3 | | Model 4 | | Model 5 | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Variables** | **Coefficient** | ***t*** | **Coefficient** | ***t*** | **Coefficient** | ***t*** | **Coefficient** | ***t*** | **Coefficient** | ***t*** |
| Intercept | -0.01 | -0.15 | -0.01 | -0.17 | 0.00 | -0.04 | 0.00 | -0.08 | 0.00 | -0.02 |
| LN_Pop. Change Due to Net Migration | -0.35 | -8.37*** | -0.38 | -8.98*** | -0.38 | -8.78*** | -0.37 | -8.50*** | -0.33 | -8.42*** |
| Labor Force Participation | -0.43 | -10.97*** | -0.50 | -11.13*** | -0.47 | -10.27*** | -0.45 | -9.51*** | -0.40 | -9.77*** |
| Region to U.S. Median House Value | -0.43 | -10.00*** | -0.50 | -10.32*** | -0.52 | -10.72*** | -0.52 | -10.60*** | -0.49 | -11.14*** |
| Manufacturing Employment | -0.12 | -3.12** | -0.09 | -2.32* | -0.07 | -1.88 | -0.09 | -2.15* | -0.11 | -2.79** |
| LN_MSA Population | -0.13 | -2.96** | -0.16 | -3.65*** | -0.16 | -2.57* | -0.13 | -1.69 | -- | -- |
| Share of Pop. With BA or Higher | -- | -- | 0.17 | 3.04** | 0.15 | 2.44* | 0.12 | 1.79 | -- | -- |
| High STEM Employment | -- | -- | -- | -- | -0.15 | -2.99** | -- | -- | -- | -- |
| High Soft Employment | -- | -- | -- | -- | 0.10 | 1.29 | -- | -- | -- | -- |
| High STEM/High Soft Employment | -- | -- | -- | -- | -- | -- | 0.02 | 0.30 | 0.03 | 0.64 |
| High STEM/Low Soft Employment | -- | -- | -- | -- | -- | -- | -0.13 | -3.07** | -0.18 | -4.68*** |
| Low STEM/High Soft Employment | -- | -- | -- | -- | -- | -- | -0.03 | -0.37 | -0.10 | -1.79 |
| Low STEM/Low Soft Employment | -- | -- | -- | -- | -- | -- | 0.01 | 0.33 | -0.03 | -0.64 |
| | $R^2$ = 0.52<br>Adj. $R^2$ = 0.51<br>$F$ (df) = 82.16 (5, 383)*** | | $R^2$ = 0.53<br>Adj. $R^2$ = 0.52<br>$F$ (df) = 71.49 (6, 382)***<br>$R^2$ change = 0.01<br>$F$-change = 9.27** | | $R^2$ = 0.54<br>Adj. $R^2$ = 0.53<br>$F$ (df) = 55.72 (8, 380)***<br>$R^2$ change = 0.01<br>$F$-change = 4.5* | | $R^2$ = 0.54<br>Adj. $R^2$ = 0.53<br>$F$ (df) = 44.87 (10, 378)***<br>$R^2$ change = 0.01<br>$F$-change = 2.85* | | $R^2$ = 0.54<br>Adj. $R^2$ = 0.53<br>$F$ (df) = 54.91 (8, 380)*** | |

$N$ = 388 MSAs and NECTAs

*p ≤ .05 level; **p ≤ .01 level; ***p ≤ .001 level

## What the Findings Mean to Regions

Understanding what the findings mean to regions in real terms requires converting the standardized coefficients of the statistically significant occupation-based human capital measures from Model 5 back into their original units of measurement. Holding all other variables constant:

- Regions that had a 1 standard deviation (specifically, 3.1 percentage points) larger share of employment in High STEM/High Soft occupations had a regional median wage that was $7,469 higher and $13,340 greater total factor productivity.
- Regions that had a 2.6 percentage point (1 standard deviation) larger share of employment in High STEM/Low Soft occupations had a median wage $2,086 higher, had growth in GRP that was 2.8 percentage points greater, total factor productivity that was $40,418 higher, a $7,433 higher per capita income, and a regional poverty rate that was 2.9 percentage points lower.

- Regions where the share of regional employment in Low STEM/High Soft occupations was 3.1 percentage points (1 standard deviation) larger had a regional median wage $5,955 higher, $17,023 higher total factor productivity, and a $7,141 higher per capita income.
- Regions where the share of regional employment in Low STEM/Low Soft occupations was 4.3 percentage points (1 standard deviation) larger had a regional median wage that was $9,656 lower, had GRP growth that was 1.1 percentage points lower, had total factor productivity that was $18,616 lower, and had a per capita income that was $2,840 less.

As can be seen in the models, a number of the control variables were shown to have large effect on regional economic wellbeing. To provide some context, holding all other variables in Model 5 equal:

- A 1 standard deviation (4.9 percentage points) increase in labor force participation was associated with a $3,432 increase in regional median wage, a 1.4 percentage point increase in GRP growth, an $8,853 increase in per capita income, and a 6.3 percentage point decrease in poverty.
- A 1 standard deviation (5.7 percentage points) increase in MSA median house value to U.S. median house value was associated with a regional median wage that was $16,452 higher, total factor productivity that was $43,703 higher, per capita income that was $26,309 higher, and a poverty rate 7.7 percentage points lower. As noted earlier, it is difficult to identify the direction of the relationship because, for example, higher wages may lead to higher house

values and higher house values may contribute to higher wages. Given that median house value is a being used as a proxy for regional cost of living, the poverty findings should be interpreted cautiously: a smaller share of residents in regions with comparatively higher median house values may fall below the national poverty level, but their above-poverty wages may simply reflect a higher cost of living.

- A 5.3 percentage point increase (1 standard deviation) in the share of regional employment engaged in manufacturing was associated with a $4,105 increase in regional median wage and a poverty rate that was 1.7 percentage points lower.

**CONCLUSION**

Regional human capital defined as the skill sets required of an area's distinct mix of occupations provides a measure of human capital directly tied to the regional economy. It also provides an opportunity to view regional human capital through a lens befitting the "high skill" or "STEM field" focus of policy interventions and the popular media. The analysis indicates that measuring regional human capital in terms of the share of regional employment in occupations requiring above-average or below-average STEM and Soft KSAs offers greater explanatory power than the typical educational attainment proxy, especially as it relates to indicators of regional economic performance other than median wage. Certainly, there is some overlap between the two approaches, as was demonstrated in Chapter IV, but the more fine-tuned occupation-based measure appears to offer improved understanding of the relationship between human capital investments and regional economic wellbeing.

Similar to the challenges encountered with the educational attainment proxy, regional variation in employment in the four High/Low STEM/Soft occupation categories does not shed light on the various economic indicators in quite the straightforward manner assumed in human capital theory. Table 17 summarizes the findings regarding the statistical significance and the direction of the four STEM/Soft human capital variables on the five dependent variables from Model 5, where variables were removed to address multicollinearity. As can be seen, only one measure – the share of regional employment in High STEM/Low Soft occupations – is associated with desired outcomes for all five economic indicators. Regions that had higher levels of High STEM/Low Soft employment also had higher regional median wages, saw greater growth in GRP, enjoyed greater productivity, had higher per capita incomes, and had less poverty. On the surface, this seems to provide support for policy rhetoric and intervention directed at "high STEM" fields and jobs. However, the High STEM/Low Soft occupations that, at this point in time, are associated with regions experiencing higher wages, GRP growth, higher productivity, higher per capita incomes and lower levels of poverty are actually ones that largely require less than a bachelor's degree.

The only economic measures for which all four STEM/Soft variables were significant, holding all other variables equal, were median wage and total factor productivity. As human capital theory would suggest, the three categories that described some manner of above-average skill were associated with higher wages and higher productivity, while the category indicating below-average STEM and Soft KSAs had a negative effect on wages and total factor productivity. The Low STEM/Low Soft variable was significant on four of the five measures of economic wellbeing, suggesting that regions with a larger share of such employment had lower wages, lower growth in GRP, lower productivity and lower per capita incomes.

**Table 17. Summary of Regression Findings on High/Low Regional Human Capital Concentrations[a]**

| Independent Variable | Regional Median Wage | % Change in GRP, 2009-2013 | Productivity, 2013 | Per Capita Income, 2013 | Poverty Rate, 2013 |
|---|---|---|---|---|---|
| **High STEM/ High SOFT** | +*** | n.s. | +* | n.s. | n.s. |
| **High STEM/ Low SOFT** | +** | +*** | +*** | +*** | -*** |
| **Low STEM/ High SOFT** | +*** | n.s. | +*** | +*** | n.s. |
| **Low STEM/ Low SOFT** | -*** | -*** | -*** | -* | n.s. |

a. Controlling for share of population change due to net migration, labor force participation rate and median house value (Model 5).

* = $p < .05$; ** = $p < .01$; *** = $p < .001$; n.s. = not significant

Thus, as can be seen in Table 17, the regression analyses offer clear support for only one of the four hypotheses:

**H1.** A higher share of regional employment in high human capital occupations, measured as above-average STEM skill requirements and above-average Soft KSA requirements, should lead to greater regional economic wellbeing. This hypothesis was confirmed for two common measure of regional economic wellbeing, median wage and productivity, but the share of regional employment in High STEM/High Soft occupations had no effect on the other three measures of regional economic wellbeing that were tested. Regions with a higher share of employment in High STEM/High Soft occupations had higher wages and higher productivity than regions with a lower share of such employment.

**H2.** Regions with a larger share of employment in occupations requiring above-average STEM skills despite below-average Soft skill requirements will also see greater economic benefit. This hypothesis was confirmed. Regions with a higher share of employment in High STEM/Low Soft occupations had higher wages, greater growth in GRP, higher productivity, higher per capita incomes, and lower poverty rates than regions with a lower share of such employment.

**H3.** Regions with greater shares of employment in occupations requiring above-average Soft skills but below-average STEM KSAs are hypothesized to see economic benefit, although less than regions with a greater share of employment in high-STEM occupations. This hypothesis was confirmed for two common measures of regional economic wellbeing, median wage and per capita income. However, the share of regional employment in High STEM/High Soft occupations had an opposite effect than hypothesized on percent change in GRP and had no effect on the other two measures of regional economic wellbeing that were tested. Regions with a higher share of employment in Low STEM/High Soft occupations had higher wages and higher per capita incomes but lower growth in GRP than regions with a lower share of such employment.

**H4.** Regions with a larger share of employment in occupations requiring neither above-average STEM nor above-average Soft skills will be more likely to face threats to their economic wellbeing. This hypothesis was largely confirmed. Regions with a higher share of employment in Low STEM/Low Soft occupations had lower wages, lower growth in GRP, lower productivity, and lower per capita incomes than regions with a lower share of such employment. Only on one measure of economic wellbeing – regional poverty rate – did the measure lack significance.

In 2013, regions with greater shares of computer programmers and geological and petroleum technicians had better economic performance than regions with software applications developers and mathematicians. Regional employment variation in the typically high-education-requiring High STEM/High Soft occupations that are often the focus of policy makers and media accounts were only associated with higher wages and higher productivity levels. Variation in regional employment in Low STEM/High Soft occupations, which also often come with higher education requirements, were only associated with higher wages and higher per capita incomes. Conversely, such occupations appear to have suppressed GRP growth. As predicted, regions with higher shares of employment in Low STEM/Low Soft occupations suffered because of it: They had lower or even negative GRP growth, lower wages, lower productivity and lower per capita incomes. Frequently, the drag on regional prosperity associated with greater employment in low-skill jobs was as large or larger than the boost regions experienced from having more high-skill employment. This suggests that regions should perhaps be focusing as much attention on offsetting the negative effects of low-skill work as they do anticipating the assumed positive results of more high-skill jobs.

The fact that variation in regional employment in High STEM/Low Soft occupations was the only skill measure associated with desired outcomes on all five economic indicators underscores human capital's role as a factor of production. In other words, its value is in how it matches the needs of the economy. Arguing that too much of economic development strategy was directed at industry instead of occupation, Feser (2003) asserted that more attention should be paid to "what regions do rather than make." However, this research indicates that what regions make by and large determines what they do. Occupations support and reflect industry. This has important implications for policy interventions targeted at increasing human capital supply: Regions – or states and even nations – that invest in developing human capital that does not fit the human capital demanded by the region's industrial mix will likely not enjoy the desired benefit of such expenditures of public resources. Workers with ill-fitting human capital will either accept jobs below the skill levels they have acquired or they will relocate to other regions where the skills they possess match those in demand. Either scenario means the area will see little return on its human capital investment.

# CHAPTER VI

# BETWIXT AND BETWEEN: MIDDLE-SKILL OCCUPATIONS REPRESENT MIXED-BAG ASSET FOR REGIONS

After decades of focus on “high” skills and abilities as a means of fueling the modern economy’s need for “knowledge,” heightened policy and media attention is being paid to jobs that require skills beyond high school but less than a bachelor’s degree. Headlines and program titles often include words like “forgotten,” “overlooked” or “vanishing” and espouse the need to “fix,” “restore,” or “close the gap” in middle skills.

Driving these headlines is an ongoing assertion by employers and trade and professional associations that large numbers of jobs are going unfilled because of an undersupply of workers with suitable skills. A 2011 report sponsored by the Manufacturing Institute suggested the nation was reaching a “Boiling Point,” suggesting as many as 600,000 jobs were going unfilled despite an era of high unemployment. Although there have been numerous articles in the academic and popular press questioning any notion of shortage, concerns over middle skills have launched public and private action: President Obama announced in 2015 a $60 billion effort to provide two years of community college tuition free to qualified students; a $100 million TechHire initiative; and $175 million in apprenticeship grants. J.P. Morgan Chase & Co. launched a $250 million 5-year "New Skills at Work" initiative to prepare workers for "high growth, high-demand, middle-skill jobs." Moreover, many states have initiatives targeting the "forgotten" middle.

Although the primary benefactors of such initiatives presumably are the workers who are assumed to earn higher wages for their in-demand middle skills and the businesses who purportedly need workers with middle skill sets to thrive, policies and initiatives targeting middle skill development assume that economic growth stems from such deliberate investments. Many of these initiatives explicitly or implicitly target manufacturing and technical fields. The efforts appear to acknowledge that much of the intense policy and media focus over the past three decades on science, technology, engineering and mathematics – STEM – fields had reflected a bias toward "high-skill" jobs, defined as those requiring a bachelor's degree or higher, and had ignored the importance of jobs in such fields that required less than a college degree. Despite an overt focus on specific, technical skills, improving the levels of generic, "soft" skills, such as communication and critical-thinking, presumably are supported.

Chapter V suggests that occupations requiring skill sets that are not at the highest end of the skills spectrum pay higher wages than occupations with low skill set requirements. Regions with a larger share of employment in occupations requiring skills that are neither the highest nor lowest exhibited better performance on certain economic indicators in 2013 than did other regions.

As noted earlier, "middle-skill" is largely defined at the job level by educational credential: Jobs requiring less than a bachelor's degree but more than high school diploma are considered the labor market middle. According to a report from the National Skills Coalition, 54% of all jobs in 2012 fit such a definition. This practice of defining "skill" in terms of educational credential would seem to obscure a wide variation in workforce demand, wage and associated economic outcomes. The fact that so much policy attention is on reported and projected challenges in the manufacturing, technology and health-care sectors would seem to support this observation.

This chapter presents a refined conceptualization of "middle skill" while also acknowledging the policy primacy of STEM. The research draws on the specific knowledge, skills and abilities (KSAs) required of occupations to sort regional occupational employment on the basis of "high," "middle" and "low" STEM and "high," "middle" and "low" Soft. Wide variation in regional employment is clearly evident across the various occupational skill sets.

This chapter proceeds with an overview of the middle-skill literature, focusing on the benefits to regional economies. Section 3 provides a synopsis of the methodology detailed extensively in Chapter III. Section 4 presents the results a series of regression analyses. Section 5 puts the findings into regional context. Discussion of policy implications, limitations and opportunities for further research are addressed in Chapter VIII.

## LITERATURE REVIEW

Public-sector and private-sector rhetoric and initiatives directed at growing the number of middle-skill workers give the impression that today's labor market resembles a snake that swallowed a rat, large in the middle but tapered on both ends. The literature paints two decidedly different pictures: One portrays job demand as an hourglass, with growth occurring at the top and bottom while jobs in the middle have been “hollowed out” (Autor, Katz & Kearney, 2006; Jaimovich & Sui, 2012). The other image suggests the U.S. labor market resembles a pear, with a thicker set of jobs in the middle than at the top but with the largest girth appearing at the bottom (Holzer & Lerman, 2007 & 2009). Despite differing views about middle girth, both Autor, Katz and Kearney (2006) and Holzer and Lerman (2007 & 2009) observed potentially troubling prospects of jobs becoming increasingly concentrated at the high and low ends of the skills spectrum.

Middle-skill jobs are often defined by their wages relative to jobs paying more or less or by their educational requirements (Autor, Katz & Kearney, 2006; Goos & Manning, 2007; Autor, 2010; Holzer & Lerman, 2007 & 2009). Higher wages are largely assumed to reward higher levels of skill, and lower wages reflect lower skill demands. However, this would seem to ignore the effects of supply and demand. Jobs requiring relatively high skill may be relatively low-paying because a plentiful supply of candidates may be drawn to the job because of social prestige or psychic income. Jobs that require more than a high school diploma but less than a bachelor’s degree are taken to represent middle requirements of skill. However, neither measure assesses skill sets directly. Moreover, they mask broad variation. Although higher wages broadly are associated with higher levels of educational attainment, a substantial number of occupations, particularly in technical fields, pay higher wages than occupations requiring a bachelor’s degree or higher (Carnevale, Smith & Strohl, 2010; Carnevale, Smith & Melton, 2011).

This discrepancy highlights the challenge arising from the common practice of using educational attainment, or lack thereof, to infer skill. Somewhat problematic proxies move from theoretical to real implications when they are used to shape policies and programs. Overreliance on educational attainment makes it difficult to identify specific in-demand skills and where gaps in supply may lie (Lerman, 2008). Rothwell (2013) drew on actual knowledge requirements of occupations to explore an apparent higher-education bias in research and policies promoting STEM skills. Rothwell (2013) noted the importance of a “hidden” set of middle STEM skills to regional median wages and other performance measures.

Much of the recent political interventions focusing on middle-skill jobs appear to have arisen out of a number of articles and reports, such as the Manufacturing Institute’s “Boiling Point?” paper, sounding alarms about current or looming shortages of critical middle skills. Such reports have been met with skepticism among scholars despite their seeming success in generating government action (Cappelli, 2012; Davidson, 2012; Osterman & Weaver, 2014). Krugman (2014) labeled any suggestion of a structural problem contributing to a shortage of skills as a “zombie idea” that continued to live on even though it should have been “killed by evidence.” Cappelli (2012) postulated that the shortage in technical skills may actually stem from a "technical" issue: Rigid software programs and keyword searches filter out many candidates who would otherwise qualify. Moreover, despite programs defining middle-skill jobs as those requiring education beyond high school, Osterman and Weaver (2014) found that only 38 percent of manufacturers required math skills beyond the high school level.

Despite this preponderance of skepticism, Holzer (2015) offered up a “tale of two middles”: The traditional “middle” of good-paying construction and production jobs requiring little in terms of formal education have seen substantial declines, but the new middle includes a number of growing occupations in health care and mechanical maintenance that require higher levels of education. Holzer (2015) also noted a rise in educational demands for traditional low-skilled work.

Technological change may lie at the heart of this observed “up-skilling” or “up-credentialing” of occupations, as clerical workers and dispatchers are now expected to use increasingly sophisticated computer programs and mechanics service increasingly complex machines. However, technological change that emanates from investment in higher levels of knowledge, skill and other human capital and that drives economic growth, as described by Romer (1990), frequently leads to labor-saving devices and automations that remake work environments and eliminate jobs (Autor, Levy & Murnane, 2002 & 2003). This double-edged sword of technological advancements – wrought of human capital but potentially ravaging labor – has been particularly visible in the manufacturing sector, where productivity increased roughly 4 percent annually from 1990 to 2007, but employment plummeted by some 6 million workers between 2000 and 2009, according to the Bureau of Labor Statistics. Automation has been shown to disrupt and even de-skill occupations (Cappelli, 1996; Goldin & Katz, 1998; Autor, Levy & Murnane, 2002 & 2003; Goos & Manning, 2007; Brynjolfsson & McAfee, 2011; Markoff, 2012; Jaimovich & Siu, 2012; Autor & Dorn, 2013), as increasingly complex and sophisticated machines and computer programs eliminate the need for math skills, facilitate decision-making and diagnose mechanical problems.

Technological change doesn't "just happen." It is frequently incremental and complementary of existing technology and skills (Acemoglu, 1998). Moreover, the ubiquity of computer technology may lead political and business leaders, as well as researchers, to make assumptions about demands for increasingly higher levels of skill and education. An observed positive correlation between computer use and demand for more highly skilled workers is often interpreted as indicative of skill-biased technological change, where technology both complements and enhances the productivity of higher skilled workers (Acemoglu, 1998; Berman, Bound & Machin, 1998; Card & DiNardo, 2002) and thus makes them more valuable to employers.

Although skill-biased technological change may lie at the heart of government programs and interventions targeted toward growing the share of highly skilled workers, especially in STEM fields, the phenomenon is often accompanied by particularly thorny policy challenges at the lower end of the skills spectrum. Technology that allows high-skilled workers to be more productive, enabling them to command higher wages, often eliminates routinized work typically requiring a mid-level of skill. As a result, higher levels of unemployment and higher wage inequality are frequently associated with skill-biased technological change (Berman, Bound & Machin, 1998).

Crafting policies designed to seize on the benefits of changing technologies is further confounded by challenging dynamics: The workplace effects of technological change may be somewhat difficult to predict and harness. Noting disagreement among economists regarding what exactly constituted "skill-biased technological change," Autor, Levy and Murnane (2002) found that computerization eliminated jobs through rules-based automation, but also led to a reorganization of non-computerized activities into specialized jobs requiring more specialized skills. Although industries with rapid technological change may pay a larger wage premium for higher levels of education than industries experiencing less technological change, the wage premium often only accrues to workers with the highest level of educational attainment (Choi & Jeong, 2007).

Aside from the potential policy challenges that accompany technological changes, there are other reasons to question the intense focus on growing the supply of workers with technical, often specialized, skills. Employers tend to talk more about "character" issues than specific academic and technical skills (Cappelli, 2012). Moreover, employers indicate a desire for workers with higher levels of communication and problem-solving skills (Robles, 2012). Similar to the higher-education bias noted by Rothwell (2013), the value of such "soft" skill sets are often assumed to be at the high end of the spectrum.

The middle-skill literature, combined with the human capital and new growth literature discussed in earlier, indicates a gap in understanding, largely due to how "middle skill" is defined and operationalized. Measuring middle skill as an educational middle ground between high school completion and bachelor's degree completion seems of rather dubious value: According to 2014 Occupational Employment Statistics data, only 23.6% of total U.S. employment had a mode educational requirement of an associate's degree (8.7%), some college (7.6%) or post-high school credential (7.4%). Moreover, wages for occupations requiring some college or post-high school credential were higher, on average, than for occupations requiring only a high school diploma or less, but they were still below the national average. Policies are increasingly focused on middle STEM skills, but the literature rarely tests such skills directly. An exception is Rothwell (2013), who identified significant differences in demand for mid-level knowledge in various STEM domains across regions.

Moreover, the policy focus on "hard" or "specific" STEM skills despite literature indicating the importance of "generic" or "soft" skills suggest another gap in understanding what human capital investments are associated with improved regional economic performance.  However, the existing literature does indicate a general hypothesis:

**H1.** A higher share of regional employment in occupations requiring a middle-level of STEM skills and a middle-level of Soft KSAs should be associated with positive regional economic performance.

Similar to Chapter V, five measures of regional economic wellbeing will be used to assess the occupation-based measures of the regional human capital asset. Regions with a larger share of employment in occupations requiring mid-level STEM and mid-level Soft KSAs are hypothesized to pay higher wages, see greater economic growth, have higher productivity, enjoy higher per capita incomes and experience lower rates of poverty. Table 18 summarizes the hypothesized relationship between regional human capital deployment and regional economic wellbeing:

**Table 18. Hypothesized Relationships Between High/Mid/Low Occupation-Based Human Capital Measures and Economic Indicators**

**Median Regional Wage; Change in GRP; Productivity & Per Capita Income**

| | Low STEM | Mid STEM | High STEM |
|---|---|---|---|
| High Soft | ++ | +++ | ++++ |
| Mid Soft | + | ++ | +++ |
| Low Soft | - | + | ++ |

**Regional Poverty Rate**

| | Low STEM | Mid STEM | High STEM |
|---|---|---|---|
| High Soft | -- | --- | ---- |
| Mid Soft | - | -- | --- |
| Low Soft | + | - | -- |

## METHODOLOGY

This chapter builds on the methodology for developing an Integrated Database of Occupational Human Capital (IDOHC), which was described in Chapter III. For this study, each skill in the STEM and Soft groupings were sorted into three categories: "high," "mid" and "low." This step, building but slightly amending earlier work dividing the skills into only "high" and "low," was guided by literature suggesting that a high skills bias in policy, practice and the literature has overlooked the important role "middle skills," especially in STEM fields, play in the economy (Holzer, 2008; Rothwell, 2013). An occupation was categorized as High STEM if its total score across all 35 STEM KSAs was at least 1 standard deviation above the mean STEM score for all occupations. An occupation was categorized as Low STEM if its total score across all 35 STEM KSAs was 1 standard deviation or more below the STEM score for all occupations. The remaining occupations were categorized as Mid STEM. The process was repeated for the 50 Soft KSAs.

Of the 942 occupations in the O*NET sample, 161 were classified as "High STEM," 620 were labeled "Mid STEM," and 161 were categorized as "Low STEM." Using the same technique for the collection of 50 Soft KSAs yielded 191 occupations were categorized as "High Soft," 557 "Mid Soft" and 194 "Low Soft" occupations. Given that many occupations classified as high STEM were also likely to require a high level of critical-thinking, problem solving and other soft KSAs, the occupations were further sorted into nine categorical measures: "High STEM/High Soft," "High STEM/Mid Soft," "High STEM/Low Soft," "Mid STEM/High Soft," "Mid STEM/Mid

Soft," "Mid STEM/Low Soft," "Low STEM/High Soft," Low STEM/Mid Soft," and "Low STEM/Low Soft."

The steps taken to match the occupational skill categories to data on occupational employment and wages available from the Department of Labor's Occupational Employment Statistics, as well as regional demographic and economic information available from the Census Bureau's American Community Survey, are detailed in Chapter III. In brief, the 942 O*NET occupations were matched to OES employment and wage data for 764 occupations: 106 High STEM, 515 Mid STEM, and 143 Low STEM; 139 High Soft, 439 Mid Soft, and 186 Low Soft. Table 19 provides the number of occupations sorted into the nine categories on the two skill dimensions, as well as the total employment in each category. No occupations were sorted into the High STEM/Low Soft category, indicating that occupations that require a high level of STEM knowledge and ability also require at least a moderate amount of communication and critical thinking skills.

