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Human Capital in the City: Exploring the Relationship Between Skill and Productivity in US Metropolitan Areas

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HUMAN CAPITAL IN THE CITY:
EXPLORING THE RELATIONSHIP BETWEEN SKILL AND PRODUCTIVITY IN US METROPOLITAN AREAS

A Thesis Presented
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ABSTRACT

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In economics, new growth theory suggests that knowledge creation and innovation are key drivers of growth. As a result, the 'new economy' is increasingly reliant upon the knowledge, skills, and abilities embodied in its workforce, also known as human capital, that facilitate the stimulation and generation of new ideas (Romer 1986, 1990 and Lucas 1988). This research contributes to the understanding of the relationship between stocks of human capital and economic output. I construct metrics to measure concentrations of basic worker skills using the Bureau of Labor Statistics Occupational Information Network (O*NET) and employment estimates for 353 US metropolitan areas. In general, I find that basic skills are positively correlated with higher productivity. Specifically, I find that higher levels of the skills math and critical thinking partially explain higher levels of regional productivity. Science, though not statistically significant, has a negative correlation between higher levels of skill and regional output.

Keywords: new growth theory, human capital, tacit skill, economic development, productivity

TABLE OF CONTENTS

LIST OF TABLES

TABLE

LIST OF FIGURES

FIGURE

CHAPTER 1

INTRODUCTION

1.1 Background on human capital and skill

The last several decades have witnessed a dramatic shift in the economic base of the United States away from traditional strengths in manufacturing and heavy industrial activity to an economy driven by services; the likes of which depend upon innovation and knowledge creation to fuel economic growth. As a result, the 'new economy' or 'knowledge economy' is increasingly reliant upon the knowledge, skills, and abilities embodied in its workforce which facilitate the stimulation and generation of new ideas (Romer 1986, 1990 and Lucas 1988). The need to understand these fundamental changes has shifted regional economic analysis towards the requirements of the workforce of the 'new economy' and what is often referred to as human capital.

Human capital can be defined as those skills, abilities, and knowledge embodied in an individual which contribute to a productive process by creating value, whether it be economic or social. Concentrations of human capital have been demonstrated to contribute to higher levels of economic activity; a result of higher individual productivity and knowledge spillovers (Lucas 1988, Rauch 1993, Acs et al. 1994). In empirical studies, the measurement of human capital has overwhelmingly been limited to educational attainment, defined as the percentage of population holding a four year college degree or higher. However, most leading thinkers on the role of human capital in economic development have recognized that the skills and knowledge embodied in an individual are not limited to his or her formal schooling, but are also gained through basic innate skills, on-the job-training, work experience, and formal and informal social networks (Mincer 1958 & 1962, Becker 1964, Lucas 1988, Romer 1990, for example). Little research has been done to understand which skills, abilities, and knowledge have the greatest impact on economic growth, and therefore which areas policies can have the most impact.

New growth theory suggests that economic activity is directly dependent upon the creation of new knowledge and innovative activity which results from the productive process itself (Romer 1986 and 1990, Lucas 1988, Cortright 2001). As economies have shifted to a system where services and knowledge creation are the vital components of growth, the driving force to innovate is highly dependent upon human capital possessed in the workforce.

This research sets out to contribute to the understanding of human capital and its influence on regional economic development and the productivity of the regional workforce. I attempt to fill some of the existing measurement gaps, by exploring alternative measures of the different types of human capital as identified in the literature; specifically that of basic skills. This work attempts to contribute to the understanding of the role skill might play in economic activity and to identify which basic skills are most significant in explaining variations in regional productivity.

In this thesis I attempt to explore the effects of human capital, measured by basic skill requirements, on the productive process. I use a literature review as an exploratory tool to determine the ways human capital is conceptualized in scholarly research and how it may be measured to evaluate the impacts on economic activity. I focus on knowledge identified as tacit; skills embodied in individuals which facilitate the accumulation, acquisition, and creation of more knowledge. In effect, I analyze the core skills themselves which contribute to innovative activity and the productive process.

I use methodology employed by Feser (2003) and Koo (2005) to construct regional skill indices representative of the basic requirements necessary for the accumulation and acquisition of knowledge. They include such skills as reading, speaking, math, science, and critical thinking. Indices are developed by calculating a weighted occupational skill concentration by employing two datasets created by the US Bureau of Labor Statistics; the Occupational Employment and Wage Series and the Occupational Information Network. I then test through a regression analysis whether higher concentrations of these skill indices explain higher levels of regional economic activity in urban areas, which is measured by average gross metropolitan product per capita for the period 2005 through 2008.

I find that most of the ten basic skills that I measure (which include communicative skills, process skills, and math and science) are complimentary and perhaps dependent upon the relative presence of other basic skills. My models suggest that aggregate total skill, in general, has a positive influence on urban economic activity. The influence of some skills vary more than others, while some have no impact at all and others appear to have a negative effect. I find that math and critical thinking skills have the most significant and positive impact on regional productivity, while science appears to have a negative correlation, though not statistically significant. The variation in average gross metropolitan product per capita can also be explained by total population, education attainment, and industry effects, all used as control variables in the models.

1.2 Contributions of this thesis

This thesis attempts to understand the sources of regional and urban economic growth in the modern economy. This helps to inform the ongoing policy debates about the best strategies to increase regional prosperity and job creation. In doing so, I extend the literature in several ways. First, I attempt to explain whether and to what degree certain skills essential to learning and knowledge discovery, explain variations in productivity levels in and across cities and their metropolitan regions. These findings expand the existing literature base on human capital and economic development by addressing and measuring alternative dimensions of human capital that have received limited attention in the academic literature. I build upon the understanding of the role tacit knowledge plays in the productive process. I also attempt to contribute to the theoretical understanding of the functions by which individuals receive, process, produce, and distribute knowledge and information, with particular emphasis to new knowledge. In effect, I explore the essential basic skills that facilitate the process of knowledge accumulation, knowledge discovery, and learning.

Second, this thesis uses a new measure to capture regional productivity and economic activity. Previous studies that construct endogenous models of growth have measured economic activity at an individual level through patent activity, income levels, and employment growth (Jaffe 1989, Audretsch and Feldman 2004, Glaeser et al 1995, etc). However, this study attempts to measure aggregate economic activity broadly. I employ a relatively new dataset reported by the US Bureau of Economic Analysis which captures the value of all final goods and services produced by a metropolitan region; also known as gross domestic product (GDP). I have identified only one other study, as of the date of this research, that employs regional GMP to study regional variations in human capital (Abel and Gabe 2010). This study follows a similar methodology as Abel and Gabe, but differs in that it analyzes other dimensions of human capital.

Third, I develop new measures of human capital not yet employed in past studies. Using the BLS Occupation Information Network (O*NET), I construct measures of regional concentrations of basic skills necessary for the creation of new knowledge and innovative processes. Prior to the release of the O*NET, studies have overwhelmingly used educational attainment as a proxy for human capital levels. Thus, this study will extend those measures and explore other dimensions of human capital.

1.3 Research questions

This thesis explores the relationship between human capital and productivity in metropolitan areas. In order to understand this relationship I ask the following questions in developing this research.

- How is human capital defined and how is knowledge conceptualized?
- What are the types of skills which facilitate the acquisition and creation of new knowledge?
- What are the basic types of knowledge and skill that are essential to the development of new knowledge and innovative activity?
- Do the levels of basic skills embodied in the workforce contribute to higher productivity levels in the regional economy?
- Which basic skills are most significant in explaining regional productivity?
- What are the best ways to measure these types of skill?
- How can they be measured with existing data?
- What other factors might influence or explain variations in regional productivity?

1.4 Goals and objectives

To answer these questions I define a list of goals and objectives outlining the structure of this research for working through these ideas. They are defined as:

1. To identify how human capital is thought about, defined, and conceptualized in the existing literature.

    a. This will help to identify the core basic skills which help transform existing knowledge into new knowledge.
    b. This will inform decisions on which metrics to construct as proxies for human capital attainment.
        i. I achieve this through an intensive review of the literature.
2. To develop measures of human capital dimensions not previously employed in the literature, including the basic skills which contribute to knowledge accumulation and knowledge processing.
3. To measure aggregate skill as represented by regional occupational structure.
    a. For goals 2 and 3, these indices will allow analysis of approximate levels of human capital that exist in regions.
        i. This is achieved through a quantitative data analysis using the BLS O*NET dataset and occupational employment measures in the BLS Occupational Employment and Wage Series estimates. These are discussed in detail in Chapter 3 on Methodology.
4. To test whether concentration in the levels of basic tacit skill explain variations in regional output.
    a. This will inform conclusions on how and to what magnitude human capital influences economic activity in regions.

i. I run OLS (ordinary least squares) regression models using a regional output variable measured by GMP (gross metropolitan product).