**Table 19. Occupations by High/Mid/Low STEM/Soft Category**

| | Low STEM | Mid STEM | High STEM | Total |
|---|---|---|---|---|
| **High Soft** | 3<br>*0.4%* | 103<br>*13.5%* | 33<br>*4.3%* | 139<br>*18.2%* |
| **Mid Soft** | 81<br>*10.6%* | 285<br>*37.3%* | 73<br>*9.6%* | 439<br>*57.5%* |
| **Low Soft** | 59<br>*7.7%* | 127<br>*16.6%* | 0<br>*0.0%* | 186<br>*24.3%* |
| **Total** | 143<br>*18.7%* | 515<br>*67.4%* | 106<br>*13.9%* | 764<br>*100.0%* |

*N*=764

Table 20 provides the total U.S. employment by STEM/Soft skill category. As can be seen, although the category Mid STEM/Mid Soft accounts for 37.3% of all occupations, it only accounts for 30.9% of employment. Only 7.7% of occupations are categorized as Low STEM/Low Soft, but nearly 21% of employment is in the lowest skill category. High STEM/High Soft accounts for 4.3% of all occupations but only 1.7% of employment. This supports findings in the literature that high-skill jobs tend to employ fewer workers and low-skill occupations tend to employ more. Only 7.1% of U.S. employment is in occupations requiring STEM skills 1 standard deviation above the mean, but 44.1% of employment is in occupations requiring Low STEM capabilities. That compares to 29.9% of employment in occupations requiring Low Soft skills.

**Table 20. U.S. Employment by High/Mid/Low STEM/Soft Category[a]**

| | Low STEM | Mid STEM | High STEM | Total |
|---|---|---|---|---|
| **High Soft** | 115,520 | 11,719,650 | 2,182,010 | 14,017,180 |
| | *0.1%* | *8.9%* | *1.7%* | 10.6% |
| **Mid Soft** | 30,389,400 | 40,747,210 | 7,226,930 | 78,363,540 |
| | *23.0%* | *30.9%* | *5.5%* | 59.4% |
| **Low Soft** | 27,677,660 | 11,754,770 | 0 | 39,432,430 |
| | *21.0%* | *8.9%* | *0.0%* | 29.9% |
| **Total** | 58,182,580 | 64,221,630 | 9,408,940 | 131,813,150 |
| | *44.1%* | *48.7%* | *7.1%* | *99.9%* |

a. Total U.S. 2013 employment = 131,974,860.

As with Chapter V, the IDOHC provided the framework for a series of regression analyses exploring the effects of regional employment categorized by STEM/Soft occupations on measures of regional economic wellbeing. The series of regression analyses use the same five measures of regional economic wellbeing – median wage, change in GRP, total factor productivity, per capita income and poverty rate – used in Chapter V. This chapter also makes use of the same control variables as used in Model 5 in the previous chapter, except for one change in calculation. To facilitate interpretability, the migration variable was recalculated. Instead of the natural log of the share of population change due to net migration, the variable was calculated as the ratio of regional share of population due to migration compared to the U.S. population change due to migration. As discussed in Chapter V, the natural log of 2013 population was shown to have unacceptably high levels of correlation with the human capital variables so it was removed from the analysis in Model 5 to reduce collinearity. As such, regional population was not used as a control variable for the regression analyses presented in this chapter.

Table 21 lists the variables, their definitions and source. Due to the small share occupations and employment in the Low STEM/High Soft category, that variable was also omitted from the regression analyses, leaving seven occupational variables to capture variation in the regional human capital asset.

**Table 21. How Variables Were Defined and Calculated for Analysis of Regional Concentrations of High/Mid/Low Skills**

| Variable | Definition | Source |
|---|---|---|
| *Dependent Variables* | | |
| Median Wage | MSA median wage for all occupations | OES, May 2014 |
| % Chg in GRP | Percent change in gross regional product, 2009-2013 | Calculated using Moody's Analytics |
| Productivity | MSA GRP divided by total MSA employment, 2013 | Calculated using Moody's Analytics |
| Per Capita Income | MSA per capita income for the previous 12 months in 2013 $ | ACS 5-year estimate, 2013 |
| Poverty Rate | Share of MSA population below the poverty line | ACS 5-year estimate, 2013 |
| *Independent Variables* | | |
| High STEM/High Soft EMP | Share of MSA employment in occupations requiring both STEM and SOFT skills at least 1 standard deviation above the mean. | Calculated using O*NET 19.0 and OES, May 2014 |
| High STEM/Mid Soft EMP | Share of MSA employment in occupations requiring STEM skills ≥ 1 SD above the mean and SOFT skills > -1 but <1 SD. | Calculated using O*NET 19.0 and OES, May 2014 |
| Mid STEM/High Soft EMP | Share of MSA employment in occupations requiring both STEM skills >-1 but <1 SD and SOFT skills at least 1 SD above the mean | Calculated using O*NET 19.0 and OES, May 2014 |
| Mid STEM/Mid Soft EMP | Share of MSA employment in occupations requiring both STEM and SOFT skills >-1 but <1 SD from the mean. | Calculated using O*NET 19.0 and OES, May 2014 |
| Mid STEM/Low Soft EMP | Natural log of share of MSA employment in occupations requiring above-average STEM but below-average SOFT skills | Calculated using O*NET 19.0 and OES, May 2014 |
| Low STEM/Mid SOFT EMP | Share of MSA employment in occupations requiring STEM skills ≤-1 SD and Soft skills >-1 but <1 SD from the mean. | Calculated using O*NET 19.0 and OES, May 2014 |
| Low STEM/Low SOFT EMP | Share of MSA employment in occupations requiring STEM and SOFT skills both 1 SD below the mean. | Calculated using O*NET 19.0 and OES, May 2014 |
| *Control Variables* | | |
| Population | Natural log of MSA population, 2013 | Calculated using ACS 5-year estimate, 2013 |
| Region to U.S. Pop. Change Due to Migration | Share of regional population change due to net migration compared to share of U.S. population due to migration, 2010-2013 | Calculated using ACS estimate, 2010 & 2013 |
| Labor Force Participation | Share of the MSA population age 16 and over in the labor force, 2013 | Calculated using ACS 5-year estimate, 2013 |
| Manufacturing Employment | Share of the MSA total employment in manufacturing | Calculated using ACS 5-year estimate, 2013 |
| Region to U.S. Median House Value | Regional median house value divided by U.S. median house value, 2013 | Calculated using ACS 5-year estimate, 2013 |
| % Population With BA or Higher | Share of the MSA population age 25 and over with a BA degree or higher, 2013 | Calculated using ACS 5-year estimate, 2013 |

## RESULTS

Table 22 provides the mean, standard deviation, coefficient of variation, minimum and maximum for the variables. Although all variables were standardized for ease of interpretation due to different units of measurement, the descriptive statistics reflect each variable's measurement before transformation for ease of discussion. What is immediately apparent is the large share of employment in low-skill occupations: The mean share of employment across all regions is nearly 20%, even though such occupations are 1 standard deviation below the mean on both the STEM and Soft skill dimensions. The region with the greatest concentration of Low STEM/Low Soft work had nearly a third of its overall employment (30.9%) in such jobs, compared to the region with the lowest share of Low STEM/Low Soft employment (12.7%). For the other extreme, occupations where skill requirements placed them 1 standard deviation above the mean on both skill dimensions accounted for only 1.2% of regional employment, on average. The best-performing region on this measure only had 3% of its employment in High STEM/High Soft occupations. Across all regions, a quarter of employment (25.9%) was in Mid STEM/Mid Soft occupations, meaning skill requirements were within 1 standard deviation above or below the mean on both dimensions. However, the region with the highest share of such employment doubled the employment accounted for in the region with the least (33.4% to 16.2%, respectively). The coefficients of variation indicate greater dispersion across regions of employment requiring a high level of skill.

**Table 22. Descriptive Statistics for Variables in the High/Mid/Low Skill Analysis[a]**

| Variable | Mean | Std. Dev. | CV | Minimum | Maximum |
|---|---|---|---|---|---|
| % High STEM/High Soft Employment | 1.2% | 0.5% | 0.4 | 0.2% | 3.1% |
| % High STEM/Mid Soft Employment | 4.2% | 1.6% | 0.4 | 1.6% | 14.0% |
| % Mid STEM/High Soft Employment | 6.8% | 1.8% | 0.3 | 2.8% | 13.3% |
| % Mid STEM/Mid Soft Employment | 25.9% | 3.1% | 0.1 | 16.2% | 33.4% |
| % Mid STEM/Low Soft Employment | 7.6% | 2.5% | 0.3 | 3.0% | 24.2% |
| % Low STEM/Mid Soft Employment | 21.4% | 2.5% | 0.1 | 13.0% | 34.1% |
| % Low STEM/Low Soft Employment | 19.8% | 2.6% | 0.1 | 12.6% | 30.9% |
| 2013 Population | 739,794 | 1,242,150 | 1.7 | 54,061 | 11,926,639 |
| Region to U.S. Population Chg. Due to Migration | 0.9 | 5.8 | 6.6 | -33.8 | 42.8 |
| % Labor Force Participation | 63.7% | 4.9% | 0.1 | 44.1% | 75.3% |
| % Employment in Manufacturing | 11.1% | 5.3% | 0.5 | 2.1% | 36.5% |
| Region to U.S. Median House Value | 1.1 | 0.6 | 0.5 | 0.5 | 4.6 |
| % Population With BA or Higher | 26.9% | 8.4% | 0.3 | 11.9% | 58.3% |
| Median Wage ($) | $33,644 | $4,713 | 0.1 | $22,780 | $57,430 |
| % Change in GRP | 6.5% | 8.9% | 1.4 | -9.2% | 70.0% |
| Productivity ($) | $99,552 | $22,579 | 0.2 | $63,244 | $199,263 |
| Per Capita Income ($) | $41,761 | $8,547 | 0.2 | $23,073 | $87,897 |
| % Population Below Poverty Line | 15.8% | 4.4% | 0.3 | 5.5% | 34.8% |

N = 390, except for per capita income (389) GRP and Productivity (379)

a. Descriptives are in raw data for ease of understanding; for the analysis, population and migration variables

The following series of tables provide the results of two regression models exploring the effects of human capital on regional median wage, regional change in GRP, total factor productivity, per capita income and poverty rate. The first model tested the relationship between a region's share of the population age 25 and over with a bachelor's degree or higher, controlling for differences in regional rates of migration compared to the nation overall, labor force participation, median house value compare to the U.S. median value, and manufacturing employment. One goal of this research is to explore whether human capital measured in terms of occupational skill requirements better explains regional economic wellbeing than the commonly used human capital proxies that are related to educational attainment. However, as demonstrated in Chapter V, the educational attainment measure was, not surprisingly, highly correlated with the skill variables, preventing its use as a control variable in Model 2. As such, the education-based and occupation-based measures of regional human capital are entered into separate models, while maintaining the same control variables for the two analyses.

**The Greater the Share of High-Skill Employment, the Higher the Regional Wage**

As human capital theory indicates, regions with a larger share of employment in high-skill occupations tend to enjoy higher regional wages than regions with lower high-skill employment. The reverse is also true: Regions with a larger share of employment in low-skill occupations tend to have lower median wages. As can be seen in Table 23, the occupational skill measures have substantially more explanatory power than the education variable (Adj. $R^2 = .80$ compared to Adj. $R^2 = .60$; both significant at $p < .001$). As the literature would suggest, the education-based human capital measure in Model 1 was positively associated with regional median wage ($b = .25$, $t = 5.23$). Its effect was smaller than the variable approximating cost of living (median house value compared to the nation) but larger than the other control variables. In Model 2, three of the occupation-based human capital variables – all three high on at least one dimension – were positively associated with median wage: High STEM/High Soft ($b = .08$), High STEM/Mid Soft ($b = .18$), and Mid STEM/High Soft ($b = .22$). Three occupation-based human capital variables – all three low on at least one dimension – were negatively associated (all at $p < .001$) with median wage: Mid STEM/Low Soft ($b = -.12$); Low STEM/Mid Soft ($b = -.18$); and Low STEM/Low Soft ($b = -.20$). The Mid STEM/Mid Soft variable was the only human capital variable not significant in explaining regional variation in median wage. Three of the control variables were significant in Model 2, all positively. The median house value had the largest effect of all the variables in the model (*b* = .47).

**Table 23. Relationship Between High/Mid/Low Human Capital Measures and Median Wage, 2014[a]**

| Variables | Model 1 | | Model 2 | |
|---|---|---|---|---|
| | Coefficient | *t* | Coefficient | *t* |
| Intercept | 0.00 | 0.00 | 0.00 | 0.00 |
| Region to U.S. Pop. Change from Migration | 0.03 | 0.76 | 0.02 | 0.80 |
| Labor Force Participation | 0.20 | 4.79*** | 0.12 | 4.36*** |
| Region to U.S. Median House Value | 0.49 | 11.97*** | 0.47 | 16.68*** |
| Manufacturing Employment | 0.10 | 2.92** | 0.09 | 3.12** |
| Share of Pop. with BA or Higher, 2013 | 0.25 | 5.23*** | -- | -- |
| High STEM/High Soft Employment | -- | -- | 0.08 | 2.23* |
| High STEM/Mid Soft Employment | -- | -- | 0.18 | 5.56*** |
| Mid STEM/High Soft Employment | -- | -- | 0.22 | 5.75*** |
| Mid STEM/Mid Soft Employment | -- | -- | 0.05 | 1.42 |
| Mid STEM/Low Soft Employment | -- | -- | -0.12 | -4.60*** |
| Low STEM/Mid Soft Employment | -- | -- | -0.18 | -6.22*** |
| Low STEM/Low Soft Employment | -- | -- | -0.20 | -8.33*** |
| | $R^2$ = 0.60 | | $R^2$ = 0.81 | |
| | Adj. $R^2$ = 0.60 | | Adj. $R^2$ = 0.80 | |
| | *F* (df) = 115.61 (5, 383)*** | | *F* (df) = 144.01 (11, 378)*** | |

*N* = 389 MSAs and NECTAs

a. Education & occupation human capital measures entered separately due to issues of collinearity.

**p* ≤ .05 level; ***p* ≤ .01 level; ****p* ≤ .001 level

**Middle Skill Employment Contributes to GRP Growth, But Effect Is Small**

Table 24, below, provides the results of the two regression models exploring the effects of regional human capital concentrations on 2009-2013 percent change in GRP. As can be seen, the education-based measure of human capital had no effect on regional variation in GRP. The occupation-based human capital measures were statistically significant but explained little of the variation in regional GRP (Adj. $R^2$ = .19). Only the Mid STEM/Mid Soft (*b* = .16) and Mid STEM/Low Soft (*b* = .13) were positively associated with growth in GRP. Two of the occupation variables were negatively associated with change in GRP – Mid STEM/High Soft (*b* = -.33) and Low STEM/Low

Soft ($b$ = -.12). The other three occupation-based human capital variables were not significant for the change in regional GRP variable.

**Table 24. Relationship Between High/Mid/Low Human Capital & Percent Change in GRP, 2009-2013[a]**

| | Model 1 | | Model 2 | |
|---|---|---|---|---|
| **Variables** | **Coefficient** | ***t*** | **Coefficient** | ***t*** |
| Intercept | 0.00 | -0.07 | -0.01 | -0.11 |
| Region to U.S. Pop. Change from Migration | 0.05 | 1.01 | 0.05 | 1.15 |
| Labor Force Participation | 0.33 | 5.27*** | 0.288 | 5.19*** |
| Region to U.S. Median House Value | -0.03 | -0.54 | -0.05 | -0.83 |
| Manufacturing Employment | 0.09 | 1.60 | 0.03 | 0.47 |
| Share of Pop. with BA or Higher, 2013 | -0.14 | -1.91 | -- | -- |
| High STEM/High Soft Employment | -- | -- | 0.05 | 0.73 |
| High STEM/Mid Soft Employment | -- | -- | 0.07 | 1.08 |
| Mid STEM/High Soft Employment | -- | -- | -0.33 | -4.14*** |
| Mid STEM/Mid Soft Employment | -- | -- | 0.16 | 2.17* |
| Mid STEM/Low Soft Employment | -- | -- | 0.13 | 2.52* |
| Low STEM/Mid Soft Employment | -- | -- | -0.11 | -1.85 |
| Low STEM/Low Soft Employment | -- | -- | -0.12 | -2.32* |
| | $R^2$ = 0.09<br>Adj. $R^2$ = 0.08<br>$F$ (df) = 7.49 (5, 373)*** | | $R^2$ = 0.21<br>Adj. $R^2$ = 0.19<br>$F$ (df) = 8.90 (11, 367)*** | |

$N$ = 378 MSAs and NECTAs
a. Education & occupation human capital measures entered separately due to issues of collinearity.
*$p \leq$ .05 level; **$p \leq$ .01 level; ***$p \leq$ .001 level

**2 Skill Combinations Associated With Higher Regional Total Factor Productivity**

Table 25, below, provides the results of the two regression models exploring the effects of regional human capital on 2013 total factor productivity. As can be seen, the occupation-based skill explained regional variation in productivity significantly better than the education-based human capital variable (Adj. $R^2$ = .43 compared to Adj. $R^2$ = .62). Despite the assumed connection between higher levels of human capital and higher worker productivity, human capital measured as the common proxy in terms of educational attainment was not significant. Two of the occupation-based human capital variables in Model 2 were positively associated with regional total factor productivity:

High STEM/Mid Soft employment (*b* = .25) and Mid STEM/Mid Soft employment (*b* = .20). Low STEM/Mid Soft employment (*b* = -.12) was negatively associated with regional total factor productivity. The remaining occupational measures were not statistically significant. The standardized coefficients indicate that regional share of employment in High STEM/Mid Soft occupations had the largest effect on regional productivity among the human capital measures. The median house value variable (*b* = .44) was the only control variable statistically significant in Model 2 and had the largest standardized coefficient of all the variables.

**Table 25. Relationship Between High/Mid/Low Human Capital Measures and Productivity, 2013[a]**

| | Model 1 | | Model 2 | |
|---|---|---|---|---|
| **Variables** | **Coefficient** | ***t*** | **Coefficient** | ***t*** |
| Intercept | 0.00 | 0.08 | 0.01 | 0.24 |
| Region to U.S. Pop. Change from Migration | 0.01 | 0.33 | -0.02 | -0.54 |
| Labor Force Participation | 0.19 | 3.88*** | 0.06 | 1.50 |
| Region to U.S. Median House Value | 0.51 | 10.44*** | 0.44 | 11.21*** |
| Manufacturing Employment | -0.02 | -0.58 | -0.06 | -1.43 |
| Share of Pop. with BA or Higher, 2013 | 0.07 | 1.22 | -- | -- |
| High STEM/High Soft Employment | -- | -- | 0.08 | 1.56 |
| High STEM/Mid Soft Employment | -- | -- | 0.25 | 5.45*** |
| Mid STEM/High Soft Employment | -- | -- | 0.07 | 1.35 |
| Mid STEM/Mid Soft Employment | -- | -- | 0.20 | 4.04*** |
| Mid STEM/Low Soft Employment | -- | -- | 0.05 | 1.51 |
| Low STEM/Mid Soft Employment | -- | -- | -0.12 | -2.94** |
| Low STEM/Low Soft Employment | -- | -- | 0.00 | -0.03 |
| | $R^2$ = 0.44<br>Adj. $R^2$ = 0.43<br>$F$ (df) = 58.85 (5, 373)*** | | $R^2$ = 0.63<br>Adj. $R^2$ = 0.62<br>$F$ (df) = 57.02 (11, 367)*** | |

*N* = 378 MSAs and NECTAs
a. Education & occupation human capital measures entered separately due to issues of collinearity.
*p ≤ .05 level; **p ≤ .01 level; ***p ≤ .001 level

### 2 Skill Combinations Associated With Higher Per Capita Income

Table 26, below, provides the results of the two regression models exploring the effects of education-based and occupation-based measures of human capital on per capita income, controlling for regional variation in migration, labor force participation, median house value, and manufacturing employment. As can be seen, the occupational skill-based measures of human capital explained only slightly more of the regional variation in per capita income than the education-based human capital variable (Adj. $R^2$ = .60 compared to Adj. $R^2$ = .63). As human capital theory would suggest, the education variable was positively significant in Model 1 ($b$ = .17). High STEM/Mid Soft ($b$ = .11) and Mid STEM/Mid Soft ($b$ = .21) were both significantly associated with higher regional per capita incomes, while Mid STEM/Low Soft ($b$ = -.08) and Low STEM/Low Soft employment ($b$ = -.07 were both negatively significant. The other three occupation-based human capital measures were not significant. The large standardized coefficients for median house value in both models indicates the substantial contribution of this important component of cost of living to variation in regional per capita income. Labor force participation ($b$ = .23 in Model 2) had the second-largest standardized coefficient for both models.

**Table 26. Relationship Between High/Mid/Low Human Capital Measures and Per Capita Income, 2013[a]**

| Variables | Model 1 | | Model 2 | |
|---|---|---|---|---|
| | **Coefficient** | ***t*** | **Coefficient** | ***t*** |
| Intercept | 0.00 | -0.03 | 0.00 | -0.06 |
| Region to U.S. Pop. Change from Migration | 0.03 | 0.77 | 0.02 | 0.66 |
| Labor Force Participation | 0.24 | 5.86*** | 0.23 | 6.12*** |
| Region to U.S. Median House Value | 0.51 | 12.28*** | 0.58 | 15.07*** |
| Manufacturing Employment | -0.02 | -0.64 | -0.01 | -0.34 |
| Share of Pop. with BA or Higher, 2013 | 0.17 | 3.58*** | -- | -- |
| High STEM/High Soft Employment | -- | -- | -0.04 | -0.85 |
| High STEM/Mid Soft Employment | -- | -- | 0.11 | 2.55* |
| Mid STEM/High Soft Employment | -- | -- | -0.06 | -1.15 |
| Mid STEM/Mid Soft Employment | -- | -- | 0.21 | 4.22*** |
| Mid STEM/Low Soft Employment | -- | -- | -0.08 | -2.28* |
| Low STEM/Mid Soft Employment | -- | -- | -0.02 | -0.51 |
| Low STEM/Low Soft Employment | -- | -- | -0.07 | -2.07* |
| | $R^2$ = 0.60<br>Adj. $R^2$ = 0.60<br>$F$ (df) = 114.96 (5, 383)*** | | $R^2$ = 0.64<br>Adj. $R^2$ = 0.63<br>$F$ (df) = 61.42 (11, 377)*** | |

*N* = 388 MSAs and NECTAs
a. Education & occupation human capital measures entered separately due to issues of collinearity.
*p ≤ .05 level; **p ≤ .01 level; ***p ≤ .001 level

## Mid Skills Have Mixed Effect on Regional Poverty Rates

Table 27, below, provides the results of the two regression models exploring the effects of education-based and occupation-based measures of human capital on the share of regional population living in poverty. As can be seen, Model 2 had greater explanatory power than the education-based human capital measure in Model 1 (Adj. $R^2$ = .42 compared to Adj. $R^2$ = .46). However, neither model of the four control variables and the human capital variables explained even half of regional variation in poverty. The education variable in Model 1 was not significant. Mid STEM/Mid Soft employment ($b$ = -.25) was the only occupation-based human capital variable statistically significant in the desirable direction: Regions with larger shares of Mid STEM/Mid Soft employment had lower levels of poverty. Mid STEM/High Soft and Mid STEM/Low Soft employment were both positively significant, meaning regions with larger shares of such employment had higher levels of poverty, controlling for all other variables. The apparent link between Mid STEM/High Soft occupations, many of which also require higher levels of education, and higher poverty rates would seem to support findings in the literature that have associated rising concentrations of higher education with rising regional income inequality (e.g., Andreason, 2015). This may be due to better-educated regions attracting lower skilled migrants who hope to find work in population-serving jobs. Another possible explanation is that labor-saving technological advancements may create greater demand for better skilled workers but lead to fewer workers being employed in the region overall. This may explain, at least in part, the apparent link between greater concentrations of Mid STEM/Low Soft employment and higher regional poverty rates. All of the control variables except for the migration measure had a statistically significant, negative relationship with regional poverty.

**Table 27. Relationship Between High/Mid/Low Human Capital Measures and Poverty, 2013[a]**

| | Model 1 | | Model 2 | |
|---|---|---|---|---|
| **Variables** | **Coefficient** | ***t*** | **Coefficient** | ***t*** |
| Intercept | 0.00 | 0.00 | 0.00 | 0.00 |
| Region to U.S. Pop. Change from Migration | -0.04 | -1.02 | -0.03 | -0.74 |
| Labor Force Participation | -0.46 | -9.28*** | -0.40 | -8.34*** |
| Region to U.S. Median House Value | -0.37 | -7.54*** | -0.43 | -8.74*** |
| Manufacturing Employment | -0.13 | -3.05** | -0.18 | -3.86*** |
| Share of Pop. with BA or Higher, 2013 | 0.04 | 0.60 | -- | -- |
| High STEM/High Soft Employment | -- | -- | 0.04 | 0.70 |
| High STEM/Mid Soft Employment | -- | -- | -0.09 | -1.61 |
| Mid STEM/High Soft Employment | -- | -- | 0.25 | 4.01*** |
| Mid STEM/Mid Soft Employment | -- | -- | -0.25 | -4.17*** |
| Mid STEM/Low Soft Employment | -- | -- | 0.11 | 2.72** |
| Low STEM/Mid Soft Employment | -- | -- | -0.04 | -0.81 |
| Low STEM/Low Soft Employment | -- | -- | 0.02 | 0.58 |
| | $R^2$ = 0.43 | | $R^2$ = 0.48 | |
| | Adj. $R^2$ = 0.42 | | Adj. $R^2$ = 0.46 | |
| | $F$ (df) = 57.84 (5, 384)*** | | $F$ (df) = 31.58 (11, 378)*** | |

$N$ = 390 MSAs and NECTAs

a. Education & occupation human capital measures entered separately due to issues of collinearity.

*p ≤ .05 level; **p ≤ .01 level; ***p ≤ .001 level

## What the Findings Mean to Regions

Holding all other variables in Model 2 constant:

- Regions with a 1 standard deviation (.49 percentage points) larger share of employment in High STEM/High Soft occupations had a $2,725 higher regional median wage.
- Regions that had regional employment in High STEM/Mid Soft occupations 1 standard deviation (1.59 percentage points) larger had a regional median wage $6,123 higher, 2.7 percentage points greater growth in GRP, $24,688 higher total factor productivity, and a 1.36 percentage lower poverty rate.
- Regions with a 1.77 percentage point (1 standard deviation) higher share of employment in Mid STEM/High Soft occupations had a regional median wage

$7,334 higher, but GRP growth 2.12 percentage points lower and poverty rates 3.94 percentage points higher.