1.5 Statement of hypotheses

I hypothesize that human capital as measured by basic occupational skill requirements contribute to higher levels of regional economic activity and productivity. More specifically, I hypothesize that higher levels of skill that are synonymous with the knowledge economy (ie. math and science), will correlate with higher levels of economic activity. Higher levels of tacit skills which facilitate the acquisition and rapid accumulation of more knowledge should thus lead to greater levels of urban economic activity.

This may happen for two reasons. First, higher skilled workers tend to be more efficient and productive. Thus, regions with a greater stock of productive workers should naturally experience higher aggregate productivity. Second, the spatial concentration of highly skilled workers with complementary forms of human capital generate positive knowledge spillovers that increase a region's productivity beyond the mere sum of its parts.

1.6 Organization of thesis

This thesis is organized in the following manner. Chapter 2 continues with a review of the existing literature that explores different conceptions of human capital and its presumed relationship with economic activity, and how both are measured in the empirical literature. Chapter 3 follows with a discussion of the methodology employed by this study, including a detailed review of model development, the calculation of variables and skill indices, and a brief descriptive analysis of these variables. Chapter 4 presents the results from the regression model calculations. In Chapter 5 I discuss the findings of my research and discuss the implications for policy and economic development planners. The study concludes in Chapter 6 in which I review the key points of the study and identify areas for future research.

CHAPTER 2

LITERATURE REVIEW

The literature review is a major component in the methodology of this thesis as it will inform and help in the development of variables used to answer my research questions. The main goals of this literature review are to gain an understanding into how technological change is accounted for in the growth process; the ways in which human capital is conceptualized in the scholarly literature; and to analyze the types of skills which may influence productivity and economic growth. I draw primarily from the economics literature, specifically that which analyzes the influences of human capital on economic growth, while also drawing on the geographic and planning literature with emphasis on agglomeration economies.

Specifically, this study engages the theoretical components of new growth theory and addresses the different types of human capital that have been identified in the literature. In evaluating different types of knowledge, I review methods for measuring levels of human capital used in the existing literature. Finally, I cover measures of regional productivity that have been used in past studies that will inform the development of the variables which I use in the regression analysis discussed in Chapter 3.

2.1 Modeling Economic Growth

2.1.1 Neoclassical growth models

To understand how human capital is accounted for in the productive process, it is useful to begin with a basic framework for modeling economic growth. Traditionally, growth is modeled as a function of capital and labor inputs. In these models, growth is achieved by adding more inputs of labor and capital to production. However, each addition is subject to decreasing returns, which result in increasing marginal costs. In theory, diminishing returns and increasing marginal costs will eventually lead to a steady state equilibrium, where growth stops and the economy continues functioning at a constant rate (Cortright 2001). Cortright points out that this framework is useful to economists in modeling the economy but it does not explain historical growth rates.

Drawing from neoclassical theory, Solow (1956) sought to address this problem by accounting for the decreasing returns of capital and labor. He did this by inserting a variable into the neoclassical model to account for all growth not explained by labor and capital inputs: a variable he termed the 'technology residual'. Solow considered technological advancement a significant force that moved productivity and growth forward. The most basic form of Solow's model can be expressed as $Y=f(K,AL)$ where Y output is a function of capital 'K', labor 'L', and technological change, which is represented by the term '*A*'. The term '*A*L' represents the productivity of the labor force in efficiency units in which the labor force is constrained to the level of technology available (Mankiw, Phelps, and Romer 1995).

Growth is thus directly determined by capital and labor inputs into the production function and the technology available to the workforce.

Despite the recognition that technology plays an important part in the growth process, little attention is paid as to what causes technological change. In general, Solow and neoclassical models deem technology a constant, evolving over time unaffected and unrelated to the supply of labor and capital or the productive process. These models assume technological change is determined by exogenous forces, through which technology disperses evenly and instantaneously. By treating technological change as an exogenous factor in production, the models attribute most economic growth to increasing levels of labor and capital introduced into the productive process. To Solow and other neoclassical economists, technology was viewed as something that was not a result of economic forces. Therefore, they did not attempt to determine the actual causes of technological change throughout the course of time (Cortright 2001). Nor did they view technological change as a result of the productive process itself.

Technological change does not disperse ubiquitously and instantaneously upon its creation. But rather spatial, capital, and legal constraints add friction to the spread of technology across regions and firms (Romer 1986). For instance, patent laws designed to incentivize innovation by their very nature prevent new technology from being used by other firms in order to promote the very innovative activity they restrict. Instead, patents allow for the extraction of monopolistic rents in order to recapture research and development investment by the firm in developing new technologies and awards innovation through excess profits. Secondly, technology is not immediately or easily adopted because of firm restrictions such as location, capital costs, labor force knowledge, or the physical capability to implement the new technologies (Jaffe et al. 1993, Jaffe 1989).

Furthermore, Solow's model suggests that poorer economies should 'catch-up' to wealthy economies through higher growth rates. Income and productivity should then converge at an equal level across countries or regions. This is because labor and other capital costs are lower in poor countries, and there are low barriers to the diffusion and adoption of technologies, once created. As a result, poorer regions should attract greater investment leading to faster growth (Savvides and Stengos 2009). This provides further evidence that neoclassical models, even with Solow's technology residual do not fully explain historical rates of growth.

Thus, there must be some other phenomena that explains changes in growth rates and the lack of economic convergence among countries. Mankiw, Romer, and Weil (1992) argued that one should not expect convergence across countries, but rather each country will reach its own steady state equilibrium. In addition, if poorer countries should be growing faster than wealthy countries, then why have historical growth rates of wealthy countries increased over time?

2.1.2 New growth theory

It is these types of questions that were explored by Paul Romer (1986, 1990) and Robert Lucas (1988) in developing a new way of modeling economic growth. The centerpiece for this new theory of growth is the introduction of technological change as a direct result of the production process itself. Technological change is recognized as occurring ‘endogenously,’ rather than as part of uncontrollable outside forces, as suggested by Solow’s neoclassical model.

By introducing technological change and new knowledge accumulation as an internal function of the productive process, Romer’s model is able to recognize increasing returns of labor and capital inputs. The implications for this view directly challenge neoclassical models, which focus simply on adding more capital and labor into the mix in order to achieve growth (Cortright 2001). Rather than simply adding more inputs, the endogenous theory suggests growth results from increases in efficiency gains, productivity, and innovations that evolve from new knowledge and technological change, as applied to the existing levels of labor and capital. Therefore, implied policy prescriptions under this framework suggest a shift from labor and capital accumulation, to knowledge accumulation and application.

Romer (1990) outlines three important criteria for the role of knowledge in growth models. First, that knowledge is a vital aspect of the production function and economic growth. In essence, it is what drives economic growth and progress. Secondly, technological change is fueled by conscious and intentional decisions by firms and individuals to invest in activities that stimulate new knowledge and innovation. These acts are in direct response to market incentives, which implicitly suggests knowledge is at least a partially excludable good. Lastly, Romer points out that the instructions and processes for working with raw materials are inherently different than working with other economic goods. Once a process or innovation is documented and associated fixed costs are incurred, the process can be replicated and employed over and over again without incurring additional costs (to the development of the process itself). Thus, marginal costs are essentially zero, effectively defining these knowledge processes and instructions as non-rival goods. Once these three criteria are met, Romer's theory holds that technological change allows for increasing returns to the scale of labor and capital inputs. In effect, larger markets will create more innovative research and as a result drive economic growth. Furthermore and perhaps even more significant, by realizing increasing returns to scale, growth appears unrestricted by economic costs.

In addition to driving increasing returns, knowledge and technological change have been recognized to facilitate another process. Lucas (1988) suggests that higher levels of human capital may lower the cost of obtaining physical capital necessary for production. In his cross country analysis, Lucas concludes that one reason for the lack of physical capital and investment in poorer countries is a result of lower levels of complimentary human capital. Therefore, investors may obtain a much higher return in regions with higher levels of knowledge and human capital. This implies that human capital may play multiple roles in the production process.

2.2 Implications for Policy and Regional Economies

Understanding growth has important implications for policy, most importantly which areas to direct resources and economic development efforts.

Traditionally, regional economic development efforts have focused on the attraction of companies or industries through financial incentives and old fashioned salesmanship (Markusen 2004). Alternatively, new growth theory would suggest that efforts should be targeted at stimulating innovative and knowledge creating activities. Instead of directing resources and attention at attracting jobs, emphasis should be directed at giving a reason for firms to locate by building and strengthening a region's core assets, its workforce. New growth theory has restructured the way in which economic developers have crafter policy, moving into the once distinct areas of workforce development.