- Regions with a 3.13 percentage point (1 standard deviation) higher share of employment in Mid STEM/Mid Soft occupations had 1.05 percentage points greater growth in GRP, $20,309 higher total factor productivity, $8,853 higher per capita income, and poverty rates 3.94 percentage points lower.
- Regions with a 1 standard deviation (2.55 percentage points) increase in regional Mid STEM/Low Soft employment had GRP growth 0.85 percentage point higher, but that growth in GRP was accompanied by a $3,936 decrease in regional median wage, a $3,299 decrease in regional per capita income, and a 1.78 percentage point increase in the region's poverty rate.
- Regions with employment in Low STEM/Mid Soft occupations that was 1 standard deviation (2.5 percentage points) higher had regional median wages that were $6,056 lower and $11,946 lower total factor productivity.
- Regions with employment in Low STEM/Low Soft occupations that was 1 standard deviation (2.58 percentage points) higher had a regional median wage $6,863 lower, had GRP growth that was 0.75 percentage points less, and a per capita income $2,882 lower.

Among the control variables, variation in labor force participation and cost of living had the most significant effects. Holding all other variables in Model 2 equal:

- Regions with a labor force participation rate 1 standard deviation (4.90 percentage points) higher had median wages $3,970 higher, GRP growth

1.87 percentage points greater, $9,437 higher per capita incomes, and poverty rates 6.3 percentage points lower.

- Regions with a 1 standard deviation (5.84) higher ratio of regional median owner-occupied house value to U.S. median house value had a median wage $15,779 higher, $43,504 greater total factor productivity, $24,179 higher per capita income, and poverty rates 6.75 percentage points lower.
- Regions with 1 standard deviation (5.33 percentage points) higher share of employment engaged in manufacturing had $2,994 higher median wages and poverty rates 2.9 percentage points lower.
- The migration variable was not significant on any of the five economic wellbeing variables in Model 2 after controlling for regional variation in occupational human capital, labor force participation, cost of living and manufacturing employment.

Model 1 provides some opportunity for comparison of human capital measured in terms of occupation skill requirements versus the commonly used human capital proxy of population educational attainment. Holding the migration, labor force participation, median house value and manufacturing employment variables constant:

- Regions where the share of the population with a bachelor’s degree or higher was 1 standard deviation (8.4 percentage points) higher had a region median wage $8,545 higher and a per capita income $7,266 higher. Variation in the share of a region’s population with a bachelor’s degree or higher was not shown to have a statistically significant effect on a region’s growth in GRP, productivity or poverty levels.

## CLOSING THOUGHTS

This chapter is specifically interested in the impact of "middle" skills on regional economic wellbeing. Holzer (2008) and Rothwell (2013) have indicated a bias toward "high skills" in policy and media, ignoring the importance of skill levels that are neither among the highest nor among the lowest.

However, first it is constructive to explore how the findings presented here further refine the findings reported in earlier chapters. As discussed in Chapter V, echoing conclusions in Andreason (2015) and perhaps helping to explain frequent mixed results in the literature, the effect of human capital on economic wellbeing is not nearly as straightforward as largely assumed. Higher levels of human capital may have the desired beneficial effect on some measures of economic performance, while having no effect or, worse, a negative impact on other measures. As can be seen in Table 28, which summarizes the findings for all human capital variables discussed earlier, none of the human capital measures was significant on all five measures of regional economic well-being. Two occupation-based human capital measures were significant for four measures, one: Higher shares of Mid STEM/Mid Soft employment was associated with desirable outcomes on GRP, productivity, per capita income and poverty but had no statistically significant effect on regional median wage. Higher shares of Mid STEM/Low Soft employment contributed to greater growth in GRP, but lower regional wages, lower per capita incomes and higher poverty levels. Larger shares of regional employment in High STEM/Mid Soft occupations were associated with higher median wages, higher productivity and higher per capita incomes.

**Table 28. Summary of Regression Findings on High/Mid/Low Measures of Regional Human Capital Asset**

| Human Capital Variable | Regional Median Wage | % Change in GRP, 2009-2013 | Productivity, 2013 | Per Capita Income, 2013 | Poverty Rate, 2013 |
|---|---|---|---|---|---|
| **BA or higher** | +*** | N.S. | N.S. | +*** | N.S. |
| **High STEM/ High SOFT** | +* | N.S. | N.S. | N.S. | N.S. |
| **High STEM/ Mid SOFT** | +*** | N.S. | +*** | +* | N.S. |
| **Mid STEM/ High SOFT** | +*** | -*** | N.S. | N.S. | +*** |
| **Mid STEM/ Mid SOFT** | N.S. | +* | +*** | +*** | -*** |
| **Mid STEM/ Low SOFT** | -*** | +* | N.S. | -* | +** |
| **Low STEM/ Mid SOFT** | -*** | N.S. | -** | N.S. | N.S. |
| **Low STEM/ Low SOFT** | -*** | -* | N.S. | -* | N.S. |

*p ≤ .05 level; **p ≤ .01 level; ***p ≤ .001 level; n.s. = not significant

Although so much policy attention is devoted to encouraging students into High STEM majors to support growing High STEM jobs, occupations requiring a high or mid level of STEM skill but a mid level of education appear to be those having the broadest impact on regional economic wellbeing. As would be expected, nearly all the occupations

(94%) in the highest occupational skill category (1 standard deviation above the mean for both STEM and Soft skill requirements) required a bachelor's degree or higher. Included in this category are the occupations policymakers frequently mean when they talk about the critical need for High STEM workers: physicists, several varieties of engineers, doctors, medical scientists, and computer and information research scientists, for example. As human capital theory would suggest, regions with a higher share of occupations requiring such high human capital intensity have higher median wages. However, regions with a higher share of High STEM/Mid Soft occupations have higher median wages, higher productivity and higher per capita incomes. Only 45% of occupations in the skill category require a bachelor's degree or higher; these occupations include software developers, computer network architects, mathematicians, petroleum engineers, mechanical engineers and chemists. However, 9.6% of occupations in the High STEM/Mid Soft category, such as service unit operators in the oil, gas, and mining industries and chemical plant and system operators, require only a high school education or less. The remaining 45% of occupations in the category indicating STEM skills 1 standard deviation above the mean but mid-level Soft skills require some education or certification beyond high school but less than a bachelor's degree. Such occupations include industrial engineering technicians, electrical and electronics repairers of commercial and industrial equipment, and computer numerically controlled (CNC) machine tool programmers. Although such occupations were categorized in this analysis as "High STEM," the findings support the academic literature suggesting the continued economic importance of occupations requiring mid-level educational attainment (i.e., more than high school but less than a bachelor's degree).

Employment in occupations requiring a mid level of both STEM and Soft skills also were shown to be important to regional economic wellbeing. Roughly a third of occupations in this category (31.7%) required a bachelor's degree or higher. Such occupations included computer and information systems managers, economists, information security analysts, sociologists, editors, and healthcare support workers. A third of occupations in this skill category (33.8%) had mid-level educational requirements, such as computer user support specialists, web developers, chemical technicians, and health technologists and technicians. The remaining third (34.5%) required only a high school education; these included pharmacy technicians, nursing assistants, carpenters and derrick operators. The wide range of educational levels and occupational activities grouped into this category certainly reflects the breadth of this category, reflecting skill requirements on both dimensions falling between 1 standard deviation above and below the mean, but it also reflects the fact that a wide range of occupations require that workers possess a moderate level of STEM and Soft skills and that a wide range of occupations require a relatively moderate range of abilities in order to perform adequately.

It's interesting to note that 92.2% of occupations in the Mid STEM/High Soft category required at least a bachelor's degree. These occupations included chief executive officers, financial managers, social scientists and related workers, pharmacists, exercise physiologists, family and general practitioners, and chiropractors. Although regions with higher concentrations of employment in these occupations requiring a relatively high level of human capital enjoyed higher median wages, the regions saw lower rates of GRP growth and higher poverty rates. This might indicate the population-serving nature of much of the health-related occupations in this category.

What is clear is the negative effect on regional economic wellbeing of high levels of regional employment in occupations requiring low levels of human capital. Regions with a higher share of employment in occupations with STEM and Soft skill requirements 1 standard deviation below the mean had lower median wages, lower (or negative) GRP growth and lower per capita incomes. Such occupations include dishwashers, janitors, postal service mail carriers, telemarketers, bailiffs, taxi drivers, and fast-food cooks. None of such occupations required education beyond the high school level. Regions with higher levels of employment in Low STEM/Mid Soft occupations, such as customer service representatives, childcare workers, executive secretaries, choreographers, and radio and television announcers, had lower median wages and lower levels of total factor productivity. Although the vast majority of occupations in this skill category required a mid level of education or less, 13.6% of Low STEM/Mid Soft occupations, such as human resource specialists, reporters and correspondents, judicial law clerks, and kindergarten teachers required a bachelor's degree or higher.

The results presented here largely confirm the hypothesis that a higher share of regional employment in occupations requiring a middle-level of STEM skills and a middle-level of Soft KSAs are associated with positive regional economic performance. Regions with a larger share of employment in Mid STEM/Mid Soft occupations had greater growth in GRP, higher total factor productivity, higher per capita incomes and lower poverty rates. However, regions with higher shares of such employment also had lower median wages. Regions with higher employment in Mid STEM/High Soft occupations had higher regional wages, but lower GRP growth and higher poverty. Regions with a greater share of employment in Mid STEM/Low Soft occupations had lower wages, higher GRP growth, lower per capita incomes and higher rates of poverty. As such, whether the hypothesis is confirmed depends on how “middle-skill” is defined and the measure of interest.

# CHAPTER VII

## AN ALTERNATE METHOD OF MEASURING MIDDLE-SKILL

This chapter presents an alternative measurement of "middle skill." The hypotheses, that regions with a larger share of employment in occupations requiring a middle-level of skill enjoy better economic wellbeing, are the same for this chapter as those described in Chapter VI. The only difference is in how middle-skill is conceived and measured.

For this set of analyses, individual occupations were assessed on whether their skill requirements fell into the top third, middle third or bottom third for each of the 35 STEM and 50 Soft KSAs. An occupation with an attribute score less than or equal to the 33$^{rd}$ percentile of scores across all 942 occupations were labeled "low" on that particular attribute. An occupation with an attribute score greater than or equal to the 67$^{th}$ percentile was labeled "high." The remaining occupations were labeled "mid." This step was repeated for all 35 STEM attributes and all 50 Soft KSAs. Multiplying the number of "high" KSAs by 3, the number of "mid" KSAs by 2, and each "low" descriptor by 1 allowed for calculating a total score for each occupation across the 35 STEM KSAs and a score across the 50 Soft KSAs. Occupations with STEM or Soft scores that were less than or equal to the 33rd percentile of scores across all occupations were labeled "low," and those with scores greater than or equal to the 67th percentile of scores across all occupations were labeled "high." The remaining occupations were labeled as "mid."

Of the 942 occupations in the study sample, 332 were classified as "High STEM," 275 were labeled "Mid STEM," and 335 were categorized as "Low STEM." Using the same technique for the collection of 50 Soft KSAs yielded 314 "High Soft," 309 "Mid Soft" and 319 "Low Soft" occupations. As demonstrated in earlier chapters, given that many occupations classified as high STEM were also likely to require a high level of critical-thinking, problem solving and other soft KSAs, the occupations were further sorted into nine categorical measures: "High STEM/High Soft," "High STEM/Mid Soft," "High STEM/Low Soft," "Mid STEM/High Soft," "Mid STEM/Mid Soft," "Mid STEM/Low Soft," "Low STEM/High Soft," Low STEM/Mid Soft," and "Low STEM/Low Soft." Table 29 provides the number of occupations sorted into each of the nine categories. The Appendix presents a complete list of occupations by skill category.

**Table 29. Occupations Sorted by High/Mid/Low Skill Requirer**

| | Low STEM | Mid STEM | High STEM | Total |
|---|---|---|---|---|
| **High Soft** | 53 | 74 | 95 | 222 |
| | *6.9%* | *9.7%* | *12.4%* | *29.1%* |
| **Mid Soft** | 98 | 54 | 92 | 244 |
| | *12.8%* | *7.1%* | *12.0%* | *31.9%* |
| **Low Soft** | 141 | 104 | 53 | 298 |
| | *18.5%* | *13.6%* | *6.9%* | *39.0%* |
| **Total** | 292 | 232 | 240 | 764 |
| | *38.2%* | *30.4%* | *31.4%* | *100.0%* |

*N*=764

Table 30 provides the overall employment in each category, as well as the share of the total U.S. employment captured by the OES survey.

**Table 30. U.S. Employment by High/Mid/Low Skill Requirements[a]**

| | Low STEM | Mid STEM | High STEM | Total |
|---|---|---|---|---|
| High Soft | 5,278,770 | 14,919,310 | 9,759,870 | 29,957,950 |
| | *4.0%* | *11.3%* | *7.4%* | 22.7% |
| Mid Soft | 27,867,710 | 7,849,100 | 8,722,820 | 44,439,630 |
| | *21.1%* | *5.9%* | *6.6%* | 33.7% |
| Low Soft | 45,030,810 | 6,630,800 | 5,915,670 | 57,577,280 |
| | *34.1%* | *5.0%* | *4.5%* | 43.6% |
| Total | 78,177,290 | 29,399,210 | 24,398,360 | 131,974,860 |
| | *59.2%* | *22.3%* | *18.5%* | *100.0%* |

a. OES U.S. 2013 employment = 131,974,860.

Table 31 provides the share of occupations in the nine STEM/Soft categories that required a bachelor's degree or higher. As discussed in Chapter IV, overlaying the occupational education requirement on the occupational skill requirement appears to provide support for the view of higher education as a proxy for higher skill: 83.2% of occupations with the highest skill requirements also required a bachelor's degree or higher. What is most interesting, however, is the high share of occupations falling into the top third in terms of Soft skill demands that require a bachelor's degree or higher; 87.8% of the Mid STEM/High Soft and 96.2% of the Low STEM/High Soft occupations required a 4-year college degree or more. Advanced education appears not nearly so necessary to occupations that demand STEM skills falling in the top third. This may partly be a reflection of the nature of the work in each category. However, as suggested in

Chapter IV, this may also indicate that, for many employers, a bachelor's degree either imparts or helps signal the presence of hard-to-assess Soft skills. What is also interesting is the difference in employment between the High STEM/High Soft and Low STEM/High Soft categories. Occupations requiring a higher level of education related to STEM employ far fewer workers than those requiring a higher level of education related to Soft skills. Again, this may indicate differences in the nature of work, where technology-intensive activities likely require fewer workers than people-intensive ones.

**Table 31. Share of Occupations by High/Mid/Low Skill Category Requiring Bachelor's Degree or Higher**

| Skill Category | No. of OCCs BA+ | Share of OCCs BA+ | Share of Employment BA+ |
|---|---|---|---|
| High STEM/High Soft | 79 | 83.2% | 58.6% |
| High STEM/Mid Soft | 22 | 23.9% | 24.8% |
| High STEM/Low Soft | 0 | 0.0% | 0.0% |
| Mid STEM/High Soft | 65 | 87.8% | 61.1% |
| Mid STEM/Mid Soft | 12 | 22.2% | 22.1% |
| Mid STEM/Low Soft | 1 | 1.0% | 0.0% |
| Low STEM/High Soft | 51 | 96.2% | 99.0% |
| Low STEM/Mid Soft | 31 | 31.6% | 21.1% |
| Low STEM/Low Soft | 2 | 1.4% | 0.2% |

Table 32 lists the variables used in this analysis, their definitions and source. As discussed in Chapter VI, a test of normality revealed that two of the three control variables – share of population change due to net migration, and median owner-occupied house value, 2013 – had distributions that were skewed beyond an acceptable threshold of an absolute value of 2. This was not an unexpected finding. However, one of the independent variables of interest – Mid STEM/Low Soft – also had a skewed distribution.

The migration and median house value measures were recalculated as ratios to U.S. migration and median house value. This facilitated interpretation of the results. Despite the Mid STEM/Low Soft variable having a somewhat skewed distribution, a preliminary analysis showed little difference between the logged variable and the non-transformed variable. As such, the variable was not logged despite the skewed distribution for ease of interpretation.

Using all nine occupation-based human capital variables would be expected to introduce unacceptably high levels of multicollinearity into the regression models due to the fact that the variables would, presumably, capture 100% of regional employment. However, it is important to note that the OES data do not cover all U.S. employment due to exclusions from the survey, such as for the self-employed and partners in firms, as well as due to suppression of MSA data at the detailed level if individual establishments may be revealed. Moreover, government workers and private household employment were not included in this analysis. The nine occupation-based human capital variables did capture up to 95% of employment in some regions, but they only accounted for about two-thirds of employment in other regions. On average, the measures accounted for about 87% of regional employment.

**Table 32. How Variables for Alternate Approach to High/Mid/Low Skill Analysis Were Defined and Calculated**

| Variable | Definition | Source |
|---|---|---|
| *Dependent Variables* | | |
| Median Wage | MSA median wage for all occupations | OES, May 2014 |
| % Change in GRP | Percent change in gross regional product, 2009-2013 | Calculated using Moody's Analytics |
| Productivity | MSA GRP divided by total MSA employment, 2013 | Calculated using Moody's Analytics |
| Per Capita Income | MSA per capita income for the previous 12 months in 2013 $ | ACS 5-year estimate, 2013 |
| Poverty Rate | Share of MSA population below the poverty line | ACS 5-year estimate, 2013 |
| *Independent Variables* | | |
| High STEM/High Soft Employment | Share of MSA employment in occupations requiring both top 33% STEM and top 33% SOFT skills | Calculated using O*NET 19.0 and OES, May 2014 |
| High STEM/Mid Soft Employment | Share of MSA employment in occupations requiring top 33% STEM skills but mid 33% SOFT skills | Calculated using O*NET 19.0 and OES, May 2014 |
| High STEM/Low Soft Employment | Share of MSA employment in occupations requiring top 33% STEM skills but bottom 33% SOFT skills | Calculated using O*NET 19.0 and OES, May 2014 |
| Mid STEM/High Soft Employment | Share of MSA employment in occupations requiring mid 33% STEM but top 33% SOFT skills | Calculated using O*NET 19.0 and OES, May 2014 |
| Mid STEM/Mid Soft Employment | Share of MSA employment in occupations requiring both mid 33% STEM skills and mid 33% SOFT skills | Calculated using O*NET 19.0 and OES, May 2014 |
| Mid STEM/Low Soft Employment | Share of MSA employment in occupations requiring mid 33% STEM skills but bottom 33% SOFT skills | Calculated using O*NET 19.0 and OES, May 2014 |
| Low STEM/High Soft Employment | Share of MSA employment in occupations requiring bottom 33% STEM but top 33% SOFT skills | Calculated using O*NET 19.0 and OES, May 2014 |
| Low STEM/Mid Soft Employment | Share of MSA employment in occupations requiring bottom 33% STEM skills but mid 33% SOFT skills | Calculated using O*NET 19.0 and OES, May 2014 |
| Low STEM/Low Soft Employment | Share of MSA employment in occupations requiring both bottom 33% STEM skills and bottom 33% SOFT skills | Calculated using O*NET 19.0 and OES, May 2014 |
| *Control Variables* | | |
| Population | Natural log of MSA population, 2013 | Calculated using ACS 5-year estimate, 2013 |
| Region to U.S. Pop. Change Due to Migration Share | Share of regional population change due to net migration compared to share of U.S. population due to migration, 2010-2013 | Calculated using ACS estimate, 2010 & 2013 |
| Labor Force Participation | Share of the MSA population age 16 and over in the labor force, 2013 | Calculated using ACS 5-year estimate, 2013 |
| Manufacturing Employment | Share of the MSA total employment in manufacturing | Calculated using ACS 5-year estimate, 2013 |
| Region to U.S. Median House Value | Regional median house value divided by U.S. median house value | Calculated using ACS 5-year estimate, 2013 |
| % Population With BA or Higher | Share of the MSA population age 25 and over with a BA degree or higher, 2013 | Calculated using ACS 5-year estimate, 2013 |

## RESULTS

Table 33 provides the mean, standard deviation, coefficient of variation, minimum and maximum for the variables in the regression analyses. For the regression analyses, the natural log of the population variable was calculated due to a distribution unacceptably skewed, and all variables were standardized for ease of interpretation due to different units of measurement. However, the descriptive statistics reflect each variable's measurement before transformation for ease of discussion. The Mid STEM/Low Soft variable was also shown to have a distribution skewed beyond absolute value of 2. However, after running the analysis with the variable logged and not logged and having little difference in results, the variable was not logged for the final analysis for ease of interpretability.

What is immediately apparent in the descriptive statistics is the large share of employment in low-skill occupations: Despite the nine possible skill categories, nearly a third of regional employment, on average, was in occupations where KSA requirements fell in the bottom third on both the STEM and Soft dimensions. The region with the greatest concentration of Low STEM/Low Soft work had nearly half of its overall employment (44.8%) in such jobs, compared to the region with the lowest share of Low STEM/Low Soft employment (22.1%). For the other extreme, occupations where skill requirements placed them in the top third on the STEM/Soft dimensions accounted for only 5.6% of regional employment, on average. However, some regions had as much as 15% of employment in such high-skill occupations, whereas other regions had less than 1 in every 50 jobs requiring such skill levels.

**Table 33. Descriptive Statistics for Variables Used in Alternate Approach to High/Mid/Low Skill Analysis[a]**

| Variable | Mean | Std. Dev. | CV | Minimum | Maximum |
|---|---|---|---|---|---|
| % High STEM/High Soft Employment | 5.6% | 1.9% | 0.3 | 1.9% | 15.0% |
| % High STEM/Mid Soft Employment | 5.2% | 1.4% | 0.3 | 2.0% | 10.4% |
| % High STEM/Low Soft Employment | 4.0% | 1.2% | 0.3 | 1.5% | 10.7% |
| % Mid STEM/High Soft Employment | 9.8% | 1.7% | 0.2 | 5.1% | 14.1% |
| % Mid STEM/Mid Soft Employment | 4.8% | 1.0% | 0.2 | 2.2% | 8.4% |
| % Mid STEM/Low Soft Employment | 4.2% | 2.3% | 0.5 | 0.9% | 20.4% |
| % Low STEM/High Soft Employment | 2.7% | 1.1% | 0.4 | 0.6% | 7.3% |
| % Low STEM/Mid Soft Employment | 18.8% | 2.4% | 0.1 | 11.3% | 25.7% |
| % Low STEM/Low Soft Employment | 31.7% | 3.4% | 0.1 | 22.1% | 44.8% |
| 2013 Population | 739,794 | 1,242,150 | 1.7 | 54,061 | 11,926,639 |
| MSA to U.S. Population Change Due to Migration | 0.9 | 5.8 | 6.6 | -33.8 | 42.8 |
| % Labor Force Participation | 63.7% | 4.9% | 0.1 | 44.1% | 75.3% |
| % Employment in Manufacturing | 11.1% | 5.3% | 0.5 | 2.1% | 36.5% |
| Region to U.S. Median House Value | 1.1 | 0.6 | 0.5 | 0.5 | 4.6 |
| % Population with BA or Higher | 26.9% | 8.4% | 0.3 | 11.9% | 58.3% |
| Median Wage ($) | $33,644 | $4,713 | 0.1 | $22,780 | $57,430 |
| % Change in GRP | 6.5% | 8.9% | 1.4 | -9.2% | 70.0% |
| Productivity ($) | $99,552 | $22,579 | 0.2 | $63,244 | $199,263 |
| Per Capita Income ($) | $41,761 | $8,547 | 0.2 | $23,073 | $87,897 |
| % Population Below Poverty Line | 15.8% | 4.4% | 0.3 | 5.5% | 34.8% |

N = 390, except for per capita income (389) GRP and Productivity (379)

a. Descriptives are in raw data for ease of understanding; for the analysis, the population variable was logged, and all variables were standardized.

## Five Occupational Human Capital Variables Contribute to Higher Regional Wages

Table 34, below, provides the results of two regression models exploring the effects of human capital on regional median wage. The first model tested the relationship between a region's share of the population age 25 and over with a bachelor's degree or higher, controlling for differences in regional net migration, labor force participation, median house value and manufacturing employment. One other control variable drawn from the literature – regional population– was removed from the regression models due to multicollinearity. Not surprisingly, the educational attainment measure was highly correlated with the skill measures, particularly the High Soft skill variables, preventing its use as a control variable in Model 2. As can be seen in Table 34, the occupational skill measures have substantially more explanatory power than the education variable (Adj. $R^2$ = .82, compared to Adj. $R^2$ = .60). As the literature would suggest, the education-based human capital measure in Model 1 was positively associated with regional median wage ($b$ = .24). In Model 2, five of the occupation-based human capital variables were positively associated with regional median wage: High STEM/High Soft ($b$ = .20), High STEM/Mid Soft ($b$ = .10), High STEM/Low Soft ($b$ = .08), Mid STEM/High Soft ($b$ = .07), and Low STEM/High Soft ($b$ = .28). Four occupation-based human capital variables were negatively associated (all at $p < .001$) with median wage – Mid STEM/Mid Soft ($b$ = -.08), Mid STEM/Low Soft ($b$ = -.11), Low STEM/Mid Soft ($b$ = -.15), and Low STEM/Low Soft ($b$ = -.20). Three of the control variables were significant in Model 2: The ratio of regional median house value to U.S. median house value ($b$ = .43) had the largest effect size of all the tested variables, as indicated by the coefficients, but variation in labor force participation ($b$ = .09) and the share of employment in manufacturing ($b$ = .07) also contributed to observed differences in regional wages.

**Table 34. Relationship Between High/Mid/Low Occupational Skill Requirements and Median Wage, 2014[a]**

| | Model 1 | | Model 2 | |
|---|---|---|---|---|
| **Variables** | **Coefficient** | ***t*** | **Coefficient** | ***t*** |
| Intercept | 0.06 | 2.06* | 0.05 | 2.53* |
| Region to U.S. Pop. Change from Migration | 0.02 | 0.73 | 0.02 | 0.81 |
| Labor Force Participation | 0.18 | 4.78*** | 0.09 | 3.39*** |
| Region to U.S. Median House Value | 0.46 | 11.92*** | 0.43 | 17.28*** |
| Manufacturing Employment | 0.09 | 2.85** | 0.07 | 2.75** |
| Share of Pop. with BA or Higher, 2013 | 0.24 | 5.24*** | -- | -- |
| High STEM/High Soft Employment | -- | -- | 0.20 | 5.54*** |
| High STEM/Mid Soft Employment | -- | -- | 0.10 | 2.64** |
| High STEM/Low Soft Employment | -- | -- | 0.08 | 2.82** |
| Mid STEM/High Soft Employment | -- | -- | 0.07 | 2.42* |
| Mid STEM/Mid Soft Employment | -- | -- | -0.08 | -2.57* |
| Mid STEM/Low Soft Employment | -- | -- | -0.11 | -4.71*** |
| Low STEM/High Soft Employment | -- | -- | 0.28 | 8.45*** |
| Low STEM/Mid Soft Employment | -- | -- | -0.15 | -5.02*** |
| Low STEM/Low Soft Employment | -- | -- | -0.20 | -8.60*** |
| | $R^2$ = 0.60<br>Adj. $R^2$ = 0.60<br>$F$ (df) = 115.61 (5, 383)*** | | $R^2$ = 0.83<br>Adj. $R^2$ = 0.82<br>$F$ (df) = 136.03 (13, 375)*** | |

$N$ = 388 MSAs and NECTAs

a. Education & occupation human capital measures entered separately due to issues of collinearity.