The intersection of economic and workforce development raises questions as to whether policies should target specific industries that have a higher skilled workforce, generating higher investment returns. Industries which demand skills such as science, technology, engineering, and math (STEM), are often characterized as the high growth sectors of the new economy. These industries rely much more heavily on higher levels of human capital, knowledge creation and innovation, rather than hard physical capital and labor. This raises the question whether policies should focus on these specific skills that are high growth, or should policies target the development of basic forms of knowledge that are more applicable across many different industries? In addition, what are the factors that might inform policy in making investment decisions?

2.2.1 Historical, institutional, and locational factors

Cortright (2001) discusses these implications by classifying them into three categories: historical, institutional, and locational, in that all three have significance in the growth of economies. History has shown that increasing returns tend to set a trajectory towards that which is not always easily altered, resulting in path dependence on a new technology. Economies have also exhibited ‘evolutionary’ tendencies, rather than those defined in neoclassical models which suggest a constant shift towards steady state equilibrium. New growth theory handles this approach by altering the ways which technological change is accounted for. However, that change Cortright claims, is more along the lines of Schumpeter’s creative destruction, in which new technologies and ideas make previous concepts obsolete.

When referring to institutional components, Cortright (2001) sites the work of David North (1990) for his explanation of the relationship non-market institutions have on economic development. Institutions, administered by non-market forces including government, can play an important role in the economy by directly influencing the types of knowledge and technology that is generated. For example, government expenditure on research and development within land grant universities focus on certain types of technology development. This is perhaps most recognizable by military and defense technologies developed through US Department of Defense expenditures.

Perhaps the most significant implication laid out by Cortright pertaining to this study is in regard the importance of location or place. Particularly for knowledge spillovers, the benefits of proximity have been widely analyzed in the literature. Marshall (1890) was one of the first to make explicit reference to the advantages of geographic proximity. Marshall observed that being close to similar companies allowed access to more specialized supply networks, labor pooling opportunities, and an atmosphere conducive to knowledge accumulation. Workers are able to learn from one another as they move across firms, while regions developed specialized knowledge of the particular area's industrial concentration.

Jacobs (1969) acknowledged that cities are where ideas are formed and generated. In fact, Jacobs concludes that the mere reasons cities exist are as a means to facilitate knowledge and idea transfer. It seems that these notions follow a pattern of human survival in that in order for regions and people to survive, they must innovate. Jacobs exemplified this by the need for cities to reinvent themselves every so often as their comparative advantages and specializations become obsolete. Glaeser (2003) finds this in his analysis of the city of Boston and its continuous ability to reinvent itself again and again over the years. He considers this a direct result of Boston's high levels of human capital in the workforce, which is skilled at creating new ideas.

2.2.2 Human capital and the firm

Further evidence of the economic benefits of knowledge can be demonstrated by the fact that human capital is being accepted and viewed by firm management as essential to the success of a company. Firms are now valuing, in a quantitative manner, the capital possessed by their workforce in a way that has never before been perceived. It is no longer assets, capital stock, or real estate that are the distinguishing feature of companies, but rather the quality and value of its workforce (Fitz-enz 2009).

2.3 Defining Human Capital

"The most valuable of all capital is that invested in human beings" (Marshall 1890).

An internet search of the term 'human capital' returns a fairly conclusive definition as 'the relative stock of skills and knowledge an individual possesses which contribute to or have some form of economic value'.[1] Alternatively, these skills can be thought of as those that which make an individual more productive. The economic literature defines human capital in much the same way. This section will cover the dimensions of human capital that have been discussed in the literature in order to gain an understanding of how knowledge creation can influence the productive process and economic growth.

[1] A search of Google on March 31, 2010 revealed almost 6.5 million search results. A request to define 'human capital' resulted in roughly 25 entries all using some form or another of the phrases referenced here.

2.3.1 Formal education as human capital

The term capital can be defined as something that generates wealth and income or yields outputs over time through the production process (Savvides and Stengos 2009). The notion that human knowledge plays an important role in the production of goods and services can be traced back to Adam Smith in his Wealth of Nations (1776) and Alfred Marshall (1890). Therefore, investment in human beings could be considered a form of capital as well.

The earliest explicit reference to the term human capital stems from the pioneering papers of Jacob Mincer (1958, 1962) in which he attempted to explain the correlation between abilities of a person and their earnings. In doing so, Mincer developed a 'human capital model' which explained that earnings are a function of the levels of human capital possessed by a person (Haveman et al 2003). An individual's level of human capital, Mincer explained, was built upon some initial level of basic ability. It is through these basic skills and abilities that which facilitate the garnering and acquisition of more knowledge and skills.

Each individual is able to then build upon this basic level through accumulating more human capital, or knowledge, through the means of formal schooling, job training, and work experience. Mincer demonstrated that work experience has a direct effect on the amount of capital an individual possesses. These conclusions suggest that a person's level of human capital is dependent upon their age and the amount and types of schooling and training received by the individual. Mincer claimed this demonstrates that human capital is accumulated through knowledge and skill building activities such as formal education, on the job training, and work experience. Therefore, by investing in these knowledge and skill building activities there are economic returns to be had.

Although Mincer was the first to characterize human capital as having economic value, Gary Becker is perhaps most notably associated with the concept of human capital and the returns to be gained from formal schooling; a culmination of his work first published in the 1964 book titled *Human Capital: A theoretical and empirical analysis, with special reference to education* (Becker 1964 and 1993). Becker, like Mincer, recognized differences in knowledge types and sources. There are those skills derived from formal schooling and those that are also gained from on-the-job training, including both general and specialized training. Becker’s studies investigated the relationship of investments in schooling, particularly college level education, to a person’s earnings. These investments were shown to have a dramatic increase in a person’s income levels even after accounting for the cost of education and forgone earnings during the years at school.

While Becker focused on the individual returns, Schultz (1961) argued that education is a public good resulting in positive externalities to society and to the productive process. Lucas (1988) went on to define human capital as an individual’s overall general skill level, indicating that different levels of which can be measured by an individual’s relative difference in productivity. Barro (2001) and several others empirically explored the relationship of economic growth and education levels in a series of cross country analyses where they found that education levels at least partially explained economic growth.

In a similar study, Rauch (1993) explicitly dealt with positive externalities received by society associated with formal schooling. Rauch notes that the labor economics literature treats human capital as having two components, which are able to be quantitatively examined. Those include education and average experience. In his empirical analysis, Rauch found that education had a much more significant effect on output productivity than work experience. However, Rauch used a general and broad measure of average experience across the workforce and did not weight the experience of individual workers.

2.3.2 Skills, on-the-job training, and learning-by-doing

Until recent years, empirical studies attempting to measure human capital have been limited by available data. The overwhelming measure of human capital in the literature has been education as measured by years of schooling, degree attained, or entry/exit rates (see studies referenced above). Therefore, these studies make implicit assumptions that formal schooling is the most important measure or type of human capital levels. However, education is not the only source of human capital accumulation and does not measure skill levels adequately (Ingram and Neumann 2006). The traditional measure, typically the percentage of population with a bachelor's degree or higher, are broadly defined and do not describe the types of skills or education and knowledge-base that workers possess in a region.

Similarly, graduates with a degree in the fine arts do not necessarily possess the same productive skill set as a graduate with an engineering degree, for instance. Their contribution to the productive process can be expected to be quite different, while still serving important societal needs. Yet, in the existing measures of educational attainment, each is weighted the same.

Furthermore, the presence or absence of a college degree says nothing specific about the variables contributing to innovative activity and knowledge spillovers enhancing production (Abel and Gabe 2010). For instance, the mechanisms for knowledge spillovers and new ideas spring from social interaction and occupations requiring higher levels of critical thinking, problem solving, and other cognitive skills. While education levels undoubtedly play a function in skill and worker development, educational attainment is not the primary indicator of the triggers by which new ideas are generated. Learning-by-doing and on-the-job training are just as important to the formation of human capital as formal schooling (Lucas 1988).

As noted earlier, this is not by fault of previous research but rather the lack of descriptive data available to conduct such analyses. It has long been recognized since early discussions on human capital that the primary means of accumulation are through worker experience, the productive process or job itself, and social interactions. These ideas have simply not been subjected to empirical analysis until recently. Ingram and Neumann (2006) investigate the differences in return between the interaction of physical capital and skilled labor versus unskilled labor. They found that while the returns to skilled labor have risen substantially, this notion "... cannot be exploited by simply sending more workers to college. In fact, we find that workers who attend college but do not invest in specific skills have flat income growth over the period covered in our dataset" (p. 55). Therefore, it is important to recognize that not all education and not all skill sets contribute in the same way to economic growth.

2.3.3 Tacit knowledge, codifiable information, and knowledge spillovers

There are two types of knowledge as Cortright points out; knowledge that is codifiable and knowledge that is tacit. Tacit knowledge refers to knowledge which Romer (1990) deemed as skills tied to an individual such as reading, decision making, adding, or how to work a machine. Meanwhile, codifiable refers to knowledge which is written down and accessible by more than one individual in a formalized process; otherwise referred to as information (Audretsch and Feldman 2004). For example, this would include knowledge such as an operations manual, a documented process, or statistical equations. Tacit knowledge can be thought of more as a skill or ability possessed by an individual rather than hard, documented facts.

The implications of these differences are that tacit knowledge is spatially bound to the individual who possesses it and is not easily transferred. Codifiable knowledge can be shared and transferred beyond spatial boundaries with ease. Furthermore, once codifiable information is documented it remains accessible. Conversely, tacit knowledge is tied to the individual. When that individual dies so does the tacit knowledge they possess, while the knowledge they created in their lifetime (codifiable), lives on.

As referenced previously, Mincer (1958) suggested there are basic knowledge and skills such as reading, writing, math, communicating and problem-solving, which help the accumulation and interpretation of other types of knowledge, such as that which is codifiable. These basic skills must be in place before all else. Therefore, one might expect that the higher the level of basic skills, the faster the accumulation and development of new and additional knowledge.

One important distinction between these two knowledge types is the role tacit knowledge plays in spillover externalities. Because tacit knowledge is embodied in an individual, that knowledge is dependent upon the location of the person. In order to be transmitted, people need to be in proximity to other people. Therefore, geography matters in the spillover effects of this type of knowledge (Audretsch and Feldman 2004). Since tacit knowledge in effect has the qualities of a non-rival good it can be easily transmitted between individuals. Furthermore, it is tacit skills through which new ideas are communicated, explained, and transferred.

Audretsch and Feldman go on to distinguish between transmission costs of codifiable information and tacit knowledge. Due to the proliferation of internet and telecommunication technologies the marginal costs of transporting information across individuals is low. However, the marginal costs of tacit knowledge spillovers are lowest when individuals engage in frequent social and face-to-face interaction. Therefore, in a model where innovation based on knowledge accumulation is the driving force of growth, human capital can be expected to cluster spatially by agglomerative forces in order to minimize the transaction costs of knowledge transmittal.

2.4 Understanding Human Capital in the Regional Economy

2.4.1 A two-dimensional economy

Thompson and Thompson (1987) make reference to the notion that a regional economy is made up of two distinct dimensions: industry and occupation. Both are vital to understanding the full picture of the regional economy. Regional economic development policies and strategies have traditionally focused their attention on the industry component by offering tax and financial incentives to attract businesses, while paying less attention on workforce and occupational development promotion (Koo 2005). However, studies by Greenstone and Moretti (2003) have shown that policies offering massive financial incentives to attract companies to a region have proven to be a worthless effort. Policies and strategies focusing on the industry component have often fallen short because of failure to account for the equally important occupational dimension (Koo 2005 and Feser 2003). This has been especially true throughout the transition of the US economy to service based occupations. This has had the effect of shifting the importance of productive assets from hard capital to the worker and the capital they possess. Strategies failing to invest or account for human capital in their development approach have neglected to understand the interactions between these two dimensions.

For instance, regions with similar industries can exhibit very different productive processes and operations. In a study by Koo (2005), substantial differences appeared in the spatial distribution of operations within one specific industry. Innovative activities in the Rubber Manufacturing industry have tended to concentrate in the northeastern states while production operations occurred in southern states. Thus, one might expect higher levels of skill and knowledge pertaining to science and mathematics to be concentrated in areas requiring more innovative occupations. While production occupations may not require these same types of human capital, but rather be based more on production and technical knowledge and thus have very different occupational requirements. Alternatively put, levels of human capital are tied to the occupational component of the regional economy rather than the industrial. Although, industry is somewhat representative of a region's occupational structure and therefore its levels of human capital, it is the workforce which embodies the skills, knowledge, and education vital to economic growth.

2.4.2 Shifting focus from industrial to occupational development

It has become increasingly important to focus attention in understanding the second aspect of the regional economy for economic development practitioners. As a result, a body of literature has been stimulated towards a focus from what a region makes, to what a region does (Feser 2003). Focus has drifted towards the occupational element of a regional economy as a centrifuge for growth because of the increased reliance on human capital in the development process (Mathur 1999). As new growth theory would suggest, economic advance is derived from the accumulation of knowledge generated by the workforce and labor inputs. Therefore, it seems natural for policy to focus investment of constrained resources on this aspect of the production process in stimulating regional development. This has logical implications for building a region's long term and most important asset, its workforce.

Regions may become more attractive for large multinational firms. Those may include that which display or provide assets distinguishable from competitor regions and transferable across industries of benefit to more than one company. For example, return on investment for a $3 million tax incentive for a particular company, may be better spent and achieve higher long-term gains, by building the assets installed in people and physical infrastructure; rather than subsidize a corporation that may leave in ten years when the next good deal comes along. It would seem a more worthwhile approach to invest capital and assets in things that are more tied to the region, which will in turn naturally attract industry. Therefore, investing in an asset such as human beings, the investment may be less likely to 'leak' out of the regional economy, and economic practitioners might get more bang for their buck.

This shift towards focusing on both industrial composition and occupational structure has required the development of new tools in assessing the requirements of the regional workforce. Several studies have begun descriptive analyses using a relatively new database constructed by the Bureau of Labor Statistics. Works by Feser (2003), Koo (2005), Abel and Gabe (2010), Scott (2009a, 2009b), and Gabe (2009) among others have used the O*NET database to determine concentrations of different types of human capital and to understand the occupational dimension of regional economies.

2.5 Alternative Sources of Human Capital Measures

2.5.1 The O*NET database

The Occupational Information Network was first released to the public in 1998 replacing the older Dictionary of Occupational Titles which had been used to describe US occupations. Developed by the US Bureau of Labor Statistics, the O*NET database was designed to describe the world of work in a way which allows for cross occupational analysis using the same descriptive language. The database allows for comparisons of occupational information across jobs, sectors or industries, and within occupations themselves (Hadden et al 2004). It is used in the realms of occupational psychology, career counseling, human resource departments, and by workforce development professionals.

O*NET data is collected through survey based methods applied to incumbent workers and occupational analysts which specialize in particular fields. Occupations are classified and reported using the Standard Occupational Classifications (SOC) system used by several other statistical agencies including the BLS, to report employment, income, and wage information. Therefore, O*NET data can be merged with SOC occupational data derived from the US Census or Bureau of Labor Statistics, limited by geographic constraints,[2] to understand regional occupational structures, characteristics, and concentrations. It has since evolved through several versions at least annually, with the most recent version 14.0 released in June of 2009[3]. As a workforce development tool, an analyst or policy maker is able to identify potential labor pooling opportunities and cross industry comparisons for training purposes.

2.5.2 The O*NET content model

O*NET is structured around a content model which characterizes work in six core domains: Worker Characteristics, Worker Requirements, Experience Requirements, Occupation-Specific Information, Workforce Characteristics, and Occupational Requirements. These domains are further broken down into over 800 sub-domains rating occupations on such things as knowledge requirements, cognitive abilities, license requirements, physical requirements and body positioning during performance. Information on occupational classifications is summarized using a taxonomic approach (Peterson et al 2001) which allows information to be assigned

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[2] BLS release of OES data is generally limited to Metropolitan Statistical areas and national level data.

[3] http://www.onetcenter.org/database.html accessed on December 3, 2009.

to fewer categories. As a result, elements should be delineated as to not overlap. However, it should be recognized that many of these categories are redundant, and overlap can be seen in domain scores across elements. In addition, several limitations have been recognized by Peterson et al (2001) relating to the collection of information for the database which was gathered through surveys and analyst judgment. In attempts to flush out redundancy, several papers have used factor analysis to detect areas of overlap with O*NET variables (see Smith and Campbell 2006, Feser 2003).

O*NET has been employed in numerous studies across academia, government, and professional practice. Aside from studies already discussed, many uses have been reported by the National Center for O*NET Development (NCOD). Most state level workforce development offices employ the O*NET database in some form or another to identify similarities in labor pools or in the case of large economic shocks such as those resulting from B.R.A.C. or large plant closings. Career counseling centers, unemployment offices, and human resource departments use the dataset to develop profiles for potential workforce opportunities. O*NET has even been used by graduate students to determine off-shoring potential of some 800 jobs in the U.S. (NCOD 2009). The key point in citing these uses is that O*NET is a vast database with numerous applications across numerous operational functions.