*$p \leq$ .05 level; **$p \leq$ .01 level; ***$p \leq$ .001 level

### Occupations Requiring High STEM But Mid to Low Soft Skills Drive GRP Growth

Table 35, below, provides the results of the two regression models exploring the effects of regional human capital concentrations on 2009-2013 percent change in GRP. As can be seen, the occupation-based measures of human capital explained substantially more of the observed regional variation in GRP change than did the education-based human capital variable (Adj. $R^2$ = .31 compared to Adj. $R^2$ = .08). Only the High STEM/Mid Soft ($b$ = .30) and High STEM/Low Soft ($b$ = .21) were positively associated (both at $p$ < .001) with growth in GRP. Three of the occupation variables were negatively associated with change in GRP – High STEM/High Soft ($b$ = -.15), Low STEM/Mid Soft ($b$ = -.18), and Low STEM/Low Soft ($b$ = -.11). Only one of the four control variables was significant, and it was significant in both models. In Model 2, labor force participation was positively associated with GRP growth ($b$ = .27).

**Table 35. Relationship Between High/Mid/Low Occupational Skill Requirements and Percent Change in GRP, 2009-2013[a]**

| Variables | Model 1 | | Model 2 | |
|---|---|---|---|---|
| | Coefficient | *t* | Coefficient | *t* |
| Intercept | 0.00 | 0.00 | -0.01 | -0.14 |
| Region to U.S. Pop. Change from Migration | 0.05 | 1.00 | 0.04 | 0.94 |
| Labor Force Participation | 0.33 | 5.26*** | 0.27 | 4.88*** |
| Region to U.S. Median House Value | -0.03 | -0.54 | 0.01 | 0.11 |
| Manufacturing Employment | 0.08 | 1.58 | -0.04 | -0.67 |
| Share of Pop. with BA or Higher, 2013 | -0.14 | -1.90 | -- | -- |
| High STEM/High Soft Employment | -- | -- | -0.15 | -1.95* |
| High STEM/Mid Soft Employment | -- | -- | 0.30 | 3.70*** |
| High STEM/Low Soft Employment | -- | -- | 0.21 | 3.64*** |
| Mid STEM/High Soft Employment | -- | -- | -0.11 | -1.82 |
| Mid STEM/Mid Soft Employment | -- | -- | 0.00 | 0.01 |
| Mid STEM/Low Soft Employment | -- | -- | 0.08 | 1.72 |
| Low STEM/High Soft Employment | -- | -- | -0.02 | -0.27 |
| Low STEM/Mid Soft Employment | -- | -- | -0.18 | -2.71** |
| Low STEM/Low Soft Employment | -- | -- | -0.11 | -2.20* |
| | $R^2$ = 0.09<br>Adj. $R^2$ = 0.08<br>$F$ (df) = 7.44 (5, 372)*** | | $R^2$ = 0.33<br>Adj. $R^2$ = 0.31<br>$F$ (df) = 13.88 (13, 364)*** | |

$N$ = 377 MSAs and NECTAs
a. Education & occupation human capital measures entered separately due to issues of collinearity.
*$p \leq$ .05 level; **$p \leq$ .01 level; ***$p \leq$ .001 level

### High STEM/Mid Soft & High STEM/Low Soft Employment Raise Productivity

Table 36, below, provides the results of the two regression models exploring the effects of regional human capital on 2013 productivity. As can be seen, the occupation-based skill explained regional variation in productivity significantly better than the education-based human capital variable (Adj. $R^2$ = .59 compared to Adj. $R^2$ = .34). However, the education human capital variable in Model 1 was not significant. Three of the occupation-based human capital variables in Model 2 were positively associated with regional productivity: High STEM/High Soft employment (*b* = .13), High STEM/Mid Soft employment (*b* = .26), and High STEM/Low Soft (*b* = .23). Low STEM/Mid Soft (*b* = -.11) and Low STEM/Low Soft employment (*b* = -.11) were both negatively associated with regional productivity. The remaining occupational measures were not significant. Two of the control variables – median house value (*b* = .42) and labor force participation (*b* = .09) also were positively associated with productivity. The other two control variables were not significant in either model.

**Table 36. Relationship Between High/Mid/Low Occupational Skill Requirements and Productivity, 2013[a]**

| | Model 1 | | Model 2 | |
|---|---|---|---|---|
| **Variables** | **Coefficient** | ***t*** | **Coefficient** | ***t*** |
| Intercept | 0.01 | 0.16 | -0.01 | -0.23 |
| Region to U.S. Pop. Change from Migration | 0.02 | 0.47 | -0.01 | -0.19 |
| Labor Force Participation | 0.26 | 4.81*** | 0.09 | 2.21* |
| Region to U.S. Median House Value | 0.45 | 8.50*** | 0.42 | 10.38*** |
| Manufacturing Employment | -0.01 | -0.19 | -0.04 | -0.92 |
| Share of Pop. with BA or Higher, 2013 | 0.00 | -0.03 | -- | -- |
| High STEM/High Soft Employment | -- | -- | 0.13 | 2.18* |
| High STEM/Mid Soft Employment | -- | -- | 0.26 | 4.15*** |
| High STEM/Low Soft Employment | -- | -- | 0.23 | 5.10*** |
| Mid STEM/High Soft Employment | -- | -- | 0.05 | 1.04 |
| Mid STEM/Mid Soft Employment | -- | -- | 0.09 | 1.73 |
| Mid STEM/Low Soft Employment | -- | -- | 0.04 | 1.14 |
| Low STEM/High Soft Employment | -- | -- | 0.07 | 1.29 |
| Low STEM/Mid Soft Employment | -- | -- | -0.11 | -2.22* |
| Low STEM/Low Soft Employment | -- | -- | -0.11 | -2.78** |
| | $R^2$ = 0.35 | | $R^2$ = 0.61 | |
| | Adj. $R^2$ = 0.34 | | Adj. $R^2$ = 0.59 | |
| | *F* (df) = 40.08 (5, 372)*** | | *F* (df) = 42.88 (13, 364)*** | |

*N* = 377 MSAs and NECTAs

a. Education & occupation human capital measures entered separately due to issues of collinearity.

*p ≤ .05 level; **p ≤ .01 level; ***p ≤ .001 level

**2 Human Capital Occupation Variables Raise & 2 Lower Per Capita Incomes**

Table 37, below, provides the results of the two regression models exploring the effects of education-based and occupation-based measures of human capital on per capita income, controlling for regional variation in migration, labor force participation, median house value and manufacturing employment. As can be seen, the occupational skill-based measures of human capital explained more of regional variation in per capita income than did the education-based human capital variable (Adj. $R^2$ = .65 compared to Adj. $R^2$ = .6). As human capital theory indicates, the education variable was positively significant in Model 1 ($b$ = .17). High STEM/Low Soft ($b$ = .21) and Mid STEM/High Soft ($b$ = .11) were both positively related to regional per capita incomes, while Mid STEM/Low Soft ($b$ = -.11) and Low STEM/Low Soft employment ($b$ = -.09) were negatively associated. Two of the four control variables were positively associated with regional per capita, with median house value (a proxy for cost of living) having by far the largest effect of all the variables in Model 2 ($b$ = .58). Labor force participation ($b$ = .58) was also positively associated with per capita income in both models.

**Table 37. Relationship Between High/Mid/Low Occupational Skill Requirements and Per Capita Income[a]**

| | Model 1 | | Model 2 | |
|---|---|---|---|---|
| **Variables** | **Coefficient** | ***t*** | **Coefficient** | ***t*** |
| Intercept | 0.00 | 0.01 | 0.00 | -0.08 |
| Region to U.S. Pop. Change from Migration | 0.03 | 0.77 | 0.02 | 0.56 |
| Labor Force Participation | 0.24 | 5.86*** | 0.21 | 5.43*** |
| Region to U.S. Median House Value | 0.51 | 12.28*** | 0.58 | 15.69*** |
| Manufacturing Employment | -0.02 | -0.64 | -0.04 | -1.07 |
| Share of Pop. with BA or Higher, 2013 | 0.17 | 3.58*** | -- | -- |
| High STEM/High Soft Employment | -- | -- | 0.03 | 0.61 |
| High STEM/Mid Soft Employment | -- | -- | 0.07 | 1.28 |
| High STEM/Low Soft Employment | -- | -- | 0.21 | 5.16*** |
| Mid STEM/High Soft Employment | -- | -- | 0.11 | 2.73** |
| Mid STEM/Mid Soft Employment | -- | -- | -0.03 | -0.55 |
| Mid STEM/Low Soft Employment | -- | -- | -0.11 | -3.19** |
| Low STEM/High Soft Employment | -- | -- | 0.02 | 0.38 |
| Low STEM/Mid Soft Employment | -- | -- | 0.05 | 1.13 |
| Low STEM/Low Soft Employment | -- | -- | -0.09 | -2.59** |
| | $R^2$ = 0.60 | | $R^2$ = 0.66 | |
| | Adj. $R^2$ = 0.60 | | Adj. $R^2$ = 0.65 | |
| | $F$ (df) = 114.96 (5, 383)*** | | $F$ (df) = 56.71 (13, 375)*** | |

*N* = 388 MSAs and NECTAs
a. Education & occupation human capital measures entered separately due to issues of collinearity.
*p ≤ .05 level; **p ≤ .01 level; ***p ≤ .001 level

## 2 Occupation Variables Associated With Lower Regional Poverty Rates

Table 38, below, provides the results of the two regression models exploring the effects of education-based and occupation-based measures of human capital on the share of regional population living in poverty. As can be seen, Model 2 had greater explanatory power than Model 1 (Adj. $R^2$ = .5 compared to Adj. $R^2$ = .42). Moreover, the education-based human capital measure in Model 1 was not significant. Only two of the nine occupation-based human capital variables in Model 2 were negatively related to regional poverty rates –High STEM/Low Soft employment (*b* = -.24) and Low STEM/Mid Soft employment (*b* = -.21). Mid STEM/Low Soft employment (*b* = .13) and Low STEM/Low

Soft employment (*b* = .12) were also statistically significant, positively, meaning that an increase in the share of such employment increased regional poverty rates. Three of the four control variables were negatively associated with regional poverty across both models. In Model 2, the median house value (*b* = -.41) and labor force participation (*b* = -.35) had the largest effect sizes of all the variables. Manufacturing employment (*b* = -.17) was also significant.

**Table 38. Relationship Between High/Mid/Low Occupational Skill Requirements and Poverty, 2013[a]**

| | Model 1 | | Model 2 | |
|---|---|---|---|---|
| **Variables** | **Coefficient** | ***t*** | **Coefficient** | ***t*** |
| Intercept | 0.00 | -0.10 | 0.00 | -0.09 |
| Region to U.S. Pop. Change from Migration | -0.04 | -0.96 | -0.03 | -0.72 |
| Labor Force Participation | -0.45 | -9.33*** | -0.35 | -7.74*** |
| Region to U.S. Median House Value | -0.37 | -7.49*** | -0.41 | -9.19*** |
| Manufacturing Employment | -0.12 | -2.90** | -0.17 | -3.67*** |
| Share of Pop. with BA or Higher, 2013 | 0.03 | 0.56 | -- | -- |
| High STEM/High Soft Employment | -- | -- | 0.05 | 0.71 |
| High STEM/Mid Soft Employment | -- | -- | -0.02 | -0.36 |
| High STEM/Low Soft Employment | -- | -- | -0.24 | -4.96*** |
| Mid STEM/High Soft Employment | -- | -- | -0.04 | -0.79 |
| Mid STEM/Mid Soft Employment | -- | -- | 0.02 | 0.43 |
| Mid STEM/Low Soft Employment | -- | -- | 0.13 | 3.19** |
| Low STEM/High Soft Employment | -- | -- | 0.07 | 1.14 |
| Low STEM/Mid Soft Employment | -- | -- | -0.21 | -3.96*** |
| Low STEM/Low Soft Employment | -- | -- | 0.12 | 2.79** |
| | $R^2$ = 0.43<br>Adj. $R^2$ = 0.42<br>$F$ (df) = 58.00 (5, 383)*** | | $R^2$ = 0.52<br>Adj. $R^2$ = 0.50<br>$F$ (df) = 30.62 (13, 375)*** | |

*N* = 388 MSAs and NECTAs

a. Education & occupation human capital measures entered separately due to issues of collinearity.

*p ≤ .05 level; **p ≤ .01 level; ***p ≤ .001 level

**What Do the Findings Mean to Regions?**

Controlling for all other variables in Model 2:

- Regions with 1 standard deviation (1.9 percentage points) greater share of regional employment in High STEM/High Soft occupations had a $6,829 higher regional median wage, $13,041 higher regional total factor productivity, but 1.0 percentage point lower GRP growth.
- Regions with a 1 standard deviation (1.4 percentage points) larger share of regional employment in High STEM/Mid Soft occupations had a regional median wage $3,330 higher, 1.94 percentage points higher growth in GRP, and $25,485 higher total factor productivity.
- Regions with 1 standard deviation (1.2 percentage points) greater share of regional employment in High STEM/Low Soft occupations had a regional median wage $2,591 higher, 1.39 percentage points greater GRP growth, $22,797 higher total factor productivity, $8,853 higher per capita income, and a poverty rate 3.85 percentage points lower.
- Regions with 1.7 percentage points (1 standard deviation) higher share of Mid STEM/High Soft employment had regional median wages $2,220 higher and $4.719 higher per capita income.
- Regions with 0.98 percentage point (1 standard deviation) higher share of Mid STEM/Mid Soft employment had regional median wages $2,624 lower.

- Regions with a 2.3 percentage points (1 standard deviation) higher share of employment in Mid STEM/Low Soft occupations had a regional median wage $3,600 lower, a $4,510 lower per capita income, and a poverty rate 2.0 percentage points higher.
- Regions with 1.1 percentage points larger share Low STEM/High Soft employment had a regional median wage that was $9,319 higher.
- Regions with 2.4 percentage points higher share employment in Low STEM/Mid Soft occupations had $5,047 lower regional median wages, had 1.2 percentage points lower growth in GRP, had $11,249 higher total factor productivity and had a poverty rate 3.3 percentage points lower.
- Regions with 3.4 percentage points more employment in Low STEM/Low Soft occupations had regional median wages $6,830 lower, 0.7 percentage points lower GRP growth, $10,752 higher total factor productivity, $3,842 higher per capita income, and a poverty rate 1.9 percentage points higher.

Model 1 provides some opportunity for comparison of the commonly used human capital proxy – educational attainment. Holding net migration, labor force participation, region to U.S. median house value and manufacturing employment constant, an 8.4 percentage point (1 standard deviation) increase in a region's share of its population age 25 and older with a bachelor's degree or higher was associated with a $7,940 higher regional median wage and a $7,266 higher per capita income.

As for the effect of the control variables, holding all other variables equal in Model 2:

- Regions with a labor force participation rate 4.9 percentage points higher (1 standard deviation) had a regional median wage $2,893 higher, GRP growth 1.7 percentage points higher, total factor productivity $9,159 higher, per capita income $8,644 higher, and a poverty rate 5.6 percentage points lower.
- Regions with a median house value 5.8 times (1 standard deviation) greater than the U.S. median house value had a regional median wage $14,399 higher, total factor productivity $41,712 higher, per capita income $24,347 higher, and a poverty rate 6.4 percentage points lower.
- Regions with a share of employment engaged in manufacturing that was 5.3 percentage points higher had a median wage $2,321 higher and a poverty rate 2.6 percentage points lower.

**CONCLUSION**

As can be seen in Table 39, which summarizes the findings for all human capital variables discussed earlier, only one of the human capital measures was significant on all five measures of regional economic well-being: the share of regional employment in occupations requiring High STEM/Low Soft knowledge and capabilities. Regions with a higher share of High STEM/Low Soft employment tended to have higher median wages, greater growth in GRP, higher productivity, higher per capita incomes, and lower rates of poverty. Four of the occupation-based human capital measures were significantly related to three of the measures of regional wellbeing: Regions with a larger share of employment in High STEM/Mid Soft occupations had higher regional wages, greater growth in GRP and higher productivity. Regions with a larger share of employment in Mid STEM/High Soft occupations had higher median wages, lower GRP growth, and higher per capita incomes. Regional with a larger share of employment in Low STEM/Mid Soft employment had lower median wages, lower GRP growth, and lower poverty. Regions with a larger share of employment in occupations falling in the bottom third of STEM and Soft KSA requirements tended to have lower median wages, lower (or negative) GRP growth, and lower productivity. It is worth pointing out that the education-based human capital measure was significantly related to only three of the five measures of economic wellbeing. Regions that have a larger share of population age 25 and over with a bachelor's degree or higher have higher median wages, higher per capita incomes, and, somewhat surprisingly, higher poverty rates.

**Table 39. Summary of Regression Findings for Alternate Approach to High/Mid/Low Skill Categories**

| Human Capital Variable | Regional Median Wage | % Change in GRP, 2009-2013 | Productivity, 2013 | Per Capita Income, 2013 | Poverty Rate, 2013 |
|---|---|---|---|---|---|
| BA or higher | +*** | N.S. | N.S. | +*** | N.S. |
| High STEM/ High SOFT | +*** | -* | +* | N.S. | N.S. |
| High STEM/ Mid SOFT | +** | +*** | +*** | N.S. | N.S. |
| High STEM/ Low SOFT | +** | +*** | +*** | +*** | -*** |
| Mid STEM/ High SOFT | +* | N.S. | N.S. | +** | N.S. |
| Mid STEM/ Mid SOFT | -* | N.S. | N.S. | N.S. | N.S. |
| Mid STEM/ Low SOFT | -*** | N.S. | N.S. | -** | +** |
| Low STEM/ High SOFT | +*** | N.S. | N.S. | N.S. | N.S. |
| Low STEM/ Mid SOFT | -*** | -** | -* | N.S. | -*** |
| Low STEM/ Low SOFT | -*** | -* | -** | -** | +** |

*p ≤ .05 level; **p ≤ .01 level; ***p ≤ .001 level; n.s. = not significant

Although so much policy attention is devoted to supporting High STEM majors and jobs, a focus largely supported by the results presented here, it's worth noting that High Soft skills are also associated with higher regional wages and higher per capita incomes. This suggests that High Soft skills may be more important to the wellbeing of individuals in the region (wages and per capita incomes) than to the economic competitiveness of the region.

Occupations requiring High STEM skills, in general, appear to make a difference in regional economic performance. These findings would seem to support the considerable attention paid to STEM skills among government leaders, in policy and in the media. However, the focus may be somewhat misplaced. Although 83% of the 95 occupations requiring both High STEM and High Soft skills also require a bachelor's degree or more, only a quarter of High STEM/Mid Soft occupations and no High STEM/Low Soft occupations require such high levels of educational attainment. Keep in mind that regional employment in High STEM/Low Soft occupations was the only variable exhibiting the theorized and desired human capital effect across all five measures of regional economic wellbeing. In addition, regional employment in occupations requiring High STEM/Mid Soft had the desired effect on more measures of regional economic health than did employment in High STEM/High Soft occupations, which are the focus of much of the policy and rhetoric about the importance of STEM. This would suggest that policies are overlooking paths to connect workers to High STEM jobs by focusing too intently on educational attainment. Many occupations requiring a relatively high level of STEM skill require relatively low levels of formal education.

This finding largely bolsters arguments made by Holzer (2008) and Rothwell (2013) suggesting a higher education bias in STEM policy and conceptualization. However, this research offers little support for assertions that middle STEM skills – defined here as those falling in the middle third of occupational requirements across 35 individual KSAs – are important contributors to regional economic performance. As can be seen in Table 11, regions with a larger share of employment in occupations requiring Mid STEM/High Soft skills tend to enjoy higher median wages and higher per capita incomes. Moreover, regions with a larger share of employment in occupations requiring Mid STEM/Mid Soft or Mid STEM/Low Soft skills actually had lower median wages. However, the observed non-significance of occupations labeled “Mid” for this analysis should not necessarily undercut the importance of middle-skill jobs to individual workers as well as to regional economies. Presumably, all occupations that neither require High STEM/High Soft KSAs nor Low STEM/Low Soft KSAs can be thought of as “middle.”

Additionally, the lack of findings appears largely one of definition: A third of the occupations categorized as High STEM for this analysis – and 42% of High STEM employment – would be categorized as “middle-skill” based on the education criterion of requiring more than high school but less than a bachelor’s degree. Supporting that observation is that fact that more than half of the occupations captured in the High STEM/Low Soft category using this methodology fell into the Mid STEM/Mid Soft category using the methodology described in Chapter VI that conceptualized “middle skills” as falling between 1 standard deviation above and below the occupational mean score across the group of KSAs. These occupations include: oil and gas derrick operators, gas compressor and gas pumping station operators, machinists, structural iron and steel workers, and medical equipment preparers.

The literature includes differing opinions regarding the importance and the prevalence of middle-skill jobs (see Holzer, 2008, & Autor, 2010). Again, some of this dispute is clearly definitional. Are middle-skill jobs those requiring some middle definition of skill, those paying middle wages, those requiring education less than a bachelor’s degree, or those in certain occupations or industries? Discussion of middle-skill jobs often belies its own bias toward manufacturing and technical endeavors.

The results presented here, dividing occupations into thirds on the STEM and Soft skill groupings, suggest that the null hypothesis regarding middle-skill occupations cannot be rejected. A higher share of regional employment in occupations requiring a middle-level of STEM skills and a middle-level of Soft KSAs are not associated with positive regional economic performance. In fact, employment in occupations requiring STEM/Soft skills falling into the middle third of KSA demands across all 764 occupations was associated with lower median wages. Such employment had no significant effect on the other four indicators of economic wellbeing.

Muddying the policy efforts further is a possible conflict between what is good for a region – or state or nation – overall and what is good for the individuals making up those areas and pursuing the skills that may be economic differentiators. Although regions with larger shares of employment in occupations requiring High STEM skills, in combination with High Soft, Mid Soft or Low Soft KSAs, tend to see better economic performance, individual workers may not see similar benefit. Table 40 shows how median wages, measured across all occupations at the national level, vary by skill requirements. What is apparent is the importance of superior Soft skills to worker wages: Occupations falling in the top third in terms of Soft skill requirements pay substantially more than all other occupational skill categories. Occupations that are Mid STEM but High Soft pay substantially more than occupations that are High STEM but Mid Soft. What is also apparent is how little workers in High STEM/Low Soft occupations are rewarded for the economic benefit they may be returning to regions:

**Table 40. Median Occupational Wage by High/Mid/Low Skill Category**

| | Low STEM | Mid STEM | High STEM |
|---|---|---|---|
| High Soft | $61,450 | $72,845 | $79,930 |
| Mid Soft | $41,745 | $46,690 | $50,785 |
| Low Soft | $26,640 | $35,420 | $39,100 |

One last observation should be drawn from comparing the findings across Chapters V, VI and VII: That is the apparent link among industrial demand, occupational skill requirements and regional economic wellbeing. As is largely assumed in the literature, the media and policy initiatives, many regions that are seeing greater economic wellbeing, at least on some measures explored, are those with higher concentrations of employment in occupations such as software application developers, computer network architects. However, many regions that enjoyed greater economic wellbeing across all five measures were those that had higher concentrations of employment in occupations related to the oil and gas industry and other occupations in industries supporting oil and gas activity. The timeframe of this analysis reflected a period during which technological innovations and world energy prices fueled an economic boom in the U.S. oil and gas industry. This observation underscores how intertwined human capital demand is with industrial demand. It also highlights the challenge of identifying specific skill sets for policy support.

# CHAPTER VIII

# CONCLUDING THOUGHTS, POLICY IMPLICATIONS & FUTURE RESEARCH

This research provides support for a complex view of human capital that derives much of its value based on how it is demanded in the marketplace. What is often missing from regional economic development is an understanding and acknowledgment of how specific skills are affected by the rise and fall of the industries that demand them. Focusing policy attention so keenly on a somewhat boilerplate perception of skill supply shortcomings would seem to unfairly place the burden of insufficient human capital solely on workers without acknowledging how many occupations demand very little skill of workers.

This analysis suggests that an alternative measure of human capital reflecting the skill sets required of a region's collection of occupations may offer greater insight to policy makers and practitioners tasked with supporting and improving regional economic performance than the common focus on educational attainment of the area's population. This is especially true if policy makers and practitioners are interested in measures of economic wellbeing other than regional median wage. As the analysis shows, a larger share of residents with a bachelor's degree or higher does correspond with a higher regional median wage. However, such high levels of educational attainment do not shed light on other important measures of regional economic performance, such as growth in GRP, total factor productivity and poverty rates. These results seem somewhat in conflict with the largely rosy assumptions of human capital theory, but they bolster frequently ambiguous or even problematic findings in the literature. Equivocal findings suggest either human capital theory is more nuanced than assumed or the measure commonly used to indicate it is not up to the task – or both.

Matching the extensive details on occupational requirements now available through the government-sponsored Occupational Information Network (O*NET) to occupational and region-specific data collected by the federal government through the Department of Labor and the Census Bureau provides the means to explore whether a finer-grained measure of regional human capital will reveal the theorized economic benefit. Such a measure allows for a more nuanced understanding of occupations as a bundle of attributes.

Measuring human capital as the collection of knowledge, skills and abilities (KSAs) required of occupations has two important advantages over the common proxy of human capital as the educational attainment of an area's population: First, it more closely captures the broad concept of human capital as conceived by Schultz (1961) and as observed in economic literature as far back as Adam Smith (1776/2008). Second, it squarely acknowledges human capital as a factor of production, meaning that the value of human capital extends from how it connects into the economy. This in no way minimizes the value of education broadly, which has been shown to be associated with a number of desirable outcomes ranging from healthier living to increased voting. However, in the practical world of public policy, limited resources presumably should be applied to best effect. Human capital investments that are overallocated toward education, rather than better matched to the human capital demands of a region, mean that other potential human capital investments – such as improving the health of families or maintaining a safe environment – may go underfunded.

Certainly, elevating the potential of its people is an important role for government. However, human capital theory assumes that such investments yield economic return, bringing benefit to those, whether individuals investing private resources or governments investing public ones, who pursue "superior skills." This, by extension, means the human capital investments are in some way creating greater economic value. Resource-based theory of the firm, which has roots in the economic literature but has been explored more extensively in the business literature, may provide an important framework for regional (and state) policymakers regarding how the regional human capital asset contributes to value creation and sustained competitive advantage.

However, understanding opportunities for value creation and sustained competitive advantage requires better understanding the regional human capital asset itself. The methodology presented here, detailing the development of an Integrated Database of Occupational Human Capital built on the O*NET's extensive mapping of skill requirements, appears to offer useful refinement on the current policy preoccupation with educational attainment. The measures of regional human capital presented here enable a more nuanced understanding of occupations as a bundle of attributes and the mix of those attributes as potentially valuable regional resources.

## KEY TAKEAWAYS

The preceding chapters have demonstrated the insight that can be gleaned from integrating existing federal databases and integrating economic development and business strategy literature streams to refine current understanding of the regional human capital asset. The following is a summary of salient findings:

**The regional human capital asset is manifest in how the knowledge, skills and abilities of individual workers are deployed in a way that creates value through the region's mix of jobs.**

The resource-based literature suggests that a region's economic wellbeing arises out of how valuable, rare, inimitable and apropos its regional human capital asset is within the context of its mix of industries. Much of the discussion of regional human capital in the economic development literature focuses on some measure of educational attainment of individuals. However, a region's individual-level human capital capacity also includes worker skills developed through training, practice or self-study; it includes experience, migration, and even health. A region's human capital asset also encompasses firm human capital, which includes firm-specific practices and processes, intellectual property, branding, as well as organizational systems and structures. Both individual- and firm-level human capital have value in their own right, but they are the building blocks from which the regional human capital asset emerges. However, not all human capital capacity is channeled into the regional human capital asset. Individuals may have human capital that they cannot, or choose not to, use in the context of the local economy. Firms may have human capital, such as ideas for new products of which there is no viable market, that does not contribute to the local economy.

**The human capital asset, whether measured by educational attainment or by occupational skill requirements, varies widely across regions.**

The average level of college completion across regions was 26%, but that average belies considerable variation in regional share of population over age 25 with a bachelor's degree or higher. More than 45 percentage points separate the regions with the lowest share of higher educational attainment from those with the highest. One criticism of human capital theory is that it in essence blames workers for their own low wages because they failed to invest in developing skills that command higher pay. Yet, the wide range in regional educational attainment may, at least in part, reflect wide variation in the types of skills required by each region's mix of occupations. There was a 5-fold difference in the share of regional employment in High STEM/High Soft occupations, with the least highly skilled region employing 1 of every 20 workers in such occupations and the highest employing 1 of every 4. Conversely, some regions had more than 6 of every 10 workers employed in occupations requiring below-average STEM and below-average Soft skills, while other regions had little more than 3 of every 10 workers in such low-skill jobs.

**Measuring regional human capital in terms of occupational skill requirements offers improved explanatory power over the current educational attainment proxy.**

The regression analyses substituting the occupation-based human capital variables consistently explained variation in the five measures of regional economic wellbeing over the population-based educational attainment variable. Even the relatively blunt grouping of occupations by above-average or below-average STEM and Soft skill requirements substantially improved explanatory power over the educational variable. This would seem to be expected, given that occupations are the means by which human capital is connected to the economy. Continuing to refine the occupational variables appeared to continue to improve explanatory power on most of the five variables of economic wellbeing. For example, although the education variable was statistically significant in predicting median wage, the model in which it was added to four control variables explained only about 60% of regional variation in median wage, compared to the 82% of variation explained by the control variables and the nine occupation-based variables.

**Increasing the share of a region's population with a bachelor's degree or higher may improve some measures of regional economic performance but may not affect, or may even worsen, others.**

Consistent with human capital theory, regions with a larger share of highly educated adults tend to have higher median wages than less-educated regions. However, regions with higher levels of education did not enjoy greater GRP growth, higher productivity or higher per capita incomes than less educated regions, after controlling for labor force participation, migration, cost of living, and manufacturing employment. Somewhat surprising, better-educated regions appeared to have higher rates of poverty than less educated regions, controlling for the socioeconomic factors in Chapter V.

Moreover, a “mismatch” between the share of the population with a bachelor’s degree of higher and the share of a region’s occupations requiring such level of educational attainment may slightly lower regional wages, while slightly increasing growth in GRP.

**Increasing the share of a region’s population with a bachelor’s degree or higher in science, technology, engineering or math does not necessarily improve regional economic wellbeing.**

When policymakers and reporters tout the importance of STEM skills and STEM jobs as drivers of innovation and economic growth, they typically are referring to occupations that require both higher than average STEM capabilities and higher than average thinking and communication skills. Nearly three-fourths of the 182 occupations grouped in this category require a bachelor’s degree or higher. However, High STEM/High Soft occupations account for little more than 16% of total U.S. employment. Refining the human capital measure further to include only those occupations requiring STEM and Soft skills in the top third of occupational skill demands for each KSA category reveals that 83% of such occupations, employing only about 4.3% of total U.S. employment, require a bachelor’s degree or higher. Occupations such as physicists, computer network analysts, microbiologists, and engineers of all stripes fall into this category of High STEM/High Soft requirements, as do information security analysts, chemistry professors and nurse practitioners. Regions with a higher share of employment in High STEM/High Soft occupations enjoyed higher regional median wages and higher productivity, but such concentrations were shown to have no effect on per capita income or poverty rates.

**Occupations requiring higher than average STEM skills are important to regional economic performance, but such occupations may not require a college degree.**

Although national, state and regional policies targeted toward increasing the supply of workers with STEM knowledge have tended to display a higher education bias (Rothwell, 2013), regions with a larger share of employment in occupations requiring STEM knowledge in the top third of all occupations but Soft skills in the bottom third are those seeing gains across all five measures of economic wellbeing. Such occupations account for only about 5% of total U.S. employment. Occupations with such skill requirements include derrick operators and roustabouts for the oil and gas industry, industrial machinery mechanics, and machinists. None of these occupations require a bachelor's degree. STEM initiatives directed at occupations requiring skills beyond that of a high school diploma but less than a four-year college degree have been increasing, against a backdrop of anecdotal reports coming from manufacturers and advocacy groups indicating a need for workers with such skill sets.

**The focus of human-capital based policy interventions are typically on increasing the supply of higher-skilled workers, but the share of regional employment in occupations with the lowest skill requirements represents a stubborn challenge to economic wellbeing.**

Occupations with requirements in the bottom third of STEM and Soft skills account for 18.4% of all occupations but 34.1% of U.S. employment. Such employment is associated with lower individual wages, lower regional median wages, lower GRP growth, lower total factor productivity and lower per capita incomes.

**Human capital accumulation that most benefits regions may not be that which benefits individual workers the most.**

Although regions with a higher share of employment in High STEM/Low Soft occupations were demonstrated to see improvements on all measures of regional economic wellbeing, such occupations paid a median wage of only $39,100. That ranked such occupations near the bottom of the wage scale for the nine human capital STEM/Soft categories. The highest STEM/Soft category paid individuals the highest median wages by far – $79,930 – even though their benefit to regions was less pronounced. Occupations requiring Low STEM/High Soft paid median wages of $61,450; however, regions with a higher share of employment in such occupations saw increases in regional median wage but no improvement in the other measures of economic wellbeing.

**The regional capital asset is important, but it can only explain part of why some regions perform better than others.**

One criticism of human capital theory is that it largely places the burden of low-paying jobs on for failing to invest in upgrading their skills. However, the concentration of low-paying jobs reflect market forces beyond the control of individual workers and even regions. Although the occupation-based human capital measures improved explanatory power in all of the models, there was still substantial variation in the measures of regional economic wellbeing left unexplained. Roughly a third of the variation in per capita income and nearly half of variation in poverty rates could not be explained by regional differences in migration flows, labor force participation rates, cost of living, manufacturing employment and occupational human capital. Suggesting the impact, at least short-term, of business cycles and industry dynamics, the occupational human capital measures, combined with the control variables, explained only about a third of regional variation in GRP growth.

**POLICY IMPLICATIONS**

Occupations support and reflect industry. This has important implications for policy interventions targeted at increasing human capital supply: Regions (or states and even nations) that invest in developing human capital that does not fit the human capital demanded by the industrial mix will likely not enjoy the desired benefit of such expenditures of public resources. Workers with ill-fitting human capital will either accept jobs below the skill levels they have acquired or they will relocate to other regions where the skills they possess match those in demand. Either scenario means the area will see little return on its human capital investment.

As discussed in Chapter II, resource-based theory of the firm places human capital as central to value creation and sustained competitive advantage. However, the value arises in how those assets are developed and deployed within the context of firm strategies, strengths and capacities to respond to external market forces and seize on opportunities. Competitive advantage is not achieved simply through differences in resources but in their efficient allocation, their strategic deployment and their enabling of innovation. This would suggest that human capital-inspired economic development policies will not achieve the desired boost in economic wellbeing unless they are aligned to the particular needs and strengths of the region. Interventions that focus on regional human capital capacity instead of regional human capital deployment are likely to lead to distortions in the supply and demand equilibrium and miss opportunities to facilitate fit.

Economic development policy and practice have taken, largely, a supply-side view of human capital, assuming that increasing the educational levels of the population, especially increasing the share of workers with expertise in science, technology, engineering and math, will be rewarded with economic growth. Such policies and practices are guided by the theorized special property of knowledge and technology that is set forth in new growth theory. However, such a view neglects the importance of demand, goodness of fit and strategic deployment in transforming the regional human capital asset into a component of regional economic wellbeing.

Muddying the policy efforts further is an apparent conflict between what is good for a region – or state or nation – overall and what is good for the individuals making up those areas and pursuing the skills that appear, at this time, to be economic differentiators. Although regions with larger shares of employment in occupations requiring High STEM skills, in combination with High Soft, Mid Soft or Low Soft KSAs, tend to see better economic performance, individual workers may not see similar benefit. What is apparent is the importance of superior Soft skills to worker wages: Occupations falling in the top third in terms of Soft skill requirements pay substantially more than all other occupational skill categories. Occupations in the skill categories that appear to contribute to an across-the-board improvement in regional wellbeing appear to reward workers very little.

Regions that are fortunate enough to be home to industries that are in a stage of growth instead of decline will see greater economic benefit the better their supply of human capital match industrial demand. Instead of adopting broad, “me-too” policies targeted toward producing more bachelor’s degrees, specifically STEM degrees, regions would be wise to focus economic development and workforce development efforts on human capital “fit.” Good human capital fit allows regions to seize the gains that accompany industries that are experiencing periods of growth. That means supporting specific skills that support specific regional industries. However, fit likely isn’t sufficient to help regions transition to and seize on the benefits of new industries and new growth opportunities. The problems of “Rust Belt” cities, where skill sets too closely aligned to a handful of dominant industries, demonstrate that. Regions (and states and nations) must also think about the “fungibility” of their human capital stock. Higher levels of generic, convertible skills may provide regions with the ability to adapt when industry cycles inevitably change.

However, although human capital-based interventions more aligned to the specific needs of industry invite question about the appropriate role for government. In his essay on education, Friedman (1955) suggested that public support should be more directed at the types of broad knowledge that contribute to citizenship and leadership and cautioned against public support for varieties of human capital where benefits are mostly captured by the individuals (and, presumably, firms) themselves. Public support for enhancing Soft skills would seem to support the citizenship and leadership criterion, but higher levels of such skills seemed to reward individual workers more than regions. Public support for enhancing certain STEM skills may lead to improved regional economic wellbeing, while potentially subsidizing specific firms. Friedman's reasoning failed to recognize the potential value of knowledge spillovers, which may result in societal benefit from investments in human capital beyond the observed private benefit. However, his essay offers important insight into the delicate balance policymakers face. In the practical world of policy, limited resources presumably should be applied to best and most appropriate effect. Human capital investments that are overallocated toward education, rather than better matched to the human capital demands of a region, mean that other potential human capital investments – such as improving the health of families or maintaining a safe environment – may go underfunded.

Adding to this delicate policy balance is the need to be aspirational while also practical, the need to anticipate the human capital needs of tomorrow while supporting the needs of today. This is indeed a challenging balance to strike, especially in an environment of rapid technological change, intense global pressures, and political expectations of action. What seems clear, however, is that countless human capital-based economic development initiatives, especially at the regional (and state) level, are being undertaken with an incomplete or misguided understanding of how such efforts help to grow a regional human capital asset of greater economic value. The analyses presented here represent a step toward a greater understanding of the regional human capital asset.

## LIMITATIONS & FUTURE RESEARCH

Although the findings presented here appear to offer a more refined and robust understanding of the regional human capital asset, they should be viewed somewhat cautiously: The results reflect only a snapshot in time. The way O*NET and OES data are collected inhibit the comparison of regional skill sets and economic performance over time. Moreover, the need to use 5-year ACS data to match to the MSA delineations used by OES mean that the measures of economic wellbeing were still being affected by the long-lingering effects of the Great Recession, which officially ended in summer 2009. It is reasonable to assume that such a far-reaching and deep economic disruption may have led to skewed results and, thus, misleading inferences. For example, the occupational skill categories associated with improved economic wellbeing may simply reflect high concentrations of industries that experienced quicker or more pronounced bounce-back from the effects of the recession.

Assumptions regarding the uniformity of occupational skill sets across industries and across regions may represent serious limitations of this research. O*NET's use of only a couple of dozen workers to represent the human capital requirements across the nation assumes a homogeneity of human capital demand. This in itself undercuts the value emanating from a heterogeneity of supplied skills. Moreover, this analysis explores skill out of the context of place. Presumably, different areas may have different demands and pay different rewards to human capital. Workers with unique skill sets may not see return on the investment in acquiring that human capital if they live in an area where there is no demand for such skill. A better understanding of region-specific variation in occupational skill demands than is currently available in the O*NET database would improve on the findings presented here.

In addition, the assumed similarity of occupational skill requirements across regions and across industries ignores the importance of firm-specific, tacit knowledge and skill. Resource-based theory suggests such tacit knowledge to be both critical to creating value as well as maintain valuable human capital assets. Tacit knowledge tends to be less valuable to workers outside the specific environment of the firm; thus, it provides an incentive for workers to stay at the firm – and, by extension, in the region.

Despite these limitations, exploring human capital through the requirements and rewards of occupations would seem to offer a fruitful opportunity for research and practice.

This series of analyses has added to the human capital literature by drawing on complementary theories in the economics/economic development and business strategy/management literatures to explore the regional human capital asset as a valuable resource critical to a region's value proposition and, ultimately, its economic wellbeing. It has offered a view of the regional human capital asset that reflects skill demanded of occupations instead of the overriding policy focus on educational supply. It has indicated the potential folly of pursuing human capital-based interventions disconnected from the powerful forces of business and industry cycles.

Although the regular updating of the O*NET database adds rich refinement to the understanding of occupational requirements, potential changes in occupational definitions make it difficult to explore occupational requirements over time. This research explored the impact of occupational skill sets on regional economic wellbeing at one point in time. Future research should attempt to explore whether these same skill sets demonstrate the same value to regions over time or whether the mix of skills benefiting regions have changed over time. For example, has the number as well as intensity of occupational STEM requirements increased over time?

The sorting of 85 knowledge, skill and ability descriptors into two dimensions – STEM and Soft – may obscure a smaller number of KSAs that represent critical human capital development. Future research should explore both KSAs that seem to be of singular importance, as well as a core group of skills that cut across a wide range of occupations that both reward individuals with higher pay and reward regions with greater economic wellbeing. Such skills – those in thin, but critical demand and those with wide application – would seem to provide a reasonable foundation for human capital-based policy attention.

This research has presented three different techniques for sorting occupations based on the intensity of skills demanded. The approaches sought to match rhetoric, demonstrate statistical validity, and reflect intuitive face validity. The three techniques revealed somewhat differing results but a similar broad message of the importance of certain occupations, at the point in time assessed, to regional economic wellbeing. This suggests two avenues for future research – 1) refining a technique for sorting occupations on the basis of skill, and 2) exploring whether regional human capital assets reflected in the concentration of occupational skill demands drive or reflect industry demand.

This analysis invites future research into how the industry-occupation dynamic plays out in regions. The mean scores for a number of Soft KSAs that were substantially higher than mean scores for most of the collection of STEM KSAs, coupled with a general greater demand for higher Soft skills and higher wages associated with higher Soft skills, reveal two potential policy tensions: 1) The combination of skills that most contribute to regional economic wellbeing may not be the same combination of skills that connect workers to occupations paying higher wages; and 2) The appropriate role for regional economic development policy in balancing current demands for human capital "fit" versus the need for regional human capital "fungibility" to seize on future opportunities.

Future research may identify "stackable" skills that allow workers, particularly those in low skill occupations, to build their human capital without pursuing longer term educational credentials. The value of exploring occupational human capital requirements is it allows opportunity to identify occupations with relatively similar skill demands. In not-too-distant future, technology may be able to enable programs and techniques that enable workers to demonstrate their human capital in ways that allow them to move more easily from one skill application setting to another without the need for recredentialing. This would represent an exciting and important opportunity for future research.

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APPENDIX

**Appendix A. Occupational Wage and Employment by High/Mid/Low STEM/Soft KSAs (Scores Divided into Thirds; Described in Chapter VII)**

*Total No. of Occupations = 764; U.S. Employment = 131,974,860*

**High STEM/High Soft**

| No. of OCCs | Employment | No. of BA+ OCCs | Median Wage |
|---|---|---|---|
| 95 | 9,759,870 | 79 | $79,930 |
| **% of ALL OCCs** | **% of U.S. EMP** | **% OCCs BA+** | **Mean Wage** |
| 12.4% | 7.4% | 83.2% | $81,028 |
| **No. of OCCs Post HS** | **Post HS Emp** | **BA+ EMP** | **BA+ Med. Wage** |
| 15 | 3,842,510 | 5,718,750 | $82,050 |
| **% of H/H Occs Post HS** | **% EMP Post HS** | **% of H/H EMP BA+** | **Post HS Med. Wg** |
| 15.8% | 39.4% | 58.6% | $56,130 |

**High STEM/High Soft**

| OCC Code | Occupation Description | Employment | Education | Median Wage |
|---|---|---|---|---|
| 11-1021 | General and Operations Managers | 2,049,870 | AD | $97,270 |
| 11-3021 | Computer and Information Systems Managers | 330,360 | BA | $127,640 |
| 11-3051 | Industrial Production Managers | 167,200 | AD | $92,470 |
| 11-3061 | Purchasing Managers | 70,840 | BA | $106,090 |
| 11-9013 | Farmers, Ranchers, and Other Agricultural Managers | 4,300 | BA | $68,050 |
| 11-9021 | Construction Managers | 227,710 | BA | $85,630 |
| 11-9041 | Architectural and Engineering Managers | 179,320 | BA | $130,620 |
| 11-9051 | Food Service Managers | 198,610 | HS | $48,560 |
| 11-9081 | Lodging Managers | 31,740 | Some College | $47,680 |
| 11-9111 | Medical and Health Services Managers | 310,320 | BA | $92,810 |
| 11-9121 | Natural Sciences Managers | 53,290 | MA | $120,050 |
| 11-9161 | Emergency Management Directors | 9,770 | BA | $64,360 |
| 13-1041 | Compliance Officers | 246,970 | BA | $64,950 |
| 13-1081 | Logisticians | 125,670 | BA | $73,870 |
| 13-1199 | Business Operations Specialists, All Other | 934,370 | BA | $67,280 |
| 15-1111 | Computer and Information Research Scientists | 24,210 | MA | $108,360 |
| 15-1121 | Computer Systems Analysts | 528,320 | AD | $82,710 |
| 15-1122 | Information Security Analysts | 80,180 | BA | $88,890 |
| 17-1011 | Architects, Except Landscape and Naval | 88,900 | BA | $74,520 |
| 17-1012 | Landscape Architects | 18,110 | BA | $64,570 |
| 17-1022 | Surveyors | 41,970 | BA | $57,050 |
| 17-2011 | Aerospace Engineers | 69,080 | BA | $105,380 |
| 17-2021 | Agricultural Engineers | 2,450 | BA | $71,730 |
| 17-2031 | Biomedical Engineers | 20,080 | MA | $86,950 |
| 17-2041 | Chemical Engineers | 33,470 | BA | $96,940 |
| 17-2051 | Civil Engineers | 263,460 | BA Certificate | $82,050 |
| 17-2071 | Electrical Engineers | 174,550 | BA | $91,410 |
| 17-2072 | Electronics Engineers, Except Computer | 133,990 | BA | $95,790 |
| 17-2081 | Environmental Engineers | 53,240 | MA | $83,360 |
| 17-2111 | Health and Safety Engineers, Except Mining Safety Engineers ... | 24,530 | BA | $81,830 |
| 17-2112 | Industrial Engineers | 236,990 | BA | $81,490 |
| 17-2121 | Marine Engineers and Naval Architects | 7,570 | BA | $92,930 |
| 17-2131 | Materials Engineers | 24,990 | BA | $87,690 |
| 17-2141 | Mechanical Engineers | 270,700 | BA | $83,060 |
| 17-2151 | Mining and Geological Engineers, Including Mining Safety Engineers | 8,200 | BA | $90,160 |
| 17-2161 | Nuclear Engineers | 16,520 | BA | $100,470 |
| 17-2171 | Petroleum Engineers | 33,740 | BA | $130,050 |
| 17-2199 | Engineers, All Other | 124,570 | BA | $94,240 |
| 19-1011 | Animal Scientists | 2,350 | Doctoral | $61,110 |
| 19-1012 | Food Scientists and Technologists | 14,170 | BA | $61,480 |
| 19-1013 | Soil and Plant Scientists | 15,150 | Doctoral | $59,920 |
| 19-1021 | Biochemists and Biophysicists | 31,350 | Doctoral | $84,940 |

**High STEM/Mid Soft**

| No. of OCCs | Employment | No. of BA+ OCCs | Median Wage |
|---|---|---|---|
| 92 | 8,722,820 | 22 | $50,785 |
| **% of ALL OCCs** | **% of U.S. EMP** | **% OCCs BA+** | **Mean Wage** |
| 12.0% | 6.6% | 23.9% | $53,752 |
| **No. of OCCs Post HS** | **Post HS Emp** | **BA+ EMP** | **BA+ Med. Wage** |
| 51 | 5,415,700 | 2,159,130 | $52,525 |
| **% of H/M Occs Post HS** | **% EMP Post HS** | **% of H/M EMP BA+** | **Post HS Med. Wg** |
| 55.4% | 62.1% | 24.8% | $52,200 |

**High STEM/Mid Soft**

| OCC Code | Occupation | Employment | Education | Median Wage |
|---|---|---|---|---|
| 13-1021 | Buyers and Purchasing Agents, Farm Products | 11,250 | BA | $55,080 |
| 13-1051 | Cost Estimators | 209,130 | BA | $60,050 |
| 15-1132 | Software Developers, Applications | 686,470 | BA | $95,510 |
| 15-1141 | Database Administrators | 112,170 | BA | $80,280 |
| 15-1142 | Network and Computer Systems Administrators | 365,430 | BA | $75,790 |
| 15-1143 | Computer Network Architects | 140,080 | BA | $98,430 |
| 15-1151 | Computer User Support Specialists | 563,540 | AD | $47,610 |
| 17-2061 | Computer Hardware Engineers | 76,360 | BA | $108,430 |
| 17-3011 | Architectural and Civil Drafters | 91,520 | BA | $49,970 |
| 17-3013 | Mechanical Drafters | 64,070 | AD | $52,200 |
| 17-3021 | Aerospace Engineering and Operations Technicians | 11,230 | BA | $63,780 |
| 17-3023 | Electrical and Electronics Engineering Technicians | 137,040 | AD | $59,820 |
| 17-3024 | Electro-Mechanical Technicians | 14,430 | Post HS Certificate | $53,070 |
| 17-3025 | Environmental Engineering Technicians | 18,080 | BA | $48,170 |
| 17-3026 | Industrial Engineering Technicians | 65,680 | Some College | $53,370 |
| 17-3027 | Mechanical Engineering Technicians | 47,560 | Some College | $53,530 |
| 17-3029 | Engineering Technicians, Except Drafters, All Other | 67,640 | HS | $61,580 |
| 17-3031 | Surveying and Mapping Technicians | 50,750 | Post HS Certificate | $40,770 |
| 19-2031 | Chemists | 85,970 | BA | $73,480 |
| 19-4011 | Agricultural and Food Science Technicians | 20,640 | BA Certificate | $35,140 |
| 19-4021 | Biological Technicians | 72,640 | BA | $41,290 |
| 19-4031 | Chemical Technicians | 63,760 | AD | $44,180 |
| 19-4041 | Geological and Petroleum Technicians | 16,020 | Some College | $54,810 |
| 19-4051 | Nuclear Technicians | 6,380 | Some College | $74,690 |
| 19-4091 | Environmental Science and Protection Technicians, ... | 33,760 | BA | $42,190 |
| 19-4093 | Forest and Conservation Technicians | 30,310 | Some College | $35,260 |
| 19-4099 | Life, Physical, and Social Science Technicians, All Other | 67,140 | AD | $44,650 |
| 25-4013 | Museum Technicians and Conservators | 9,950 | BA Certificate | $39,940 |
| 25-9011 | Audio-Visual and Multimedia Collections Specialists | 8,960 | BA | $44,070 |
| 27-1021 | Commercial and Industrial Designers | 29,410 | BA | $64,620 |
| 27-4011 | Audio and Video Equipment Technicians | 60,200 | Some College | $41,780 |
| 27-4012 | Broadcast Technicians | 26,600 | Post HS Certificate | $36,560 |
| 27-4014 | Sound Engineering Technicians | 13,750 | Post HS Certificate | $49,870 |
| 29-1024 | Prosthodontists | 630 | Post Doc | $100,280 |
| 29-1124 | Radiation Therapists | 16,380 | AD | $80,090 |
| 29-1126 | Respiratory Therapists | 119,410 | AD | $56,730 |
| 29-2012 | Medical and Clinical Laboratory Technicians | 160,460 | BA | $38,370 |
| 29-2032 | Diagnostic Medical Sonographers | 59,760 | AD | $67,530 |
| 29-2033 | Nuclear Medicine Technologists | 20,320 | AD | $72,100 |
| 29-2035 | Magnetic Resonance Imaging Technologists | 33,130 | AD | $67,090 |
| 29-2054 | Respiratory Therapy Technicians | 10,610 | AD | $47,810 |
| 29-2055 | Surgical Technologists | 98,450 | Some College | $43,350 |