2.5.3 Worker requirements

"Worker requirements represent developed or acquired attributes of an individual that may be related to work performance such as work-related knowledge and skill" (O*NET Content Model Version 14.0). These domains of the model constitute a variety of worker attributes necessary to complete their job. Specifically, worker requirements are broken down into three categories including skills, knowledge, and education. Skills and knowledge are scored according to both level and importance, while education is scored using a scaled system providing a percentage of total survey responses in each of 12 education levels.[4] In total, there are 35 skill domains ranging from basic to cross-functional. The knowledge component reports scores on 33 domain areas ranging from knowledge in Engineering to knowledge of Fine Arts. The knowledge domains have been used by several studies to develop occupational knowledge clusters (see Abel and Gabe 2010; Feser 2003 for example).

It is my intention to arrive at new proxies for human capital not already employed in the literature, but representative of the nature of human capital as a contributor to productivity in the production process. Focus here is placed on the skills components of the Worker Requirements domain, primarily those relating to basic skills. These basic types of skills facilitate the learning and attainment of new knowledge. They are in effect the most rudimentary components of a worker's

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[4] The ranking system for 'Level of Education' used in the O*NET is complicated and uses rather small sample sizes based on survey responses for job incumbents and occupational analysts. For each of the 12 education levels, ranging from no education requirement, all the way to advance degrees such as doctoral.

knowledge machine. It is through these basic skills that knowledge is learned, communicated, and transferred across workers, occupations, and industries. They are in effect, the means to which information and knowledge is shared. However, while the O*NET provides a vast array of measures of skills and ability requirements, it does not distinguish between those which are learned and those which are embodied in an individual (Scott 2009a). Therefore, in using the O*NET the analyst must use personal judgment in determining which skills reported by the O*NET are most characteristic of basic or learned skills.

2.6 Indicators of Productivity – Measures of Economic Growth

2.6.1 Focus is on individual measures

Human capital appears to effect economic growth in two ways; by first increasing the productivity of the individual worker and second, by creating opportunities for knowledge spillovers where new knowledge and technology are formed. In this section, I review how these phenomena have been tested for in past research.

Higher levels of human capital have been shown to be correlated with increases in employment, population, income and wages within regional economies (see Rauch 1993, Schultz 1963, Mincer 1958). Traditional measures of economic vitality have included studies using employment and wage growth, housing prices and land rents, and growth in population. Simon (1998) explained increased productivity levels in metropolitan areas through employment growth as a function of human capital concentration. Glaeser, Sheinkman, and Shleifer (1995) found income and population growth as positively related to initial education levels in urban areas. Yet others have explained human capital contributions to innovative activity through the use of patent data (Agrawal et al 2008; Jaffe et al. 1993).

These measures focus on individual attainments and generally fail to capture a more aggregate level of production. They do little to explain how the concentration of human capital contributes to regional productivity levels, such as knowledge spillovers. If human capital propagating endogenous technological change is the key driver of economic growth and productivity levels by region, then in order to accurately understand and explain these interactions a regional aggregate measure must be employed.

2.6.2 Metropolitan gross domestic product

Gross domestic product, which measures all final goods and services, is a well accepted measure of economic conditions and growth in the economics literature. GDP per country has long been used in the developmental economics literature to make cross country comparisons of developing countries (Kuznets 1955 for example). Several studies on human capital and education have used GDP as a measure of economic growth and productivity as well (Barro 2001 and Rauch 1993 for example).

Until recently, no such measure has been available to compare regional diversity internal to the United States. The Bureau of Economic Analysis began releasing gross domestic product for US metropolitan statistical areas in 2005. It includes releases dating back to fiscal year 2001 for over 360 Metropolitan Statistical Areas. In this past year 2009, the Bureau initiated an accelerated release program which has made previous year data available much sooner on an annual basis than other data sources. The measures provide a snapshot of the value of all goods and services sold within the region for the data period. The measure presents several challenges pertaining to suppression, such as existing industry mix and geographic size variation.

Abel and Gabe (2010) recently used GDP per capita to measure productivity levels in US Metropolitan areas correlated with educational attainment. However, literature employing metropolitan GDP as a measure of regional economic activity is essentially non-existent in refereed journals. Likely, because most studies linking human capital to levels of productivity focus on individual measures such as average wage or educational attainment.

CHAPTER 3

METHODOLOGY AND DESCRIPTIVE ANALYSIS

Methodology is first comprised of the literature review discussed in Chapter 2 which helped conceptualize human capital and inform the specific areas of human capital I wish to measure. To test my research questions and hypothesis I develop a model for explaining regional production. From this, I move forward constructing skill indices tied to the regional occupational structure of metropolitan statistical areas in the United States. I then construct control variables used to isolate variation in the data in order to account for certain effects not able to be captured by my measures of skill. This chapter proceeds with a discussion of the construction of these variables, the method of developing them, and brief descriptive analysis of the variables for skill indices and GMP per capita.

3.1 Modeling Human Capital in the Production Function

This thesis seeks to develop measures of the different types of human capital not yet modeled in past studies and to determine whether these types of human capital can explain increases in regional productivity output. To do this, I construct a basic Cobb-Douglas production model using regional productivity as the output dependent variable, and measures of human capital as the primary independent variables. The model is then regressed using an ordinary least squares method, controlling for population size, educational attainment, and industrial effects.

The models follow similar methodology and framework employed by Abel and Gabe (2010). I also construct two types of indices using a similar weighted methodology used by Abel and Gabe, following Feser (2003) and Koo (2005). However, in this thesis I use different types of measures of the basic skills which facilitate the acquisition and accumulation of more knowledge. Previous studies focused on the knowledge requirements of occupations in constructing a regional knowledge index. While both measures attempt to target more specialized types of human capital, the basic skills that I analyze here, appear to be more tacit oriented skills that are linked to a worker's abilities.

3.1.1 The human capital production function

The Cobb-Douglas production function accounts for labor and capital inputs in determining final output of production. The traditional Cobb-Douglas function can be expressed: $Y=AL^{\alpha}K^{\beta}$ where '*Y*' is equal to total production and '*L*' and '*K*' refer to labor and capital inputs, respectively. Alpha 'α' and beta 'β' refer to labor and capital output elasticities respectively, determined by available technology. '*A*' *symbolizes* the total factor productivity which accounts for effects not caused by changes in labor and capital.

I construct a reduced-form equation following that of Abel and Gabe (2010), in which I represent the natural log of the Gross Metropolitan Product per capita measure (GMP PER CAPITA) as total factor output, and set it equal to alpha as measured by a regional skill index. I then control for regional and industrial effects from population and industrial composition and the influence of educational attainment on productivity. The equation can be expressed as:

$$\ell nGMPPC = \alpha SK^{ij} + \beta POP^{j} + \rho EDUC^{j} + \varphi RGE^{j}$$

Where SK_{ij} is skill index i in MSA j and POP is total population in MSA j. ρEDUC is the percentage of the over 25 population in MSA j which have obtained a bachelor's degree or higher. ϕRGE represent the regional industry concentration for natural resource and manufacturing industries in MSA j. The dependent output variable is the natural log of gross metropolitan product per capita. These variables are discussed in detail in the following sections. This model is then subjected to a multiple regression analysis using a basic Ordinary Least Squares function. The results of the regression analysis are discussed in the following chapter.

3.2 Dependent Variable

3.2.1 Gross metropolitan product

Economic activity and population are concentrated in metropolitan areas. For the years 2005 through 2008, metropolitan GMP accounted for 88 percent of US GDP (see Table 3.1).[5] Similarly, population in urban metropolitan areas accounted for close to 83 percent of total national population. Furthermore, metropolitan areas are defined to represent spatially bound coherent internal labor markets where knowledge spillovers are likely to occur. As a result, the metropolitan area is an ideal unit of analysis for measuring the effects of human capital on productivity (Abel and Gabe 2010; Lucas 1988).

Table 3.1 Metropolitan Percentage of National GDP and Population

	2005	2006	2007	2008	Average
Total US GDP	$ 12,638,400	$ 13,398,900	$ 14,077,600	$ 14,441,400	$ 13,639,075
All MSA GDP (Gross GMP)	$ 11,082,353	$ 11,772,193	$ 12,324,166	$ 12,724,270	$ 11,975,746
Percentage US GDP	88%	88%	88%	88%	88%
US Population	288,378,137	299,398,485	301,621,159	304,059,728	298,364,377
Total MSA Population	239,832,630	248,785,913	251,169,111	253,457,171	248,311,206
Percentage of US Total	83%	83%	83%	83%	83%

Source: BEA, US Census, Author's calculations

In 2004, the Bureau of Economic Analysis began reporting Gross Domestic Product by Metropolitan Statistical Area, (hereon referred to as Gross Metropolitan Product or GMP). GDP, generally reserved as a national economic indicator,

[5] This percentage accounts for the 363 metropolitan areas reported by the total BEA dataset.

measures the final market value of total goods and services. In the case of GMP, the measure is an estimate of all final goods and services produced within a metropolitan region. Metropolitan geographies are defined according to the latest release in 2003 by the Office of Budget and Management, including the preceding years of 2001 and 2002, making these years comparable from the beginning of the dataset[6] through the end of the year. However, this study is limited to a cross-sectional analysis for the years 2005 to 2008.