**Appendix A. Occupational Wage and Employment by High/Mid/Low STEM/Soft KSAs (contd.)**

*Total No. of Occupations = 764; U.S. Employment = 131,974,860*

| High STEM/High Soft | | | | |
|---|---|---|---|---|
| **OCC Code** | **Occupation Description** | **Employment** | **Education** | **Median Wage** |
| 19-1022 | Microbiologists | 20,670 | BA Certificate | $67,790 |
| 19-1023 | Zoologists and Wildlife Biologists | 18,970 | MA | $58,270 |
| 19-1029 | Biological Scientists, All Other | 32,230 | Doctoral | $74,720 |
| 19-1031 | Conservation Scientists | 19,210 | BA | $61,860 |
| 19-1032 | Foresters | 9,140 | BA | $57,980 |
| 19-1042 | Medical Scientists, Except Epidemiologists | 100,740 | Doctoral | $79,930 |
| 19-2012 | Physicists | 16,790 | Doctoral | $109,600 |
| 19-2032 | Materials Scientists | 6,900 | MA | $91,980 |
| 19-2041 | Environmental Scientists and Specialists, Including Health | 88,740 | BA | $66,250 |
| 19-2042 | Geoscientists, Except Hydrologists and Geographers | 34,000 | BA | $89,910 |
| 19-2043 | Hydrologists | 6,580 | BA | $78,370 |
| 19-2099 | Physical Scientists, All Other | 23,030 | MA | $94,030 |
| 19-3099 | Social Scientists and Related Workers, All Other | 32,010 | BA | $75,630 |
| 19-4092 | Forensic Science Technicians | 13,570 | AD | $55,360 |
| 25-1021 | Computer Science Teachers, Postsecondary | 35,410 | MA | $72,010 |
| 25-1031 | Architecture Teachers, Postsecondary | 7,190 | First Professional | $73,720 |
| 25-1032 | Engineering Teachers, Postsecondary | 36,650 | Doctoral | $94,130 |
| 25-1043 | Forestry and Conservation Science Teachers, Postsecondary | 1,850 | Doctoral | $84,090 |
| 25-1051 | Atmospheric, Earth, Marine, and Space Sciences Teachers… | 10,890 | Doctoral | $81,780 |
| 25-1052 | Chemistry Teachers, Postsecondary | 21,470 | Doctoral | $73,080 |
| 25-1054 | Physics Teachers, Postsecondary | 14,160 | Doctoral | $80,720 |
| 25-2023 | Career/Technical Education Teachers, Middle School | 14,000 | BA | $54,090 |
| 25-2032 | Career/Technical Education Teachers, Secondary School | 81,560 | BA | $55,200 |
| 25-9021 | Farm and Home Management Advisors | 8,900 | MA | $46,520 |
| 27-1025 | Interior Designers | 45,010 | BA | $48,400 |
| 27-1027 | Set and Exhibit Designers | 10,460 | BA Certificate | $49,810 |
| 29-1021 | Dentists, General | 97,990 | Doctoral | $149,540 |
| 29-1022 | Oral and Maxillofacial Surgeons | 5,120 | Post Doc | $155,740 |
| 29-1023 | Orthodontists | 6,190 | Post Doc | $118,290 |
| 29-1031 | Dietitians and Nutritionists | 59,490 | BA Certificate | $56,950 |
| 29-1041 | Optometrists | 33,340 | Doctoral | $101,410 |
| 29-1067 | Surgeons | 41,070 | Doctoral | $130,710 |
| 29-1081 | Podiatrists | 8,910 | Doctoral | $120,700 |
| 29-1128 | Exercise Physiologists | 6,660 | MA | $46,270 |
| 29-1131 | Veterinarians | 62,470 | Doctoral | $87,590 |
| 29-1151 | Nurse Anesthetists | 36,590 | MA | $153,780 |
| 29-1171 | Nurse Practitioners | 122,050 | MA | $95,350 |
| 29-1181 | Audiologists | 12,250 | Doctoral | $73,060 |
| 29-2041 | Emergency Medical Technicians and Paramedics | 235,760 | Post HS Certificate | $31,700 |
| 29-2091 | Orthotists and Prosthetists | 7,830 | BA Certificate | $64,040 |
| 29-9011 | Occupational Health and Safety Specialists | 65,130 | BA | $69,210 |
| 29-9012 | Occupational Health and Safety Technicians | 13,990 | AD | $48,120 |
| 33-1021 | First-Line Supervisors of Fire Fighting and Prevention Workers | 59,870 | Post HS Certificate | $70,670 |
| 33-2021 | Fire Inspectors and Investigators | 11,370 | Some College | $56,130 |
| 33-3021 | Detectives and Criminal Investigators | 108,720 | Post HS Certificate | $79,870 |
| 33-3031 | Fish and Game Wardens | 5,820 | BA | $50,880 |
| 35-1011 | Chefs and Head Cooks | 118,130 | AD | $41,610 |
| 39-4031 | Morticians, Undertakers, and Funeral Directors | 25,160 | AD | $47,250 |
| 41-9031 | Sales Engineers | 68,080 | BA | $96,340 |
| 43-9031 | Desktop Publishers | 13,310 | AD | $38,200 |
| 49-1011 | First-Line Supervisors of Mechanics, Installers, and Repairers | 434,810 | Post HS Certificate | $62,150 |
| 53-2011 | Airline Pilots, Copilots, and Flight Engineers | 75,760 | BA | $118,140 |
| 53-5021 | Captains, Mates, and Pilots of Water Vessels | 30,690 | Post HS Certificate | $72,340 |

| High STEM/Mid Soft | | | | |
|---|---|---|---|---|
| **OCC Code** | **Occupation** | **Employment** | **Education** | **Median Wage** |
| 29-2099 | Health Technologists and Technicians, All Other | 96,170 | AD | $41,420 |
| 33-2011 | Firefighters | 308,790 | HS | $45,970 |
| 33-2022 | Forest Fire Inspectors and Prevention Specialists | 1,630 | BA | $36,430 |
| 37-1012 | First-Line Supervisors of Landscaping, Lawn Service… | 101,190 | HS | $43,160 |
| 37-2021 | Pest Control Workers | 67,640 | HS | $30,660 |
| 45-1011 | First-Line Supervisors of Farming, Fishing, and Forestry… | 18,530 | HS | $44,880 |
| 45-4011 | Forest and Conservation Workers | 6,870 | BA | $27,160 |
| 47-1011 | First-Line Supervisors of Construction Trades … | 496,370 | Post HS Certificate | $60,990 |
| 47-2111 | Electricians | 566,930 | Post HS Certificate | $51,110 |
| 47-4011 | Construction and Building Inspectors | 88,410 | Some College | $56,040 |
| 47-4021 | Elevator Installers and Repairers | 20,590 | Post HS Certificate | $78,620 |
| 47-4071 | Septic Tank Servicers and Sewer Pipe Cleaners | 24,350 | HS | $34,810 |
| 47-5012 | Rotary Drill Operators, Oil and Gas | 26,480 | HS | $53,160 |
| 47-5013 | Service Unit Operators, Oil, Gas, and Mining | 62,080 | HS | $44,970 |
| 47-5031 | Explosives Workers, Ordnance Handling Experts… | 7,970 | HS | $52,140 |
| 49-2022 | Telecommunications Equipment Installers … | 213,620 | Post HS Certificate | $55,190 |
| 49-2091 | Avionics Technicians | 17,150 | AD | $56,910 |
| 49-2094 | Electrical and Electronics Repairers, Commercial … | 65,900 | Some College | $54,640 |
| 49-2095 | Electrical and Electronics Repairers, Powerhouse… | 22,120 | Post HS Certificate | $71,400 |
| 49-2096 | Electronic Equipment Installers and Repairers… | 11,460 | Post HS Certificate | $31,020 |
| 49-2097 | Electronic Home Entertainment Equipment Installers … | 26,590 | Post HS Certificate | $36,090 |
| 49-3011 | Aircraft Mechanics and Service Technicians | 116,830 | Post HS Certificate | $56,990 |
| 49-3023 | Automotive Service Technicians and Mechanics | 633,390 | Post HS Certificate | $37,120 |
| 49-3042 | Mobile Heavy Equipment Mechanics, Except Engines | 119,280 | Post HS Certificate | $47,580 |
| 49-9021 | Heating, Air Conditioning, and Refrigeration Mechanics … | 261,390 | Post HS Certificate | $44,630 |
| 49-9044 | Millwrights | 39,290 | HS | $50,460 |
| 49-9051 | Electrical Power-Line Installers and Repairers | 114,540 | Post HS Certificate | $65,930 |
| 49-9062 | Medical Equipment Repairers | 41,430 | Post HS Certificate | $45,660 |
| 49-9081 | Wind Turbine Service Technicians | 3,710 | Post HS Certificate | $48,800 |
| 49-9092 | Commercial Divers | 3,620 | Post HS Certificate | $45,890 |
| 49-9095 | Manufactured Building and Mobile Home Installers | 3,280 | Less than HS | $29,600 |
| 49-9099 | Installation, Maintenance, and Repair Workers… | 138,460 | HS | $37,220 |
| 51-1011 | First-Line Supervisors of Production and Operating… | 592,830 | Post HS Certificate | $55,520 |
| 51-4011 | Computer-Controlled Machine Tool Operators, Metal… | 148,040 | Post HS Certificate | $36,440 |
| 51-4012 | CNCN Machine Tool Programmers, Metal and Plastic | 24,960 | AD | $47,500 |
| 51-8011 | Nuclear Power Reactor Operators | 7,400 | HS | $82,500 |
| 51-8012 | Power Distributors and Dispatchers | 11,180 | HS | $78,240 |
| 51-8031 | Water and Wastewater Treatment Plant and System … | 111,640 | HS | $44,100 |
| 51-8091 | Chemical Plant and System Operators | 37,490 | HS | $55,900 |
| 51-8092 | Gas Plant Operators | 16,320 | Post HS Certificate | $64,100 |
| 51-8093 | Petroleum Pump System Operators, Refinery Operators… | 41,700 | HS | $62,830 |
| 51-9021 | Crushing, Grinding, and Polishing Machine Setters… | 29,980 | HS | $33,070 |
| 51-9082 | Medical Appliance Technicians | 13,290 | Some College | $35,580 |
| 53-2012 | Commercial Pilots | 38,170 | Some College | $75,620 |
| 53-4031 | Railroad Conductors and Yardmasters | 42,900 | HS | $54,770 |
| 53-5022 | Motorboat Operators | 4,060 | Post HS Certificate | $37,120 |
| 53-5031 | Ship Engineers | 10,060 | Post HS Certificate | $68,100 |
| 53-6041 | Traffic Technicians | 6,490 | BA | $43,430 |
| 53-6051 | Transportation Inspectors | 24,350 | Post HS Certificate | $69,170 |
| 53-7011 | Conveyor Operators and Tenders | 38,830 | Some College | $31,220 |

**Appendix A. Occupational Wage and Employment by High/Mid/Low STEM/Soft KSAs (contd.)**

*Total No. of Occupations = 764; U.S. Employment = 131,974,860*

**High STEM/Low Soft**

| | | | |
|---|---|---|---|
| No. of OCCs | Employment | No. of BA+ OCCs | Median Wage |
| 53 | 5,915,670 | 0 | $39,100 |
| % of ALL OCCs | % of U.S. EMP | % OCCs BA+ | Mean Wage |
| 6.9% | 4.5% | -- | $41,052 |
| No. of OCCs Post HS | Post HS Emp | BA+ EMP | BA+ Med. Wage |
| 11 | 931,290 | 0 | -- |
| % of H/L Occs Post HS | % EMP Post HS | % of H/L EMP BA+ | Post HS Med. Wg |
| 20.8% | 15.7% | -- | $47,950 |

**Mid STEM/High Soft**

| | | | |
|---|---|---|---|
| No. of OCCs | Employment | No. of BA+ OCCs | Median Wage |
| 74 | 14,919,310 | 65 | $72,845 |
| % of ALL OCCs | % of U.S. EMP | % OCCs BA+ | Mean Wage |
| 9.7% | 11.3% | 87.8% | $81,581 |
| No. of OCCs Post HS | Post HS Emp | BA+ EMP | BA+ Med. Wage |
| 9 | 5,809,770 | 9,109,540 | $74,750 |
| % of M/H Occs Post HS | % EMP Post HS | % of M/H EMP BA+ | Post HS Med. Wg |
| 12.2% | 38.9% | 61.1% | $66,640 |

**High STEM/Low Soft**

| OCC Code | Occupation | Employment | Education | Median Wage |
|---|---|---|---|---|
| 31-9093 | Medical Equipment Preparers | 50,550 | Post HS Certificate | $32,260 |
| 45-3011 | Fishers and Related Fishing Workers | 400 | HS | $35,250 |
| 47-2011 | Boilermakers | 17,210 | HS | $59,860 |
| 47-2021 | Brickmasons and Blockmasons | 59,340 | Less than HS | $47,650 |
| 47-2031 | Carpenters | 617,060 | HS | $40,820 |
| 47-2061 | Construction Laborers | 852,870 | HS | $31,090 |
| 47-2071 | Paving, Surfacing, and Tamping Equipment Operators | 54,940 | HS | $38,660 |
| 47-2131 | Insulation Workers, Floor, Ceiling, and Wall | 24,180 | Less than HS | $33,720 |
| 47-2152 | Plumbers, Pipefitters, and Steamfitters | 372,570 | HS | $50,660 |
| 47-2211 | Sheet Metal Workers | 132,530 | HS | $45,070 |
| 47-2221 | Structural Iron and Steel Workers | 60,010 | HS | $48,200 |
| 47-2231 | Solar Photovoltaic Installers | 5,170 | HS | $40,020 |
| 47-3012 | Helpers--Carpenters | 38,900 | HS | $26,600 |
| 47-4051 | Highway Maintenance Workers | 140,650 | HS | $36,580 |
| 47-4099 | Construction and Related Workers, All Other | 31,190 | HS | $35,400 |
| 47-5011 | Derrick Operators, Oil and Gas | 20,760 | Less than HS | $48,410 |
| 47-5041 | Continuous Mining Machine Operators | 11,540 | Less than HS | $48,440 |
| 47-5071 | Roustabouts, Oil and Gas | 73,450 | HS | $35,780 |
| 49-2021 | Radio, Cellular, and Tower Equipment Installers and Repairers | 13,310 | Post HS Certificate | $47,950 |
| 49-2092 | Electric Motor, Power Tool, and Related Repairers | 17,380 | HS | $39,220 |
| 49-2093 | Electrical and Electronics Installers and Repairers, Transportation… | 14,160 | Post HS Certificate | $56,000 |
| 49-3031 | Bus and Truck Mechanics and Diesel Engine Specialists | 243,080 | HS | $43,630 |
| 49-3041 | Farm Equipment Mechanics and Service Technicians | 35,320 | HS | $36,150 |
| 49-3053 | Outdoor Power Equipment and Other Small Engine Mechanics | 29,220 | HS | $32,120 |
| 49-3092 | Recreational Vehicle Service Technicians | 10,990 | HS | $35,630 |
| 49-9012 | Control and Valve Installers and Repairers, Except Mechanical Door | 41,290 | Post HS Certificate | $53,140 |
| 49-9041 | Industrial Machinery Mechanics | 313,880 | Post HS Certificate | $48,630 |
| 49-9043 | Maintenance Workers, Machinery | 90,730 | HS | $42,640 |
| 49-9052 | Telecommunications Line Installers and Repairers | 114,420 | HS | $54,450 |
| 49-9061 | Camera and Photographic Equipment Repairers | 3,150 | Post HS Certificate | $40,020 |
| 49-9071 | Maintenance and Repair Workers, General | 1,282,920 | HS | $36,170 |
| 49-9094 | Locksmiths and Safe Repairers | 17,090 | HS | $38,600 |
| 49-9097 | Signal and Track Switch Repairers | 7,880 | Some College | $60,640 |
| 51-2023 | Electromechanical Equipment Assemblers | 46,990 | HS | $32,760 |
| 51-4021 | Extruding and Drawing Machine Setters, Operators, and Tenders… | 72,520 | HS | $32,610 |
| 51-4032 | Drilling and Boring Machine Tool Setters, Operators, and Tenders… | 17,470 | Post HS Certificate | $34,500 |
| 51-4033 | Grinding, Lapping, Polishing, and Buffing Machine Tool Setters… | 70,130 | HS | $32,660 |
| 51-4041 | Machinists | 392,700 | Post HS Certificate | $39,980 |
| 51-4061 | Model Makers, Metal and Plastic | 6,140 | HS | $46,180 |
| 51-4081 | Multiple Machine Tool Setters, Operators, and Tenders… | 98,160 | HS | $34,140 |

**Mid STEM/High Soft**

| OCC Code | Occupation | Employment | Education | Median Wage |
|---|---|---|---|---|
| 11-1011 | Chief Executives | 246,240 | MA | $173,320 |
| 11-2011 | Advertising and Promotions Managers | 29,340 | BA | $96,720 |
| 11-2021 | Marketing Managers | 184,490 | BA | $127,130 |
| 11-2022 | Sales Managers | 358,920 | BA | $110,660 |
| 11-3071 | Transportation, Storage, and Distribution Managers | 106,000 | BA | $85,400 |
| 11-3121 | Human Resources Managers | 116,610 | BA | $102,780 |
| 11-3131 | Training and Development Managers | 29,870 | BA | $101,930 |
| 11-9032 | Education Administrators, Elementary and Secondary… | 231,800 | MA | $89,540 |
| 11-9039 | Education Administrators, All Other | 31,920 | MA | $77,020 |
| 11-9071 | Gaming Managers | 3,870 | Post HS Certificate | $67,310 |
| 11-9151 | Social and Community Service Managers | 116,670 | BA | $62,740 |
| 11-9199 | Managers, All Other | 361,900 | BA | $105,060 |
| 13-1023 | Purchasing Agents, Except Wholesale, Retail, and Farm… | 288,430 | BA | $60,980 |
| 13-1111 | Management Analysts | 587,450 | BA | $80,880 |
| 13-1121 | Meeting, Convention, and Event Planners | 77,940 | BA | $46,490 |
| 13-1161 | Market Research Analysts and Marketing Specialists | 468,160 | BA | $61,290 |
| 13-2099 | Financial Specialists, All Other | 137,460 | BA | $65,440 |
| 19-1041 | Epidemiologists | 5,420 | MA | $67,420 |
| 19-2011 | Astronomers | 1,660 | Post Doc | $105,410 |
| 19-2021 | Atmospheric and Space Scientists | 10,850 | BA | $87,980 |
| 19-3011 | Economists | 18,680 | Doctoral Degree | $95,710 |
| 19-3022 | Survey Researchers | 15,410 | MA | $49,760 |
| 19-3032 | Industrial-Organizational Psychologists | 1,110 | Doctoral Degree | $76,950 |
| 19-3039 | Psychologists, All Other | 11,980 | Post Doc | $92,110 |
| 19-3051 | Urban and Regional Planners | 35,820 | MA | $66,940 |
| 19-3091 | Anthropologists and Archeologists | 7,040 | MA | $59,280 |
| 19-3092 | Geographers | 1,260 | MA | $76,420 |
| 21-2011 | Clergy | 46,510 | BA | $43,950 |
| 25-1011 | Business Teachers, Postsecondary | 85,030 | Doctoral Degree | $74,090 |
| 25-1041 | Agricultural Sciences Teachers, Postsecondary | 9,890 | Doctoral Degree | $86,260 |
| 25-1042 | Biological Science Teachers, Postsecondary | 52,750 | Doctoral Degree | $74,580 |
| 25-1053 | Environmental Science Teachers, Postsecondary | 5,300 | Doctoral Degree | $77,470 |
| 25-1061 | Anthropology and Archeology Teachers, Postsecondary | 6,100 | Doctoral Degree | $74,750 |
| 25-1064 | Geography Teachers, Postsecondary | 4,440 | Doctoral Degree | $71,320 |
| 25-1066 | Psychology Teachers, Postsecondary | 37,930 | Doctoral Degree | $68,690 |
| 25-1071 | Health Specialties Teachers, Postsecondary | 168,090 | Doctoral Degree | $90,210 |
| 25-1072 | Nursing Instructors and Teachers, Postsecondary | 56,840 | MA | $66,100 |
| 25-1111 | Criminal Justice and Law Enforcement Teachers… | 14,890 | MA | $57,200 |
| 25-1192 | Home Economics Teachers, Postsecondary | 3,620 | MA | $63,390 |
| 25-1193 | Recreation and Fitness Studies Teachers, Postsecondary | 18,650 | MA | $58,280 |

**Appendix A. Occupational Wage and Employment by High/Mid/Low STEM/Soft KSAs (contd.)**

*Total No. of Occupations = 765; total U.S. Employment = 131,974,860*

| High STEM/Low Soft | | | | | Mid STEM/High Soft | | | | |
|---|---|---|---|---|---|---|---|---|---|
| OCC Code | Occupation Description | Employment | Education | Median Wage | OCC Code | Occupation | Employment | Education | Median Wage |
| 51-4111 | Tool and Die Makers | 75,950 | Post HS Certificate | $48,890 | 25-2021 | Elementary School Teachers, Except Special Education | 1,353,020 | BA | $54,120 |
| 51-4191 | Heat Treating Equipment Setters, Operators, and Tenders, Metal... | 20,980 | HS | $35,320 | 25-2022 | Middle School Teachers, Except Special & Career/Tech... | 630,620 | BA | $54,940 |
| 51-6061 | Textile Bleaching and Dyeing Machine Operators and Tenders | 11,510 | HS | $24,930 | 25-2031 | Secondary School Teachers, Except Special & Career/Tech... | 960,380 | BA | $56,310 |
| 51-7011 | Cabinetmakers and Bench Carpenters | 88,170 | HS | $31,580 | 25-2054 | Special Education Teachers, Secondary School | 135,520 | BA | $57,810 |
| 51-7032 | Patternmakers, Wood | 950 | Post HS Certificate | $37,980 | 25-2059 | Special Education Teachers, All Other | 39,620 | BA Certificate | $54,520 |
| 51-7042 | Woodworking Machine Setters, Operators, and Tenders, Except... | 70,810 | HS | $27,450 | 25-4012 | Curators | 11,200 | MA | $51,280 |
| 51-8021 | Stationary Engineers and Boiler Operators | 37,550 | HS | $56,330 | 25-9031 | Instructional Coordinators | 133,780 | MA | $61,550 |
| 51-8099 | Plant and System Operators, All Other | 11,610 | HS | $55,230 | 27-1011 | Art Directors | 33,140 | BA | $85,610 |
| 51-9012 | Separating, Filtering, Clarifying, Precipitating, and Still Machine... | 43,310 | HS | $38,590 | 27-2012 | Producers and Directors | 97,300 | BA | $69,100 |
| 51-9193 | Cooling and Freezing Equipment Operators and Tenders | 8,070 | HS | $28,280 | 27-2022 | Coaches and Scouts | 211,760 | BA | $30,640 |
| 53-5011 | Sailors and Marine Oilers | 27,640 | HS | $39,100 | 29-1011 | Chiropractors | 29,830 | Doctoral Degree | $66,720 |
| 53-7071 | Gas Compressor and Gas Pumping Station Operators | 4,700 | HS | $56,280 | 29-1051 | Pharmacists | 290,780 | First Professional | $120,950 |
| 53-7072 | Pump Operators, Except Wellhead Pumpers | 12,170 | HS | $43,500 | 29-1061 | Anesthesiologists | 30,060 | Post Doc | $151,450 |
| | | | | | 29-1062 | Family and General Practitioners | 124,810 | Doctoral Degree | $180,180 |
| | | | | | 29-1063 | Internists, General | 48,390 | Post Doc | $125,230 |
| | | | | | 29-1064 | Obstetricians and Gynecologists | 21,740 | Doctoral Degree | $156,730 |
| | | | | | 29-1065 | Pediatricians, General | 31,010 | Doctoral Degree | $163,350 |
| | | | | | 29-1066 | Psychiatrists | 25,080 | Post Doc | $181,880 |
| | | | | | 29-1069 | Physicians and Surgeons, All Other | 311,320 | Post Doc | $56,590 |
| | | | | | 29-1071 | Physician Assistants | 91,670 | MA | $95,820 |
| | | | | | 29-1122 | Occupational Therapists | 110,520 | MA | $78,810 |
| | | | | | 29-1123 | Physical Therapists | 200,670 | MA | $82,390 |
| | | | | | 29-1127 | Speech-Language Pathologists | 126,500 | MA | $71,550 |
| | | | | | 29-1141 | Registered Nurses | 2,687,310 | AD | $66,640 |
| | | | | | 29-1161 | Nurse Midwives | 5,110 | MA | $96,970 |
| | | | | | 29-2061 | Licensed Practical and Licensed Vocational Nurses | 695,610 | Some College | $42,490 |
| | | | | | 29-9091 | Athletic Trainers | 22,400 | MA | $43,370 |
| | | | | | 29-9099 | Healthcare Practitioners and Technical Workers... | 40,840 | BA | $49,430 |
| | | | | | 33-1012 | First-Line Supervisors of Police and Detectives | 101,420 | AD | $80,930 |
| | | | | | 33-3051 | Police and Sheriff's Patrol Officers | 638,810 | Some College | $56,810 |
| | | | | | 41-1012 | First-Line Supervisors of Non-Retail Sales Workers | 248,770 | AD | $71,600 |
| | | | | | 43-1011 | First-Line Supervisors of Office and Administrative... | 1,404,070 | AD | $50,780 |
| | | | | | 53-2021 | Air Traffic Controllers | 22,860 | Post HS Certificate | $122,340 |
| | | | | | 53-2022 | Airfield Operations Specialists | 7,050 | AD | $49,180 |

**Appendix A. Occupational Wage and Employment by High/Mid/Low STEM/Soft KSAs (contd.)**

*Total No. of Occupations = 764; U.S. Employment = 131,974,860*

| Mid STEM/Mid Soft | | | | Mid STEM/Low Soft | | | |
|---|---|---|---|---|---|---|---|
| No. of OCCs | Employment | No. of BA+ OCCs | Median Wage | No. of OCCs | Employment | No. of BA+ OCCs | Median Wage |
| 54 | 7,687,390 | 12 | $46,690 | 104 | 6,630,800 | 1 | $35,420 |
| % of ALL OCCs | % of U.S. EMP | % OCCs BA+ | Mean Wage | % of ALL OCCs | % of U.S. EMP | % OCCs BA+ | Mean Wage |
| 7.1% | 5.8% | 22.2% | $50,331 | 13.7% | 5.0% | 1.0% | $36,759 |
| No. of OCCs Post HS | Post HS Emp | BA+ EMP | BA+ Med. Wage | No. of OCCs Post HS | Post HS Emp | BA+ EMP | BA+ Med. Wage |
| 25 | 2,565,010 | 1,695,770 | $65,190 | 11 | 538,440 | 1,060 | $54,140 |
| % of M/M Occs Post HS | % EMP Post HS | % of M/M EMP BA+ | Post HS Med. Wg | % of M/L Occs Post HS | % EMP Post HS | % of M/L EMP BA+ | Post HS Med. Wg |
| 46.3% | 33.4% | 22.1% | $46,690 | 10.5% | 8.1% | 0.0% | $37,340 |