The gross metropolitan product measure is constructed by the BEA using estimates of county earnings by industry from its Local Area Personal Income Accounts. Measures are classified based upon the North American Industrial Classification System (NAICS) which began reporting in 2001; the same year used as the base for the GMP series. GMP is estimated for each of the major 2 digit industrial categories included in the NAICS. However, many MSAs have suppressed GMP values for the major NAICS categories, therefore making more detailed industry analysis across regions with any sort of accuracy difficult. Such complete measures could be useful in analyzing specific industries and the effects skills have on productivity, such as manufacturing and production or healthcare and services. However, totals for all industries, including government expenditures which make up total GMP, are available for 366 metropolitan statistical areas.

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[6] The MSA geographic definitions have been cross referenced with other datasets included in this study, specifically US Census ACS population estimates for the years 2005 through 2008 and the US Bureau of Labor Statistics Occupational Employment and Wage Series. Any discrepancies between metropolitan areas and reporting were left out of the final regression analysis.

Gross metropolitan product differs substantially across metropolitan areas, primarily as a result of metropolitan size and population. New York City, for example, boasted a GMP of over $1 trillion in 2005, while the smallest metro, Palm Coast, FL, claimed just over $1 billion; a 1,000 percent difference. Therefore, for the purposes of comparison it makes sense to calculate GMP on a per capita basis to produce more meaningful indicators across metropolitan areas, by directly accounting for population in the model. However, this may fail to capture full representation of the workforce across areas, which may differ in workforce size and unemployment rates.

3.2.2 Gross metropolitan product per capita

Gross metropolitan product is calculated on a per capita basis using one year estimates from the US Census Bureau's annual estimates program, the American Community Survey. Estimates for years 2005 through 2008 were used to calculate per capita GMP by corresponding year. These years were then used to obtain an average measure of GMP per capita for the four year period. I use an average of GMP per capita for the years 2005 through 2008 by US metro area as expressed in current dollars.[7] This is done not so much as to account for business cycles (Abel and Gabe 2010), but rather to establish a more accurate approximation for each metropolitan area's annual productive capacity. This is in particular consideration of

[7] The BEA reports GMP as measured in real chained 2001 dollars, which tends to smooth data and eliminate volatility in the data. However, this study uses and average over a four year period to present a more consistent idea of a regions productivity and to account for any larger than normal years. Extreme outliers are left our of the regression analysis altogether, although they are included in the descriptive analysis.

the recent economic climate and recession which began in December of 2007, a period that was preceded by several years of economic growth. By averaging across these four years, the data will better represent the relative economic strength and productive capacity of a region, as well as account for any large single year variations.

Before calculating an average, the data was examined to determine noticeable outliers and conflicts within the data which may skew results in the regression analysis. These MSAs are left out of the regression analysis, but are included in the overall descriptive analysis. Those excluded from the analysis include MSAs affected by Hurricane Katrina, specifically the New Orleans-Metairie-Kenner, LA metro area. It is well known the displacement of New Orleans residents after the destruction of thousands of homes, and the humanitarian crisis that ensued following the storm. Many residents migrated out of the city and greater metro region, which is reflected in the population estimates by the US Census.[8] Furthermore, a shift of economic activity from domestic to the subsequent restructuring and rebuilding of the area in the years following the devastation could falsely skew productivity as unrelated to human capital aggregation within the metropolitan area. Subsequently, New Orleans appears in the top twenty of average

[8] Population in the New Orleans-Metairie-Kenner, LA MSA, according to US Census Bureau ACS one year estimates, declined by 268,000 from 2005 to 2006. That equates to a 21 percent decline in one year, compared to other MSAs of this size, which maintained relatively flat or slight growth. Population did increase slightly in 2007 and by 2008 the MSA had recaptured about 100,000, however still well short of pre-hurricane levels.

GMP per capita list (see Table 3.2). A look at previous years finds the New Orleans MSA much lower in the rankings of average GMP per capita.

In addition, five metropolitan areas are left out altogether as a result of ACS population estimates not available for the target years. Furthermore, the sample was reduced to exclude some of the smaller metropolitan areas as qualified by population size [9]and for metropolitan areas with inconsistent geographic definitions. If geographic boundaries were not consistent or able to be rebuilt for a metropolitan statistical area across datasets, then they were dropped from the sample. The final sample size in our dataset was thus reduced to 289 for the regression analysis. However, the descriptive analysis of the data that follows includes a total of 363 MSAs.

[9] MSAs with total 2005 population less than 120,000 were excluded from the regression analysis, approximately 60 metropolitan areas.

Table 3.2 Average GMP Per Capita for the Top & Lower 20 MSAs, 2005 to 2008

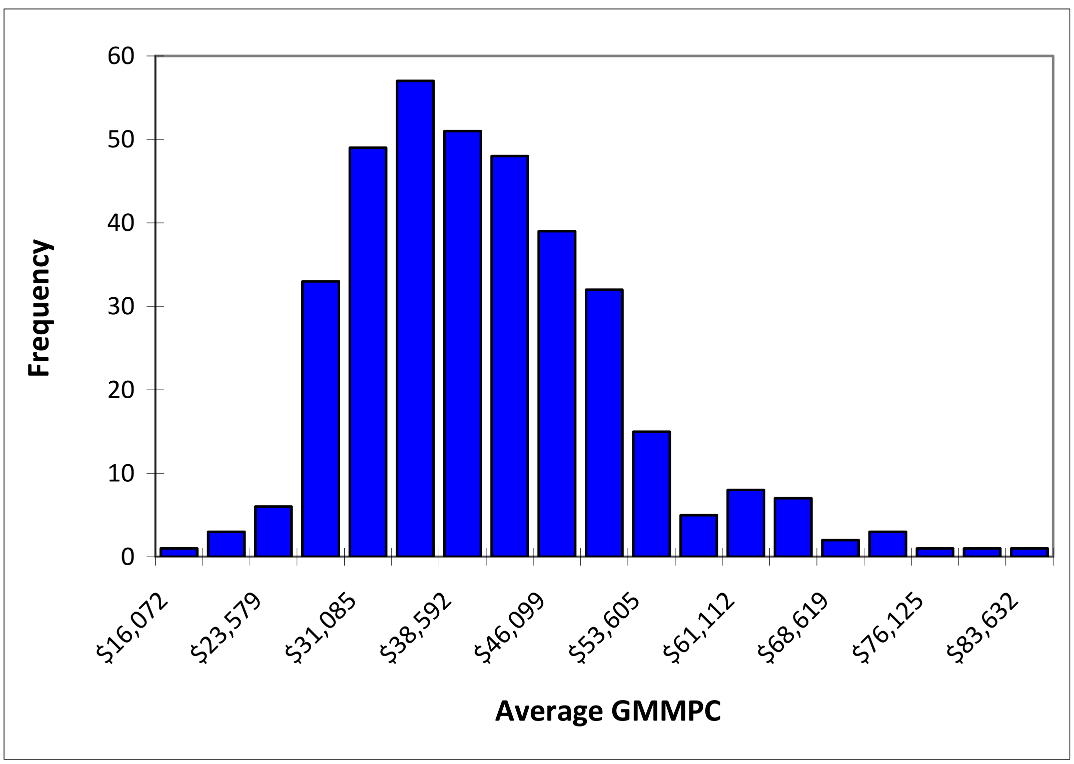
Rank	Metropolitan Statistical Area	Average GMP Per Capita
1	Bridgeport-Stamford-Norwalk, CT (MSA)	$87,385
2	Casper, WY (MSA)	$80,420
3	San Jose-Sunnyvale-Santa Clara, CA (MSA)	$77,309
4	Midland, TX (MSA)	$72,492
5	Washington-Arlington-Alexandria, DC-VA-MD-WV (MSA)	$70,422
6	San Francisco-Oakland-Fremont, CA (MSA)	$70,049
7	Charlotte-Gastonia-Concord, NC-SC (MSA)	$70,040
8	Anchorage, AK (MSA)	$68,011
9	Houston-Sugar Land-Baytown, TX (MSA)	$64,945
10	Lake Charles, LA (MSA)	$64,154
11	Lafayette, LA (MSA)	$63,938
12	Boston-Cambridge-Quincy, MA-NH (MSA)	$63,246
13	Trenton-Ewing, NJ (MSA)	$63,089
14	Durham-Chapel Hill, NC (MSA)	$63,078
15	New York-Northern New Jersey-Long Island, NY-NJ-PA (MSA)	$62,159
16	Seattle-Tacoma-Bellevue, WA (MSA)	$61,847
17	Sioux Falls, SD (MSA)	$60,401
18	Des Moines-West Des Moines, IA (MSA)	$60,302
19	New Orleans-Metairie-Kenner, LA (MSA)	$60,300
20	Hartford-West Hartford-East Hartford, CT (MSA)	$59,457
344	Monroe, MI (MSA)	$24,541
345	Deltona-Daytona Beach-Ormond Beach, FL (MSA)	$24,391
346	Logan, UT-ID (MSA)	$24,332
347	Springfield, OH (MSA)	$24,265
348	Laredo, TX (MSA)	$24,126
349	Gadsden, AL (MSA)	$24,099
350	Yuma, AZ (MSA)	$23,933
351	El Centro, CA (MSA)	$23,798
352	Cumberland, MD-WV (MSA)	$23,649
353	Pueblo, CO (MSA)	$23,609
354	Las Cruces, NM (MSA)	$23,519
355	Merced, CA (MSA)	$23,454
356	Madera-Chowchilla, CA (MSA)	$23,441
357	Ocala, FL (MSA)	$23,176
358	Punta Gorda, FL (MSA)	$22,622
359	Prescott, AZ (MSA)	$20,709
360	Lake Havasu City-Kingman, AZ (MSA)	$18,215
361	Brownsville-Harlingen, TX (MSA)	$17,719
362	McAllen-Edinburg-Mission, TX (MSA)	$17,653
363	Palm Coast, FL (MSA)	$16,072

Sources: US Bureau of EconomicAnalysis, Current Dollar Gross Domestic Product by Metropolitan Statistical Area; US Bureau of Census, American Community Survey Annual Popoulation Estimates of Metropolitan Statistical Areas

3.2.3 Dataset description of average GMP per capita

While using a per capita average relieves some of the major variability in the standalone GMP measures, the difference between the highest and lowest MSA is still quite substantial; an over 500 percent difference. Figure 3.1 below shows the frequency distribution of average GMP per capita by MSA. While much of the distribution resembles a somewhat normal curve, there are several MSAs which have a much greater average GMP per capita. Bridgeport-Stamford-Norwalk, CT tops out the list with an average GMP per capita of $87,385, while the lowest ranking MSA of Palm

Figure 3.1 Frequency Distribution of Average GMP per Capita, 2005 to 2008



Coast, FL registered an average of $16,072 (refer to Table 3.2). Overall, the mean GMP per capita was calculated to be $38,674 for the entire data set, while the median value is $37,199.

Some familiar regions appear in a list of the top twenty averages, including, San Jose, CA, San Francisco, Washington, DC, Boston, and New York City. However, some surprises round out the upper 20 on the list. Casper, WY ranked second with an average GMP per capita of $80,420 for the four years, while several MSAs in Louisiana also show up on the list. These appear to be regions where high concentrations of natural resource activity occur, such as mining and oil refining. While they extract a lot of value as a percentage of GMP, they require relatively few workers. This finding is consistent with the percentage changes in GMP per capita by MSAs between 2005 and 2008. The regions with the highest growth rates are areas with industry primarily concentrated in natural resource extraction, refining, and delivering. Those include states and regions such as Texas, Grand Junction, CO, Casper, WY, Louisiana and Mississippi. It is necessary to pay close attention to these within the distribution, in that it may be necessary to exclude these regions as outliers in the final model, or use variables to control for capital and resource inputs.

3.3 Constructing Regional Indices of Human Capital

A review of the literature concludes that the core dimensions of human capital are made up of basic cognitive skills, formal education, on-the-job skills and training, and human capital generated from work experience, as measured in years on the job. Human capital can also be obtained through formal and informal social networks, as well as the knowledge gained through parental development and cultural upbringings. The indices constructed here will focus on the first of these types of human capital; basic cognitive skills. I argue that it is these types of basic skills, such as reading, writing, and other communication which facilitate the acquisition of knowledge that are critical to new knowledge formation and increased productivity and efficiency. The higher level an individual possesses of these skills, it can be thought that the faster and more knowledge they will gain over time. The indices are generated by merging occupational to employment data in order to calculate a weighted average skill index within each MSA. The construction of these indices is discussed in detail later in this chapter.

3.3.1 Occupational Employment and Wage Statistics

In order to approximate the concentration of basic skills, I develop variables following the methodology of Feser (2003) and Koo (2005). To construct a regional skill index I use occupational data from the Bureau of Labor Statistics Occupational Wage and Employment Statistical series by metropolitan statistical area for the year 2005. The OES dataset provides employment counts for over 800 occupational categories in the US workforce and is reported under the Standard Occupational Classification system. This is substantially larger than other data series reporting on occupation, such as the US Census' PUMS dataset which reports roughly 400 occupations using the SOC. Consequently, it becomes difficult to cross-walk between these smaller sets of occupational data and the O*NET's even more detailed hierarchy, often relying on analyst judgment to match occupations. Furthermore, the OES is a superior dataset for the purposes of this study, because sample sizes are much larger than the PUMS dataset, which uses a 5 percent sample for all occupations.

The OES dataset is collected using a three year rolling survey of businesses regarding occupations, number of employees, and wage data. Data is reported in the SOC hierarchical structure, similar to that of the NAICS, with occupations broken into 22 Major Occupational Categories. Occupations are also grouped within the Major Occupational Categories by similar sub-groups which range by occupational grouping. Occupations not easily classified in a single occupation are grouped into "All-Other" categories.[10]

The year 2005 was chosen for several reasons. One relates to geographical definitional constraints posed by earlier years. The OES dataset is a three year rolling survey, where each year a third of businesses are surveyed and averaged with the prior two year surveys to attain estimates for the entire population. Consequently, metropolitan area definitions for many US metro areas changed after

[10] See Appendix B for an example of the SOC hierarchy.

the 2000 Decennial Census to account for population and economic shifts which occur across the country. Therefore to account for these definitional changes and to maintain consistency, the OES had to initiate surveys twice a year in May and November of 2003 and 2004 to bring estimates up to speed. The geographic definitions therefore need to match our other datasets, including US Census population estimates and the BEA Gross Domestic Product by metropolitan area calculations.

Second and perhaps more important, I use 2005 OES data in order to align proper causality and avoid endogeneity in the regression analysis. For example, occupational employment taken in 2006 may not be the same employment based which is responsible for the productivity for that entire year, since employment samples are taken at different times. I also view 2005 as a good indicator because of the strong economic growth that followed 2005 through most of 2007. The national unemployment rate was around 5 percent for 2005, therefore much of the workforce was active with relatively high employment figures providing a robust representation of skill.[11]

3.3.2 Occupational estimates data suppression

The OES dataset presents some challenges in regard to suppressed values because of data reporting requirements by the Bureau of Labor Statistics. Most significant here, the Bureau restricts reporting occupational employment totals and

[11] Sourced from Bureau of Labor Statistics LAUS program.

wage information that may lead to identifying workers or firms in a specific region. The BLS does not report data for occupations that do not meet reporting requirements, leaving some occupations without employment numbers in the datasets. Within a given MSA, there may be a number of occupations for which employment data is suppressed. This is particularly true of smaller MSAs, as suppression tends to be a function of MSA size, though not always the case.

This study uses occupational structure as a representation and indicator to capture regional composition and their effects. Therefore, an important part of this methodology is how to deal with suppressed occupational reporting for regions. In general, suppressed reporting is done for occupations with small employment totals, which may have minimal effects on regional composition. However, there are instances where a large employer may be present in a region, or some other characteristic in which occupations in much larger totals are suppressed as to protect identity of those workers and employers. In these instances, developing a representative and accurate estimate of suppressed occupations is imperative in order to capture those regional effects vital to this study. Working with the OES dataset required addressing over 21,000 suppressed individual occupations for 363 MSAs (though not all of these MSAs were included in the regression analysis).

One method in estimating suppressed occupational totals is to calculate national percentage shares, both as a percentage of total occupations, and also as a percentage of Major Occupational Category shares (ie. a percentage share of SOC 11-0000). This is similar to the method Koo employs to estimate occupational shares for suppressed values (Koo 2005). Statistical tests resulted in a 97 percent confidence level for his estimates. However, one problem with this methodology is the washing out any regional effects that exist in that region, by approximating based on the national occupational structure. This may be fine for occupations which are ubiquitous across regions, such as elementary teachers or police and fireman. But for occupations which concentrate by region and industry, using national shares may under estimate the true employment numbers for a region and vice versa.