**Mid STEM/Mid Soft**

| OCC Code | Occupation Description | Employment | Education | Median Wage |
|---|---|---|---|---|
| 11-9061 | Funeral Service Managers | 8,330 | AD | $68,870 |
| 11-9131 | Postmasters and Mail Superintendents | 17,930 | HS | $65,800 |
| 13-1022 | Wholesale and Retail Buyers, Except Farm Products | 110,560 | Some College | $52,270 |
| 13-1032 | Insurance Appraisers, Auto Damage | 13,690 | AD | $63,420 |
| 13-2021 | Appraisers and Assessors of Real Estate | 63,220 | AD | $52,570 |
| 15-1131 | Computer Programmers | 302,150 | BA | $77,550 |
| 15-1133 | Software Developers, Systems Software | 382,400 | BA | $102,880 |
| 15-1134 | Web Developers | 121,020 | AD | $63,490 |
| 15-1152 | Computer Network Support Specialists | 174,490 | BA | $61,830 |
| 15-1199 | Computer Occupations, All Other | 212,510 | BA | $83,410 |
| 15-2021 | Mathematicians | 3,130 | MA | $103,720 |
| 15-2031 | Operations Research Analysts | 86,950 | MA | $76,660 |
| 17-1021 | Cartographers and Photogrammetrists | 11,610 | BA | $60,930 |
| 17-3022 | Civil Engineering Technicians | 71,300 | Post HS Certificate | $48,340 |
| 19-1020 | Biological Scientists | 103,210 | MA | $71,940 |
| 19-4061 | Social Science Research Assistants | 27,780 | BA | $39,460 |
| 25-1022 | Mathematical Science Teachers, Postsecondary | 54,010 | Doctoral Degree | $65,190 |
| 27-4021 | Photographers | 52,250 | Some College | $30,490 |
| 27-4031 | Camera Operators, Television, Video, and Motion Picture | 18,310 | AD | $48,080 |
| 29-2011 | Medical and Clinical Laboratory Technologists | 161,710 | BA | $59,430 |
| 29-2031 | Cardiovascular Technologists and Technicians | 51,080 | AD | $54,330 |
| 29-2034 | Radiologic Technologists | 193,400 | AD | $55,870 |
| 29-2056 | Veterinary Technologists and Technicians | 93,300 | AD | $31,070 |
| 29-2057 | Ophthalmic Medical Technicians | 36,470 | Post HS Certificate | $35,230 |
| 29-2081 | Opticians, Dispensing | 73,110 | Post HS Certificate | $34,280 |
| 29-2092 | Hearing Aid Specialists | 5,570 | AD | $43,010 |
| 31-2011 | Occupational Therapy Assistants | 32,230 | AD | $56,950 |
| 31-2021 | Physical Therapist Assistants | 76,910 | AD | $54,410 |
| 31-9092 | Medical Assistants | 584,970 | Post HS Certificate | $29,960 |
| 31-9097 | Phlebotomists | 111,950 | Post HS Certificate | $30,670 |
| 33-3012 | Correctional Officers and Jailers | 434,420 | HS | $39,780 |
| 33-9099 | Protective Service Workers, All Other | 113,020 | HS | $28,440 |
| 35-1012 | First-Line Supervisors of Food Preparation and Serving Workers | 867,340 | HS | $29,560 |
| 37-1011 | First-Line Supervisors of Housekeeping and Janitorial Workers | 168,960 | HS | $36,270 |
| 39-1021 | First-Line Supervisors of Personal Service Workers | 161,990 | Some College | $35,250 |
| 39-4011 | Embalmers | 3,650 | AD | $41,720 |
| 39-5091 | Makeup Artists, Theatrical and Performance | 2,610 | HS | $44,310 |
| 41-1011 | First-Line Supervisors of Retail Sales Workers | 1,199,770 | HS | $37,860 |
| 41-4011 | Sales Reps, Wholesale & Manufacturing, Technical & Scientific | 335,540 | Some College | $75,140 |
| 41-9022 | Real Estate Sales Agents | 157,660 | HS | $40,990 |
| 43-5031 | Police, Fire, and Ambulance Dispatchers | 96,390 | HS | $37,410 |
| 43-5032 | Dispatchers, Except Police, Fire, and Ambulance | 190,330 | HS | $36,690 |
| 43-9011 | Computer Operators | 58,060 | Some College | $39,590 |
| 43-9111 | Statistical Assistants | 14,110 | BA | $42,070 |
| 45-2011 | Agricultural Inspectors | 13,800 | HS | $43,090 |
| 47-4041 | Hazardous Materials Removal Workers | 42,250 | HS | $38,520 |
| 49-2011 | Computer, Automated Teller, and Office Machine Repairers | 110,940 | Some College | $36,560 |
| 51-6092 | Fabric and Apparel Patternmakers | 5,440 | Post HS Certificate | $41,310 |
| 51-9011 | Chemical Equipment Operators and Tenders | 64,710 | HS | $48,090 |
| 53-1011 | Aircraft Cargo Handling Supervisors | 5,750 | HS | $47,760 |
| 53-1021 | First-Line Supervisors of Helpers, Laborers & Material Movers, Hand | 171,720 | Post HS Certificate | $46,690 |
| 53-1031 | First-Line Supervisors,Transportation & Material-Moving Machine… | 197,000 | HS | $54,930 |
| 53-6061 | Transportation Attendants, Except Flight Attendants | 16,380 | HS | $23,380 |

**Mid STEM/Low Soft**

| OCC Code | Occupation | Employment | Education | Median Wage |
|---|---|---|---|---|
| 15-2091 | Mathematical Technicians | 1,060 | BA | $54,140 |
| 17-3012 | Electrical and Electronics Drafters | 29,390 | AD | $58,790 |
| 27-1012 | Craft Artists | 4,760 | HS | $31,080 |
| 27-1013 | Fine Artists, Including Painters, Sculptors, and Illustrators | 12,100 | Some College | $43,890 |
| 37-3012 | Pesticide Handlers, Sprayers, and Applicators, Vegetation | 23,790 | Post HS Certificate | $31,240 |
| 37-3013 | Tree Trimmers and Pruners | 39,640 | HS | $32,960 |
| 39-3021 | Motion Picture Projectionists | 6,290 | HS | $20,830 |
| 43-9071 | Office Machine Operators, Except Computer | 66,530 | HS | $28,510 |
| 45-2021 | Animal Breeders | 1,110 | Post HS Certificate | $40,000 |
| 45-2091 | Agricultural Equipment Operators | 26,100 | HS | $26,910 |
| 45-2092 | Farmworkers & Laborers, Crop, Nursery, & Greenhouse | 269,650 | HS | $19,060 |
| 45-2093 | Farmworkers, Farm, Ranch, and Aquacultural Animals | 31,540 | Less than HS | $22,930 |
| 45-4021 | Fallers | 6,090 | Less than HS | $34,490 |
| 45-4022 | Logging Equipment Operators | 26,010 | Less than HS | $35,190 |
| 47-2022 | Stonemasons | 11,250 | HS | $37,880 |
| 47-2041 | Carpet Installers | 26,050 | HS | $35,880 |
| 47-2044 | Tile and Marble Setters | 31,590 | Less than HS | $38,980 |
| 47-2051 | Cement Masons and Concrete Finishers | 152,570 | Less than HS | $36,760 |
| 47-2053 | Terrazzo Workers and Finishers | 3,250 | HS | $39,090 |
| 47-2072 | Pile-Driver Operators | 3,470 | HS | $51,510 |
| 47-2073 | Operating Engineers & Other Construction Equipment … | 344,510 | HS | $43,510 |
| 47-2081 | Drywall and Ceiling Tile Installers | 85,020 | HS | $38,100 |
| 47-2132 | Insulation Workers, Mechanical | 28,660 | HS | $42,990 |
| 47-2141 | Painters, Construction and Maintenance | 204,600 | HS | $35,950 |
| 47-2142 | Paperhangers | 3,570 | HS | $32,930 |
| 47-2151 | Pipelayers | 41,080 | Less than HS | $37,000 |
| 47-2171 | Reinforcing Iron and Rebar Workers | 18,530 | HS | $50,020 |
| 47-2181 | Roofers | 103,650 | HS | $35,760 |
| 47-3011 | Helpers--Brickmasons, Blockmasons, Stonemasons… | 23,570 | HS | $28,830 |
| 47-3013 | Helpers--Electricians | 68,280 | HS | $27,940 |
| 47-3016 | Helpers--Roofers | 11,640 | HS | $26,060 |
| 47-4031 | Fence Erectors | 20,990 | HS | $31,510 |
| 47-4061 | Rail-Track Laying and Maintenance Equipment Operators | 14,820 | HS | $51,840 |
| 47-4091 | Segmental Pavers | 1,130 | HS | $32,180 |
| 47-5021 | Earth Drillers, Except Oil and Gas | 19,160 | HS | $43,540 |
| 47-5042 | Mine Cutting and Channeling Machine Operators | 6,960 | HS | $50,260 |
| 47-5051 | Rock Splitters, Quarry | 3,630 | HS | $33,240 |
| 47-5061 | Roof Bolters, Mining | 5,710 | HS | $54,860 |
| 47-5081 | Helpers--Extraction Workers | 24,130 | HS | $34,480 |
| 49-2098 | Security and Fire Alarm Systems Installers | 60,160 | HS | $42,560 |
| 49-3021 | Automotive Body and Related Repairers | 137,140 | HS | $40,320 |
| 49-3043 | Rail Car Repairers | 20,080 | HS | $54,020 |
| 49-3051 | Motorboat Mechanics and Service Technicians | 20,210 | Post HS Certificate | $37,340 |
| 49-3052 | Motorcycle Mechanics | 15,420 | Post HS Certificate | $34,010 |
| 49-3091 | Bicycle Repairers | 10,520 | HS | $26,370 |
| 49-9011 | Mechanical Door Repairers | 17,220 | HS | $37,080 |
| 49-9031 | Home Appliance Repairers | 33,270 | Post HS Certificate | $35,410 |
| 49-9045 | Refractory Materials Repairers, Except Brickmasons | 1,730 | HS | $44,910 |
| 49-9063 | Musical Instrument Repairers and Tuners | 7,660 | Post HS Certificate | $33,150 |
| 49-9091 | Coin, Vending, and Amusement Machine Servicers… | 30,840 | HS | $31,860 |
| 49-9096 | Riggers | 20,350 | HS | $41,570 |
| 49-9098 | Helpers--Installation, Maintenance, and Repair Workers | 126,980 | HS | $25,390 |
| 51-2011 | Aircraft Structure, Surfaces, Rigging & Systems Assemblers | 40,630 | HS | $48,340 |

**Appendix A. Occupational Wage and Employment by High/Mid/Low STEM/Soft KSAs (contd.)**

*Total No. of Occupations = 764; U.S. Employment = 131,974,860*

| Mid STEM/Mid Soft | | | |
|---|---|---|---|
| No. of OCCs | Employment | No. of BA+ OCCs | Median Wage |
| 54 | 7,687,390 | 12 | $46,690 |
| % of ALL OCCs | % of U.S. EMP | % OCCs BA+ | Mean Wage |
| 7.1% | 5.8% | 22.2% | $50,331 |
| No. of OCCs Post HS | Post HS Emp | BA+ EMP | BA+ Med. Wage |
| 25 | 2,565,010 | 1,695,770 | $65,190 |
| % of M/M Occs Post HS | % EMP Post HS | % of M/M EMP BA+ | Post HS Med. Wg |
| 46.3% | 33.4% | 22.1% | $46,690 |

| Mid STEM/Low Soft | | | |
|---|---|---|---|
| No. of OCCs | Employment | No. of BA+ OCCs | Median Wage |
| 104 | 6,630,800 | 1 | $35,420 |
| % of ALL OCCs | % of U.S. EMP | % OCCs BA+ | Mean Wage |
| 13.7% | 5.0% | 1.0% | $36,759 |
| No. of OCCs Post HS | Post HS Emp | BA+ EMP | BA+ Med. Wage |
| 11 | 538,440 | 1,060 | $54,140 |
| % of M/L Occs Post HS | % EMP Post HS | % of M/L EMP BA+ | Post HS Med. Wg |
| 10.5% | 8.1% | 0.0% | $37,340 |

**Mid STEM/Mid Soft**

| OCC Code | Occupation Description | Employment | Education | Median Wage |
|---|---|---|---|---|
| 11-9061 | Funeral Service Managers | 8,330 | AD | $68,870 |
| 11-9131 | Postmasters and Mail Superintendents | 17,930 | HS | $65,800 |
| 13-1022 | Wholesale and Retail Buyers, Except Farm Products | 110,560 | Some College | $52,270 |
| 13-1032 | Insurance Appraisers, Auto Damage | 13,690 | AD | $63,420 |
| 13-2021 | Appraisers and Assessors of Real Estate | 63,220 | AD | $52,570 |
| 15-1131 | Computer Programmers | 302,150 | BA | $77,550 |
| 15-1133 | Software Developers, Systems Software | 382,400 | BA | $102,880 |
| 15-1134 | Web Developers | 121,020 | AD | $63,490 |
| 15-1152 | Computer Network Support Specialists | 174,490 | BA | $61,830 |
| 15-1199 | Computer Occupations, All Other | 212,510 | BA | $83,410 |
| 15-2021 | Mathematicians | 3,130 | MA | $103,720 |
| 15-2031 | Operations Research Analysts | 86,950 | MA | $76,660 |
| 17-1021 | Cartographers and Photogrammetrists | 11,610 | BA | $60,930 |
| 17-3022 | Civil Engineering Technicians | 71,300 | Post HS Certificate | $48,340 |
| 19-1020 | Biological Scientists | 103,210 | MA | $71,940 |
| 19-4061 | Social Science Research Assistants | 27,780 | BA | $39,460 |
| 25-1022 | Mathematical Science Teachers, Postsecondary | 54,010 | Doctoral Degree | $65,190 |
| 27-4021 | Photographers | 52,250 | Some College | $30,490 |
| 27-4031 | Camera Operators, Television, Video, and Motion Picture | 18,310 | AD | $48,080 |
| 29-2011 | Medical and Clinical Laboratory Technologists | 161,710 | BA | $59,430 |
| 29-2031 | Cardiovascular Technologists and Technicians | 51,080 | AD | $54,330 |
| 29-2034 | Radiologic Technologists | 193,400 | AD | $55,870 |
| 29-2056 | Veterinary Technologists and Technicians | 93,300 | AD | $31,070 |
| 29-2057 | Ophthalmic Medical Technicians | 36,470 | Post HS Certificate | $35,230 |
| 29-2081 | Opticians, Dispensing | 73,110 | Post HS Certificate | $34,280 |
| 29-2092 | Hearing Aid Specialists | 5,570 | AD | $43,010 |
| 31-2011 | Occupational Therapy Assistants | 32,230 | AD | $56,950 |
| 31-2021 | Physical Therapist Assistants | 76,910 | AD | $54,410 |
| 31-9092 | Medical Assistants | 584,970 | Post HS Certificate | $29,960 |
| 31-9097 | Phlebotomists | 111,950 | Post HS Certificate | $30,670 |
| 33-3012 | Correctional Officers and Jailers | 434,420 | HS | $39,780 |
| 33-9099 | Protective Service Workers, All Other | 113,020 | HS | $28,440 |
| 35-1012 | First-Line Supervisors of Food Preparation and Serving Workers | 867,340 | HS | $29,560 |
| 37-1011 | First-Line Supervisors of Housekeeping and Janitorial Workers | 168,960 | HS | $36,270 |
| 39-1021 | First-Line Supervisors of Personal Service Workers | 161,990 | Some College | $35,250 |
| 39-4011 | Embalmers | 3,650 | AD | $41,720 |
| 39-5091 | Makeup Artists, Theatrical and Performance | 2,610 | HS | $44,310 |
| 41-1011 | First-Line Supervisors of Retail Sales Workers | 1,199,770 | HS | $37,860 |
| 41-4011 | Sales Reps, Wholesale & Manufacturing, Technical & Scientific | 335,540 | Some College | $75,140 |
| 41-9022 | Real Estate Sales Agents | 157,660 | HS | $40,990 |
| 43-5031 | Police, Fire, and Ambulance Dispatchers | 96,390 | HS | $37,410 |
| 43-5032 | Dispatchers, Except Police, Fire, and Ambulance | 190,330 | HS | $36,690 |
| 43-9011 | Computer Operators | 58,060 | Some College | $39,590 |
| 43-9111 | Statistical Assistants | 14,110 | BA | $42,070 |
| 45-2011 | Agricultural Inspectors | 13,800 | HS | $43,090 |
| 47-4041 | Hazardous Materials Removal Workers | 42,250 | HS | $38,520 |
| 49-2011 | Computer, Automated Teller, and Office Machine Repairers | 110,940 | Some College | $36,560 |
| 51-6092 | Fabric and Apparel Patternmakers | 5,440 | Post HS Certificate | $41,310 |
| 51-9011 | Chemical Equipment Operators and Tenders | 64,710 | HS | $48,090 |
| 53-1011 | Aircraft Cargo Handling Supervisors | 5,750 | HS | $47,760 |
| 53-1021 | First-Line Supervisors of Helpers, Laborers & Material Movers, Hand | 171,720 | Post HS Certificate | $46,690 |
| 53-1031 | First-Line Supervisors,Transportation & Material-Moving Machine… | 197,000 | HS | $54,930 |
| 53-6061 | Transportation Attendants, Except Flight Attendants | 16,380 | HS | $23,380 |

**Mid STEM/Low Soft**

| OCC Code | Occupation | Employment | Education | Median Wage |
|---|---|---|---|---|
| 15-2091 | Mathematical Technicians | 1,060 | BA | $54,140 |
| 17-3012 | Electrical and Electronics Drafters | 29,390 | AD | $58,790 |
| 27-1012 | Craft Artists | 4,760 | HS | $31,080 |
| 27-1013 | Fine Artists, Including Painters, Sculptors, and Illustrators | 12,100 | Some College | $43,890 |
| 37-3012 | Pesticide Handlers, Sprayers, and Applicators, Vegetation | 23,790 | Post HS Certificate | $31,240 |
| 37-3013 | Tree Trimmers and Pruners | 39,640 | HS | $32,960 |
| 39-3021 | Motion Picture Projectionists | 6,290 | HS | $20,830 |
| 43-9071 | Office Machine Operators, Except Computer | 66,530 | HS | $28,510 |
| 45-2021 | Animal Breeders | 1,110 | Post HS Certificate | $40,000 |
| 45-2091 | Agricultural Equipment Operators | 26,100 | HS | $26,910 |
| 45-2092 | Farmworkers & Laborers, Crop, Nursery, & Greenhouse | 269,650 | HS | $19,060 |
| 45-2093 | Farmworkers, Farm, Ranch, and Aquacultural Animals | 31,540 | Less than HS | $22,930 |
| 45-4021 | Fallers | 6,090 | Less than HS | $34,490 |
| 45-4022 | Logging Equipment Operators | 26,010 | Less than HS | $35,190 |
| 47-2022 | Stonemasons | 11,250 | HS | $37,880 |
| 47-2041 | Carpet Installers | 26,050 | HS | $35,880 |
| 47-2044 | Tile and Marble Setters | 31,590 | Less than HS | $38,980 |
| 47-2051 | Cement Masons and Concrete Finishers | 152,570 | Less than HS | $36,760 |
| 47-2053 | Terrazzo Workers and Finishers | 3,250 | HS | $39,090 |
| 47-2072 | Pile-Driver Operators | 3,470 | HS | $51,510 |
| 47-2073 | Operating Engineers & Other Construction Equipment … | 344,510 | HS | $43,510 |
| 47-2081 | Drywall and Ceiling Tile Installers | 85,020 | HS | $38,100 |
| 47-2132 | Insulation Workers, Mechanical | 28,660 | HS | $42,990 |
| 47-2141 | Painters, Construction and Maintenance | 204,600 | HS | $35,950 |
| 47-2142 | Paperhangers | 3,570 | HS | $32,930 |
| 47-2151 | Pipelayers | 41,080 | Less than HS | $37,000 |
| 47-2171 | Reinforcing Iron and Rebar Workers | 18,530 | HS | $50,020 |
| 47-2181 | Roofers | 103,650 | HS | $35,760 |
| 47-3011 | Helpers--Brickmasons, Blockmasons, Stonemasons… | 23,570 | HS | $28,830 |
| 47-3013 | Helpers--Electricians | 68,280 | HS | $27,940 |
| 47-3016 | Helpers--Roofers | 11,640 | HS | $26,060 |
| 47-4031 | Fence Erectors | 20,990 | HS | $31,510 |
| 47-4061 | Rail-Track Laying and Maintenance Equipment Operators | 14,820 | HS | $51,840 |
| 47-4091 | Segmental Pavers | 1,130 | HS | $32,180 |
| 47-5021 | Earth Drillers, Except Oil and Gas | 19,160 | HS | $43,540 |
| 47-5042 | Mine Cutting and Channeling Machine Operators | 6,960 | HS | $50,260 |
| 47-5051 | Rock Splitters, Quarry | 3,630 | HS | $33,240 |
| 47-5061 | Roof Bolters, Mining | 5,710 | HS | $54,860 |
| 47-5081 | Helpers--Extraction Workers | 24,130 | HS | $34,480 |
| 49-2098 | Security and Fire Alarm Systems Installers | 60,160 | HS | $42,560 |
| 49-3021 | Automotive Body and Related Repairers | 137,140 | HS | $40,320 |
| 49-3043 | Rail Car Repairers | 20,080 | HS | $54,020 |
| 49-3051 | Motorboat Mechanics and Service Technicians | 20,210 | Post HS Certificate | $37,340 |
| 49-3052 | Motorcycle Mechanics | 15,420 | Post HS Certificate | $34,010 |
| 49-3091 | Bicycle Repairers | 10,520 | HS | $26,370 |
| 49-9011 | Mechanical Door Repairers | 17,220 | HS | $37,080 |
| 49-9031 | Home Appliance Repairers | 33,270 | Post HS Certificate | $35,410 |
| 49-9045 | Refractory Materials Repairers, Except Brickmasons | 1,730 | HS | $44,910 |
| 49-9063 | Musical Instrument Repairers and Tuners | 7,660 | Post HS Certificate | $33,150 |
| 49-9091 | Coin, Vending, and Amusement Machine Servicers… | 30,840 | HS | $31,860 |
| 49-9096 | Riggers | 20,350 | HS | $41,570 |
| 49-9098 | Helpers--Installation, Maintenance, and Repair Workers | 126,980 | HS | $25,390 |
| 51-2011 | Aircraft Structure, Surfaces, Rigging & Systems Assemblers | 40,630 | HS | $48,340 |

**Appendix A. Occupational Wage and Employment by High/Mid/Low STEM/Soft KSAs (contd.)**
*Total No. of Occupations = 764; U.S. Employment = 131,974,860*

| Low STEM/High Soft | | | |
|---|---|---|---|
| **No. of OCCs** | **Employment** | **No. of BA+ OCCs** | **Median Wage** |
| 53 | 5,278,770 | 51 | $61,450 |
| **% of ALL OCCs** | **% of U.S. EMP** | **% OCCs BA+** | **Mean Wage** |
| 6.9% | 4.0% | 96.2% | $65,305 |
| **No. of OCCs Post HS** | **Post HS Emp** | **BA+ EMP** | **BA+ Med Wage** |
| 1 | 6,030 | 5,227,590 | $62,220 |
| **% of L/H Occs Post HS** | **% EMP Post HS** | **% of L/H EMP** | **Post HS Med Wg** |
| 1.9% | 0.1% | 99.0% | $44,250 |

Low STEM/High Soft

| OCC Code | Occupation Description | Employment | Education | Median Wage |
|---|---|---|---|---|
| 11-2031 | Public Relations and Fundraising Managers | 56,920 | BA | $101,510 |
| 11-3031 | Financial Managers | 518,030 | BA Certificate | $115,320 |
| 11-9031 | Education Administrators, Preschool and Childcare Center/Program | 47,150 | BA | $45,260 |
| 11-9033 | Education Administrators, Postsecondary | 131,070 | MA | $88,390 |
| 13-1031 | Claims Adjusters, Examiners, and Investigators | 266,280 | BA | $62,220 |
| 13-1131 | Fundraisers | 55,230 | BA | $52,430 |
| 13-1151 | Training and Development Specialists | 239,500 | BA | $57,340 |
| 13-2051 | Financial Analysts | 262,610 | BA | $78,620 |
| 13-2052 | Personal Financial Advisors | 196,490 | BA | $81,060 |
| 13-2061 | Financial Examiners | 36,830 | BA | $76,310 |
| 15-2011 | Actuaries | 21,490 | BA | $96,700 |
| 19-3031 | Clinical, Counseling, and School Psychologists | 104,730 | Doctoral Degree | $68,900 |
| 19-3041 | Sociologists | 2,240 | Doctoral Degree | $72,810 |
| 19-3094 | Political Scientists | 5,640 | Doctoral Degree | $104,920 |
| 21-1011 | Substance Abuse and Behavioral Disorder Counselors | 85,180 | MA | $39,270 |
| 21-1012 | Educational, Guidance, School, and Vocational Counselors | 246,280 | MA | $53,370 |
| 21-1013 | Marriage and Family Therapists | 30,150 | MA | $48,040 |
| 21-1014 | Mental Health Counselors | 120,010 | MA | $40,850 |
| 21-1015 | Rehabilitation Counselors | 103,890 | MA | $34,380 |
| 21-1021 | Child, Family, and School Social Workers | 286,520 | BA | $42,120 |
| 21-1022 | Healthcare Social Workers | 145,920 | MA | $51,930 |
| 21-1023 | Mental Health and Substance Abuse Social Workers | 109,460 | MA | $41,380 |
| 21-1091 | Health Educators | 57,020 | BA | $50,430 |
| 21-1094 | Community Health Workers | 47,880 | BA | $34,870 |
| 21-2021 | Directors, Religious Activities and Education | 18,850 | BA | $38,480 |
| 23-1011 | Lawyers | 603,310 | Doctoral Degree | $114,970 |
| 23-1021 | Administrative Law Judges, Adjudicators, and Hearing Officers | 14,140 | First Professional | $87,980 |
| 23-1023 | Judges, Magistrate Judges, and Magistrates | 28,090 | Doctoral Degree | $115,140 |
| 25-1062 | Area, Ethnic, and Cultural Studies Teachers, Postsecondary | 9,150 | Doctoral Degree | $68,950 |
| 25-1063 | Economics Teachers, Postsecondary | 13,710 | Doctoral Degree | $90,870 |
| 25-1065 | Political Science Teachers, Postsecondary | 17,050 | Doctoral Degree | $73,790 |
| 25-1067 | Sociology Teachers, Postsecondary | 16,900 | Doctoral Degree | $67,880 |
| 25-1081 | Education Teachers, Postsecondary | 59,980 | Doctoral Degree | $59,720 |
| 25-1082 | Library Science Teachers, Postsecondary | 4,540 | Doctoral Degree | $66,580 |
| 25-1112 | Law Teachers, Postsecondary | 15,990 | Doctoral Degree | $109,980 |
| 25-1113 | Social Work Teachers, Postsecondary | 10,970 | Doctoral Degree | $62,440 |
| 25-1121 | Art, Drama, and Music Teachers, Postsecondary | 97,500 | MA | $64,300 |
| 25-1122 | Communications Teachers, Postsecondary | 29,470 | MA | $62,550 |
| 25-1123 | English Language and Literature Teachers, Postsecondary | 76,320 | First Professional | $60,160 |
| 25-1125 | History Teachers, Postsecondary | 23,640 | Doctoral Degree | $66,840 |
| 25-2053 | Special Education Teachers, Middle School | 94,820 | BA Certificate | $56,760 |
| 25-3011 | Adult Basic and Secondary Education and Literacy Teachers... | 65,990 | MA | $49,590 |
| 25-4021 | Librarians | 133,150 | MA | $56,170 |
| 27-2032 | Choreographers | 6,030 | Some College | $44,250 |
| 27-2041 | Music Directors and Composers | 21,880 | BA | $48,180 |
| 27-3021 | Broadcast News Analysts | 4,310 | BA | $61,450 |
| 27-3031 | Public Relations Specialists | 208,030 | BA | $55,680 |
| 27-3041 | Editors | 97,350 | BA | $54,890 |
| 27-3091 | Interpreters and Translators | 49,460 | BA | $43,590 |
| 29-1125 | Recreational Therapists | 17,950 | BA | $44,000 |
| 29-9092 | Genetic Counselors | 2,180 | MA | $67,500 |
| 33-1011 | First-Line Supervisors of Correctional Officers | 45,150 | HS | $57,970 |
| 41-3031 | Securities, Commodities, and Financial Services Sales Agents | 316,340 | BA | $72,070 |

Mid STEM/Low Soft

| OCC Code | Occupation Description | Employment | Education | Median Wage |
|---|---|---|---|---|
| 51-2031 | Engine and Other Machine Assemblers | 38,330 | HS | $38,310 |
| 51-2041 | Structural Metal Fabricators and Fitters | 78,050 | HS | $36,570 |
| 51-2091 | Fiberglass Laminators and Fabricators | 18,770 | HS | $28,950 |
| 51-2093 | Timing Device Assemblers and Adjusters | 1,650 | HS | $30,060 |
| 51-4022 | Forging Machine Setters, Operators, and Tenders, Metal... | 21,340 | HS | $33,710 |
| 51-4023 | Rolling Machine Setters, Operators, and Tenders, Metal... | 33,370 | HS | $39,900 |
| 51-4031 | Cutting, Punching, & Press Machine Setters, Operators... | 190,250 | HS | $30,680 |
| 51-4034 | Lathe and Turning Machine Tool Setters, Operators... | 42,570 | HS | $36,260 |
| 51-4035 | Milling and Planing Machine Setters, Operators & Tenders... | 22,110 | Post HS Certificate | $37,100 |
| 51-4051 | Metal-Refining Furnace Operators and Tenders | 20,850 | HS | $41,140 |
| 51-4062 | Patternmakers, Metal and Plastic | 3,770 | Post HS Certificate | $41,390 |
| 51-4121 | Welders, Cutters, Solderers, and Brazers | 369,610 | Post HS Certificate | $37,420 |
| 51-4122 | Welding, Soldering & Brazing Machine Setters, Operators... | 55,360 | HS | $35,180 |
| 51-4192 | Layout Workers, Metal and Plastic | 13,070 | HS | $45,020 |
| 51-4194 | Tool Grinders, Filers, and Sharpeners | 10,860 | HS | $35,420 |
| 51-5112 | Printing Press Operators | 166,750 | HS | $35,100 |
| 51-5113 | Print Binding and Finishing Workers | 51,430 | HS | $29,500 |
| 51-6042 | Shoe Machine Operators and Tenders | 3,550 | HS | $24,750 |
| 51-6052 | Tailors, Dressmakers, and Custom Sewers | 20,200 | Less than HS | $26,460 |
| 51-6062 | Textile Cutting Machine Setters, Operators, and Tenders | 14,370 | HS | $25,590 |
| 51-6091 | Extruding and Forming Machine Setters, Operators ... | 19,770 | HS | $32,970 |
| 51-6093 | Upholsterers | 29,770 | HS | $31,890 |
| 51-7031 | Model Makers, Wood | 1,360 | HS | $30,940 |
| 51-8013 | Power Plant Operators | 40,300 | HS | $70,070 |
| 51-9022 | Grinding and Polishing Workers, Hand | 29,320 | HS | $28,340 |
| 51-9023 | Mixing and Blending Machine Setters, Operators... | 122,670 | HS | $34,340 |
| 51-9032 | Cutting and Slicing Machine Setters, Operators... | 62,570 | HS | $32,040 |
| 51-9041 | Extruding, Forming, Pressing, and Compacting Machine ... | 67,490 | HS | $32,100 |
| 51-9071 | Jewelers and Precious Stone and Metal Workers | 23,200 | HS | $36,870 |
| 51-9081 | Dental Laboratory Technicians | 35,320 | HS | $36,830 |
| 51-9083 | Ophthalmic Laboratory Technicians | 27,610 | HS | $28,890 |
| 51-9121 | Coating, Painting, and Spraying Machine Setters... | 90,590 | HS | $31,460 |
| 51-9141 | Semiconductor Processors | 23,580 | HS | $34,680 |
| 51-9151 | Photographic Process Workers and Processing Machine... | 28,800 | HS | $24,600 |
| 51-9191 | Adhesive Bonding Machine Operators and Tenders | 18,210 | HS | $31,340 |
| 51-9194 | Etchers and Engravers | 8,630 | HS | $29,250 |
| 51-9195 | Molders, Shapers, and Casters, Except Metal and Plastic | 34,610 | HS | $29,820 |
| 51-9196 | Paper Goods Machine Setters, Operators, and Tenders | 92,170 | HS | $35,260 |
| 51-9199 | Production Workers, All Other | 217,500 | HS | $28,260 |
| 53-3011 | Ambulance Drivers and Attendants, Except EMTs | 19,350 | HS | $24,080 |
| 53-3032 | Heavy and Tractor-Trailer Truck Drivers | 1,625,290 | HS | $39,520 |
| 53-4011 | Locomotive Engineers | 38,470 | HS | $54,500 |
| 53-4012 | Locomotive Firers | 1,610 | HS | $46,740 |
| 53-4013 | Rail Yard Engineers, Dinkey Operators, and Hostlers | 3,900 | HS | $43,880 |
| 53-6011 | Bridge and Lock Tenders | 3,280 | Less than HS | $48,120 |
| 53-7021 | Crane and Tower Operators | 44,540 | HS | $50,720 |
| 53-7031 | Dredge Operators | 1,900 | HS | $40,950 |
| 53-7032 | Excavating and Loading Machine and Dragline Operators | 47,470 | HS | $39,830 |
| 53-7033 | Loading Machine Operators, Underground Mining | 4,220 | HS | $50,290 |
| 53-7061 | Cleaners of Vehicles and Equipment | 321,740 | HS | $20,670 |
| 53-7073 | Wellhead Pumpers | 12,720 | HS | $47,340 |
| 53-7121 | Tank Car, Truck, and Ship Loaders | 12,490 | HS | $41,180 |

**Appendix A. Occupational Wage and Employment by High/Mid/Low STEM/Soft KSAs (contd.)**

*Total No. of Occupations = 764; U.S. Employment = 131,974,860*

| Low STEM/Mid Soft | | | | |
|---|---|---|---|---|
| No. of OCCs | Employment | No. of BA+ OCCs | Median Wage |
| 98 | 27,867,710 | 31 | $41,745 |
| % of ALL OCCs | % of U.S. EMP | % OCCs BA+ | Mean Wage |
| 12.8% | 21.1% | 31.6% | $43,589 |
| No. of OCCs Post HS | Post HS Emp | BA+ EMP | BA+ Med. Wage |
| 38 | 10,242,510 | 5,871,440 | $55,020 |
| % of L/M Occs Post HS | % EMP Post HS | % of L/M EMP BA+ | Post HS Med. Wg |
| 38.8% | 36.8% | 21.1% | $42,200 |

| Low STEM/Low Soft | | | |
|---|---|---|---|
| No. of OCCs | Employment | No. of BA+ OCCs | Median Wage |
| 141 | 45,030,810 | 2 | $26,640 |
| % of ALL OCCs | % of U.S. EMP | % OCCs BA+ | Mean Wage |
| 18.4% | 34.1% | 1.4% | $28,648 |
| No. of OCCs Post HS | Post HS Emp | BA+ EMP | BA+ Med. Wage |
| 16 | 1,811,020 | 104,760 | $33,330 |
| % of L/L Occs Post HS | % EMP Post HS | % of L/L EMPBA+ | Post HS Med. Wg |
| 11.3% | 4.0% | 0.2% | $33,495 |

Low STEM/Mid Soft

| OCC Code | Occupation | Employment | Education | Median Wage |
|---|---|---|---|---|
| 11-3011 | Administrative Services Managers | 268,730 | AD | $83,790 |
| 11-3111 | Compensation and Benefits Managers | 16,380 | BA | $108,070 |
| 11-9141 | Property, Real Estate, and Community Association Managers | 171,140 | BA | $54,270 |
| 13-1011 | Agents and Business Managers of Artists, Performers, and Athletes | 11,860 | BA | $64,200 |
| 13-1071 | Human Resources Specialists | 456,170 | AD | $57,420 |
| 13-1141 | Compensation, Benefits, and Job Analysis Specialists | 80,970 | BA | $60,600 |
| 13-2011 | Accountants and Auditors | 1,187,310 | BA | $65,940 |
| 13-2031 | Budget Analysts | 57,120 | BA | $71,220 |
| 13-2041 | Credit Analysts | 69,390 | BA | $67,020 |
| 13-2053 | Insurance Underwriters | 91,720 | BA | $64,220 |
| 13-2071 | Credit Counselors | 29,600 | AD | $42,110 |
| 13-2072 | Loan Officers | 300,580 | Some College | $62,620 |
| 13-2081 | Tax Examiners and Collectors, and Revenue Agents | 63,640 | AD | $51,120 |
| 13-2082 | Tax Preparers | 68,590 | AD | $35,990 |
| 15-2041 | Statisticians | 26,970 | MA | $79,990 |
| 19-3093 | Historians | 3,220 | MA Certificate | $55,870 |
| 21-1092 | Probation Officers and Correctional Treatment Specialists | 86,810 | BA | $49,060 |
| 21-1093 | Social and Human Service Assistants | 354,800 | BA | $29,790 |
| 23-1012 | Judicial Law Clerks | 11,660 | Doctoral Degree | $48,640 |
| 23-1022 | Arbitrators, Mediators, and Conciliators | 6,710 | BA Certificate | $57,180 |
| 23-2011 | Paralegals and Legal Assistants | 272,580 | AD | $48,350 |
| 23-2093 | Title Examiners, Abstractors, and Searchers | 52,960 | HS | $43,080 |
| 25-1124 | Foreign Language and Literature Teachers, Postsecondary | 30,880 | MA | $59,490 |
| 25-1126 | Philosophy and Religion Teachers, Postsecondary | 23,210 | Doctoral Degree | $63,630 |
| 25-1191 | Graduate Teaching Assistants | 126,030 | MA | $31,570 |
| 25-1194 | Vocational Education Teachers, Postsecondary | 121,200 | Post HS Certificate | $48,360 |
| 25-2011 | Preschool Teachers, Except Special Education | 352,420 | Some College | $28,120 |
| 25-2012 | Kindergarten Teachers, Except Special Education | 158,240 | BA | $50,600 |
| 25-3021 | Self-Enrichment Education Teachers | 202,360 | BA | $36,020 |
| 25-4011 | Archivists | 5,360 | MA | $49,120 |
| 25-9041 | Teacher Assistants | 1,192,590 | Some College | $24,430 |
| 27-1014 | Multimedia Artists and Animators | 29,000 | BA | $63,630 |
| 27-1022 | Fashion Designers | 17,840 | AD | $64,030 |
| 27-1023 | Floral Designers | 45,050 | HS | $24,750 |
| 27-1024 | Graphic Designers | 197,540 | BA | $45,900 |
| 27-2021 | Athletes and Sports Competitors | 11,520 | Less than HS | $43,350 |
| 27-2023 | Umpires, Referees, and Other Sports Officials | 17,510 | HS | $24,090 |
| 27-3011 | Radio and Television Announcers | 30,220 | Some College | $29,790 |
| 27-3012 | Public Address System and Other Announcers | 7,450 | HS | $25,730 |
| 27-3022 | Reporters and Correspondents | 42,280 | BA | $36,000 |
| 27-3042 | Technical Writers | 48,210 | AD | $69,030 |
| 27-3043 | Writers and Authors | 43,500 | BA | $58,850 |
| 27-4013 | Radio Operators | 1,100 | HS | $46,380 |
| 27-4032 | Film and Video Editors | 24,460 | AD | $57,210 |
| 29-1199 | Health Diagnosing and Treating Practitioners, All Other | 35,310 | MA | $73,400 |
| 29-2021 | Dental Hygienists | 196,520 | AD | $71,520 |
| 29-2051 | Dietetic Technicians | 28,690 | HS | $25,780 |
| 29-2052 | Pharmacy Technicians | 368,760 | HS | $29,810 |
| 29-2053 | Psychiatric Technicians | 64,540 | BA | $31,130 |
| 31-1011 | Home Health Aides | 799,080 | HS | $21,380 |
| 31-1013 | Psychiatric Aides | 72,860 | HS | $26,220 |
| 31-2012 | Occupational Therapy Aides | 8,570 | Some College | $26,550 |
| 31-9091 | Dental Assistants | 314,330 | Post HS Certificate | $35,390 |
| 31-9099 | Healthcare Support Workers, All Other | 98,980 | BA | $34,620 |
| 33-3052 | Transit and Railroad Police | 3,380 | AD | $51,690 |

Low STEM/Low Soft

| OCC Code | Occupation | Employment | Education | Median Wage |
|---|---|---|---|---|
| 13-1074 | Farm Labor Contractors | 950 | HS | $41,110 |
| 23-2091 | Court Reporters | 18,330 | Some College | $49,860 |
| 25-4031 | Library Technicians | 94,260 | BA | $31,680 |
| 27-1026 | Merchandise Displayers and Window Trimmers | 93,000 | HS | $26,590 |
| 29-2071 | Medical Records and Health Information Technicians | 184,740 | Post HS Certificate | $35,900 |
| 31-1014 | Nursing Assistants | 1,427,740 | HS | $25,100 |
| 31-2022 | Physical Therapist Aides | 48,730 | HS | $24,650 |
| 31-9011 | Massage Therapists | 87,670 | Post HS Certificate | $37,180 |
| 31-9094 | Medical Transcriptionists | 61,210 | Post HS Certificate | $34,750 |
| 31-9095 | Pharmacy Aides | 41,240 | HS | $23,200 |
| 31-9096 | Veterinary Assistants and Laboratory Animal Caretakers | 71,060 | Post HS Certificate | $23,790 |
| 33-3011 | Bailiffs | 16,310 | HS | $38,150 |
| 33-3041 | Parking Enforcement Workers | 8,680 | Post HS Certificate | $36,570 |
| 33-9032 | Security Guards | 1,077,520 | HS | $24,410 |
| 33-9091 | Crossing Guards | 66,310 | HS | $24,750 |
| 33-9092 | Lifeguards, Ski Patrol, & Other Recreational Protective... | 135,070 | HS | $19,090 |
| 35-2011 | Cooks, Fast Food | 519,910 | Less than HS | $18,540 |
| 35-2012 | Cooks, Institution and Cafeteria | 402,800 | HS | $23,440 |
| 35-2013 | Cooks, Private Household | 560 | Post HS Certificate | $22,940 |
| 35-2014 | Cooks, Restaurant | 1,104,790 | HS | $22,490 |
| 35-2015 | Cooks, Short Order | 180,800 | HS | $20,190 |
| 35-2021 | Food Preparation Workers | 850,220 | Less than HS | $19,560 |
| 35-3021 | Combined Food Preparation and Serving Workers... | 3,131,390 | Less than HS | $18,410 |
| 35-3022 | Counter Attendants, Cafeteria, Food Concession... | 476,470 | Less than HS | $18,740 |
| 35-3031 | Waiters and Waitresses | 2,445,230 | HS | $18,730 |
| 35-3041 | Food Servers, Nonrestaurant | 250,840 | Less than HS | $19,900 |
| 35-9011 | Dining Room & Cafeteria Attendants & Bartender Helpers | 410,460 | HS | $18,760 |
| 35-9021 | Dishwashers | 502,280 | Less than HS | $18,780 |
| 35-9031 | Hosts and Hostesses, Restaurant, Lounge, and Coffee Shop | 372,670 | Less than HS | $18,720 |
| 37-2011 | Janitors & Cleaners, Except Maids & Housekeeping Cleaners | 2,137,730 | HS | $22,840 |
| 37-2012 | Maids and Housekeeping Cleaners | 929,540 | HS | $20,120 |
| 37-3011 | Landscaping and Groundskeeping Workers | 868,770 | Less than HS | $24,290 |
| 39-1012 | Slot Supervisors | 7,000 | HS | $33,270 |
| 39-2021 | Nonfarm Animal Caretakers | 161,820 | HS | $20,340 |
| 39-3011 | Gaming Dealers | 96,060 | HS | $18,560 |
| 39-3012 | Gaming and Sports Book Writers and Runners | 12,160 | HS | $22,560 |
| 39-3031 | Ushers, Lobby Attendants, and Ticket Takers | 113,700 | HS | $18,760 |
| 39-3091 | Amusement and Recreation Attendants | 274,230 | Less than HS | $18,880 |
| 39-3092 | Costume Attendants | 6,270 | HS | $41,670 |
| 39-3093 | Locker Room, Coatroom, and Dressing Room Attendants | 17,830 | HS | $19,940 |
| 39-4021 | Funeral Attendants | 34,950 | HS | $23,080 |
| 39-5011 | Barbers | 14,140 | Post HS Certificate | $25,410 |
| 39-5012 | Hairdressers, Hairstylists, and Cosmetologists | 343,140 | Post HS Certificate | $23,120 |
| 39-5092 | Manicurists and Pedicurists | 79,090 | HS | $19,620 |
| 39-5093 | Shampooers | 16,560 | Post HS Certificate | $18,760 |
| 39-5094 | Skincare Specialists | 38,290 | Post HS Certificate | $29,050 |
| 39-6011 | Baggage Porters and Bellhops | 44,170 | HS | $20,930 |
| 39-7011 | Tour Guides and Escorts | 35,100 | Some College | $23,930 |
| 39-9021 | Personal Care Aides | 1,257,000 | HS | $20,440 |
| 41-2011 | Cashiers | 3,398,330 | HS | $19,060 |
| 41-2012 | Gaming Change Persons and Booth Cashiers | 19,580 | HS | $23,340 |
| 41-2021 | Counter and Rental Clerks | 437,610 | Less than HS | $23,860 |
| 41-9011 | Demonstrators and Product Promoters | 83,600 | HS | $24,520 |
| 41-9012 | Models | 5,140 | Less than HS | $19,970 |
| 41-9041 | Telemarketers | 234,520 | HS | $22,740 |

**Appendix A. Occupational Wage and Employment by High/Mid/Low STEM/Soft KSAs (contd.)**

*Total No. of Occupations = 764; U.S. Employment = 131,974,860*

| Low STEM/Mid Soft | | | | | Low STEM/Low Soft | | | | |
|---|---|---|---|---|---|---|---|---|---|
| OCC Code | Occupation Description | Employment | Education | Median Wage | OCC Code | Occupation | Employment | Education | Median Wage |
| 33-9011 | Animal Control Workers | 13,450 | Post HS Certificate | $32,560 | 41-9091 | Door-to-Door Sales Workers, News and Street Vendors… | 7,610 | Less than HS | $21,530 |
| 33-9021 | Private Detectives and Investigators | 26,880 | Some College | $44,570 | 43-2011 | Switchboard Operators, Including Answering Service | 108,890 | HS | $26,550 |
| 33-9031 | Gaming Surveillance Officers and Gaming Investigators | 10,030 | Post HS Certificate | $29,840 | 43-2021 | Telephone Operators | 10,220 | HS | $35,140 |
| 33-9093 | Transportation Security Screeners | 43,220 | HS | $38,090 | 43-3021 | Billing and Posting Clerks | 490,860 | HS | $34,410 |
| 35-3011 | Bartenders | 579,700 | HS | $19,050 | 43-3041 | Gaming Cage Workers | 16,350 | HS | $25,810 |
| 39-1011 | Gaming Supervisors | 24,100 | HS | $49,420 | 43-3051 | Payroll and Timekeeping Clerks | 166,400 | Post HS Certificate | $39,700 |
| 39-2011 | Animal Trainers | 11,170 | HS | $25,770 | 43-4031 | Court, Municipal, and License Clerks | 128,490 | HS | $35,460 |
| 39-6012 | Concierges | 31,050 | Some College | $28,170 | 43-4111 | Interviewers, Except Eligibility and Loan | 190,710 | HS | $30,790 |
| 39-7012 | Travel Guides | 3,090 | Some College | $35,100 | 43-4171 | Receptionists and Information Clerks | 981,150 | HS | $26,760 |
| 39-9011 | Childcare Workers | 582,970 | HS | $19,730 | 43-5021 | Couriers and Messengers | 71,760 | HS | $26,640 |
| 39-9031 | Fitness Trainers and Aerobics Instructors | 241,000 | Some College | $34,980 | 43-5041 | Meter Readers, Utilities | 36,210 | HS | $37,580 |
| 39-9032 | Recreation Workers | 321,110 | BA | $22,620 | 43-5051 | Postal Service Clerks | 71,910 | HS | $55,590 |
| 39-9041 | Residential Advisors | 95,750 | BA | $24,340 | 43-5052 | Postal Service Mail Carriers | 307,490 | HS | $57,200 |
| 41-2022 | Parts Salespersons | 231,240 | HS | $29,440 | 43-5053 | Postal Service Mail Sorters, Processors, … Machine Operators | 121,590 | Less than HS | $54,520 |
| 41-2031 | Retail Salespersons | 4,562,160 | HS | $21,390 | 43-5071 | Shipping, Receiving, and Traffic Clerks | 661,530 | HS | $29,930 |
| 41-3011 | Advertising Sales Agents | 154,220 | AD | $47,890 | 43-5081 | Stock Clerks and Order Fillers | 1,878,860 | HS | $22,850 |
| 41-3021 | Insurance Sales Agents | 374,700 | AD | $47,860 | 43-5111 | Weighers, Measurers, Checkers, and Samplers, Recordkeeping | 69,430 | HS | $28,570 |
| 41-3041 | Travel Agents | 64,750 | Post HS Certificate | $34,800 | 43-6012 | Legal Secretaries | 212,910 | Post HS Certificate | $42,770 |
| 41-3099 | Sales Representatives, Services, All Other | 826,650 | BA | $51,670 | 43-6013 | Medical Secretaries | 516,050 | Post HS Certificate | $32,240 |
| 41-4012 | Sales Reps, Wholesale & Manufacturing, Except Technical & Scientific | 1,394,640 | BA | $55,020 | 43-9021 | Data Entry Keyers | 205,950 | HS | $28,870 |
| 41-9021 | Real Estate Brokers | 38,720 | Some College | $57,360 | 43-9022 | Word Processors and Typists | 81,300 | HS | $36,700 |
| 43-3011 | Bill and Account Collectors | 346,960 | HS | $33,700 | 43-9041 | Insurance Claims and Policy Processing Clerks | 252,670 | HS | $36,740 |
| 43-3031 | Bookkeeping, Accounting, and Auditing Clerks | 1,575,060 | Some College | $36,430 | 43-9051 | Mail Clerks and Mail Machine Operators, Except Postal Service | 99,190 | Less than HS | $27,890 |
| 43-3061 | Procurement Clerks | 70,190 | Post HS Certificate | $39,930 | 43-9061 | Office Clerks, General | 2,889,970 | HS | $28,670 |
| 43-3071 | Tellers | 514,520 | HS | $25,760 | 43-9081 | Proofreaders and Copy Markers | 10,500 | BA | $34,980 |
| 43-4011 | Brokerage Clerks | 57,240 | AD | $47,520 | 45-2041 | Graders and Sorters, Agricultural Products | 36,100 | Less than HS | $19,910 |
| 43-4021 | Correspondence Clerks | 7,580 | HS | $35,460 | 45-4023 | Log Graders and Scalers | 2,780 | HS | $35,430 |
| 43-4051 | Customer Service Representatives | 2,511,130 | HS | $31,200 | 47-2042 | Floor Layers, Except Carpet, Wood, and Hard Tiles | 9,830 | HS | $36,670 |
| 43-4061 | Eligibility Interviewers, Government Programs | 122,400 | HS | $42,200 | 47-2043 | Floor Sanders and Finishers | 4,510 | HS | $35,770 |
| 43-4071 | File Clerks | 148,280 | Post HS Certificate | $27,580 | 47-2082 | Tapers | 16,820 | HS | $46,630 |
| 43-4081 | Hotel, Motel, and Resort Desk Clerks | 241,140 | HS | $20,610 | 47-2121 | Glaziers | 42,820 | HS | $38,410 |
| 43-4121 | Library Assistants, Clerical | 100,800 | HS | $23,910 | 47-2161 | Plasterers and Stucco Masons | 20,760 | Less than HS | $37,550 |
| 43-4131 | Loan Interviewers and Clerks | 212,440 | Some College | $36,880 | 47-3014 | Helpers--Painters, Paperhangers, Plasterers, & Stucco Masons | 11,570 | Less than HS | $25,910 |
| 43-4141 | New Accounts Clerks | 52,260 | HS | $34,000 | 47-3015 | Helpers--Pipelayers, Plumbers, Pipefitters, and Steamfitters | 51,350 | HS | $27,710 |
| 43-4151 | Order Clerks | 190,390 | HS | $31,180 | 49-3022 | Automotive Glass Installers and Repairers | 15,670 | HS | $32,590 |
| 43-4161 | Human Resources Assistants, Except Payroll and Timekeeping | 135,270 | Some College | $38,040 | 49-3093 | Tire Repairers and Changers | 100,510 | HS | $23,730 |
| 43-4181 | Reservation and Transportation Ticket Agents and Travel Clerks | 138,260 | HS | $33,510 | 49-9064 | Watch Repairers | 2,390 | HS | $35,450 |
| 43-5011 | Cargo and Freight Agents | 77,480 | HS | $41,380 | 49-9093 | Fabric Menders, Except Garment | 710 | HS | $23,930 |
| 43-5061 | Production, Planning, and Expediting Clerks | 297,050 | Post HS Certificate | $45,670 | 51-2021 | Coil Winders, Tapers, and Finishers | 14,930 | HS | $32,980 |
| 43-6011 | Executive Secretaries and Executive Administrative Assistants | 713,730 | Some College | $51,270 | 51-2022 | Electrical and Electronic Equipment Assemblers | 207,330 | HS | $29,910 |
| 43-6014 | Secretaries & Administrative Assistants, Except Legal, Medical, Executi | 2,207,220 | Some College | $33,240 | 51-2092 | Team Assemblers | 1,125,160 | HS | $28,370 |
| 53-2031 | Flight Attendants | 98,510 | Some College | $42,290 | 51-3011 | Bakers | 173,730 | HS | $23,600 |
| 53-4041 | Subway and Streetcar Operators | 11,300 | HS | $62,130 | 51-3021 | Butchers and Meat Cutters | 137,050 | HS | $28,660 |