A second option would be to simply leave out the occupations with missing OES estimates for employment. When calculating the 'Skill Index', any structural influences from the missing occupations will not be included in weighting skill requirements. This of course presents logical implications for areas which possess either large proportional numbers of occupations or many small numbers of several occupations that may require significantly higher skills than other occupations in the region. Thus, estimations of a skill index will fail to capture these slight variations in a region's occupational structure.

While estimating occupational shares based on national data does present its challenges in failing to fully capture regional effects, I felt it most appropriate to include some form of estimate rather than excluding an occupation all together. In conjunction with this, I use additional estimating techniques by scrutinizing the data and accounting for obvious opportunities for obtaining an accurate estimate.

3.3.3 Complementary estimation methods

Where relevant, occupations were estimated by looking at the difference between the major occupational employment total and the sum of other occupations in that major category. Generally, this only applied when a single occupation was missing employment totals within the major category. For instance in Chicago MSA, 'Computer Specialists, all other' was the only occupation missing from the major category 15-0000 'Computer and Mathematical Occupations.'[12] Therefore, the difference between the Major Occupational Category (15-0000) and the sum of the OES reported occupations allowed us to derive a reasonable estimate for 'Computer Specialists, all other'. This is an appropriate method when these conditions exist in order to estimate an accurate value.

This number can then be compared to the national average shares. If the actual major occupational share for a region was vastly different than the national shares, more attention and scrutiny was paid to those estimated shares and how they equate or translate into appropriate estimates within that Major occupational category. For instance, if Architecture and Engineering MAJOR Category (17-0000) for a region had a share of .0157 and the national share of total occupations was .0283, this, depending how many suppressed occupations appeared in that category, was then highly scrutinized.

If I had used a simple national share by major correlation, our estimates would have been extremely low for this particular category within the Chicago MSA.

[12] For an example of the SOC hierarchy, see Appendix B.

Computer Specialists and other high level IT occupations are known to cluster together spatially and are not necessarily equally distributed across regions and the country as a whole. Therefore, it is important to capture these regional structural differences as best as possible. However, a majority of major occupational categories with missing values contained more than one occupation with suppression.

3.4 Constructing O*NET Variables

3.4.1 Choosing variables of skill

This methodology seeks to explain whether basic cognitive skills necessary for the acquisition and speed of gaining new knowledge, correlate with higher levels of regional productivity; a result of knowledge spillovers and increased individual productivity. In doing this, I utilize a component of the O*NET database, for both the level of each skill required for an occupation, as well as the importance of using that skill in performing that occupation. These skills range from basic to cross-functional skills necessary to carry out certain occupations.

I focus on the 10 basic skills outlined in the O*NET, because these are the skills that are vital to accumulating more knowledge and learning, in general. By contrast, cross-functional skills refer to abilities which allow for the execution of activities across different jobs, such as social, technical, and systems skills. These skills appear to apply to certain job applications which may not be applicable across the occupational spectrum. An analysis of these skills shows that overall they tend to concentrate within certain occupational groups, such as manufacturing.

Basic skills are broken down into two groups; content skills, those that are defined as "background structures needed to work with and acquire more specific skills in a variety of different domains", and process skills, which are "procedures that contribute to the more rapid acquisition of knowledge and skill across a variety of domains" (O*NET Content Model). These skills are comprised of those generally associated with communicative capacities and those used in problem solving. The full list of basic skills is identified below in Table 3.3, while detailed definitions of each of these skill elements and what they measure can be found in Appendix A. This table is not designed to represent a hierarchy of basic skills, although some implicit functional organization is apparent.

Table 3.3 Basic skill elements: content skills and process skills

Element ID	Element Name
Content skills	
2.A.1.a	Reading Comprehension
2.A.1.b	Active Listening
2.A.1.c	Writing
2.A.1.d	Speaking
2.A.1.e	Mathematics
2.A.1.f	Science
Process skills	
2.A.2.a	Critical Thinking
2.A.2.b	Active Learning
2.A.2.c	Learning Strategies
2.A.2.d	Monitoring

Source: US BLS, O*NET Database

After a detailed analysis, I break the content skills into two components; communicative skills and applied skills, to provide a more conceptualized grouping of these skills. Communicative skills include Reading, Active Listening, Writing and Speaking. They all refer to ways in which information is received and given. Applied skills include math and science, and refer more to tools that are used to interpret and process information. In this sense, they overlap process skills, which interpret, diagnose, and help create new information. Process skills are left in their initial grouping.

3.4.2 Calculating an occupational skill requirement index

Skills are scored in two domains, level and importance. Level refers to the depth of a skill, or how much of a certain skill is used. Importance refers to the breadth of a skill, or how often that skill is used in a certain occupation.

The O*NET reports skill levels on a scale of 1 to 7, with a score of one requiring less of the relevant skill and 7 requiring the most level of the skill. The O*NET provides anchors to describe the processes pertaining to each skill level.[13] For instance, in the skill Reading Comprehension, a score of 2 indicates a level equivalent to 'reading step-by-step instructions for completing a form'. While a score of 6 indicates the ability to 'read a scientific journal article describing surgical procedures'. Similarly, Importance is scored on a scale of 1 through 5, with 5

[13] See Appendix A for a table of anchor indicators for the 10 skills used in this analysis.

suggesting the skill is extremely important to the occupation and 1 indicating no importance at all.

Level and importance appear to be highly correlated in the O*NET dataset by occupation. However, Feser (2003) and Koo (2005) use a weighted average of both importance and skill in developing a knowledge score for each knowledge domain. They do this by citing that inclusion of the importance measure gives more weight to occupations with higher knowledge requirements, thus providing a more robust representation of the required knowledge for each occupation. I use this same methodology in developing a regional skill index by weighting each occupation by the level of skill used and the importance of that skill to the occupation. In calculating a basic skill requirement for each occupation I simply multiply the Level score (LV) of skill *i* for occupation *j* against the Importance score (IM) of skill *i* for occupation *l* to arrive at the Skill Requirement (SK) of occupation *l*. This can be simply expressed as: $SK^{i}=LV^{il}*IM^{il}$

In calculating the skill index, there are certain estimates which require attention. Differences in the O*NET and OES-SOC reporting structure does not allow for a perfectly smooth concordance across datasets. Many O*NET-SOCs report occupations in even more detail, attempting to account for emerging occupations in the economy. In addition, the O*NET does not report scores for the 'All-other' occupational grouping included in the OES dataset. Therefore, using the SOC hierarchy, I estimate O*NET occupational scores for both skill and level, by using an average of occupations included in relative occupational categories based on the SOC hierarchy.[14]

Of the 800 occupations reported in the OES used in this study, approximately 100 required some sort of estimation of O*NET scores using similar or disaggregated occupational scores.[15] A detailed description of this methodology is included in Appendix C.

A look at histograms reveals the frequency dispersion of skill indices as seen in Figures 3.2 below.[16] Science is highly concentrated and skewed towards a lower skill index, with a vast amount of observations at or close to zero. Similarly, Math indices are clustered towards the left side of the histogram, with a long tail indicating small groups of high skilled occupations. These diagrams are not comparable across skill indices, but rather provide a sense of the relative importance these skills have in the overall occupational sample. This is interesting to note considering these are two skills considered synonymous with the knowledge economy.

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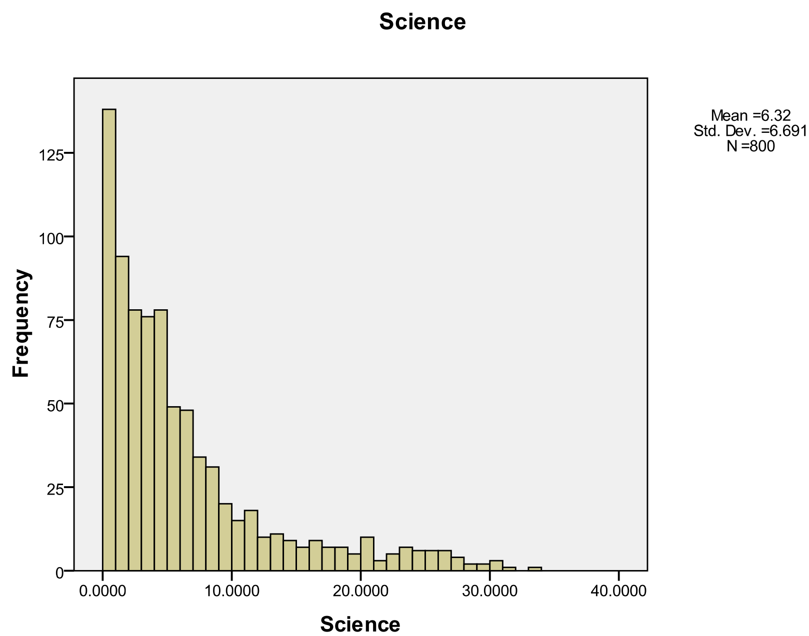
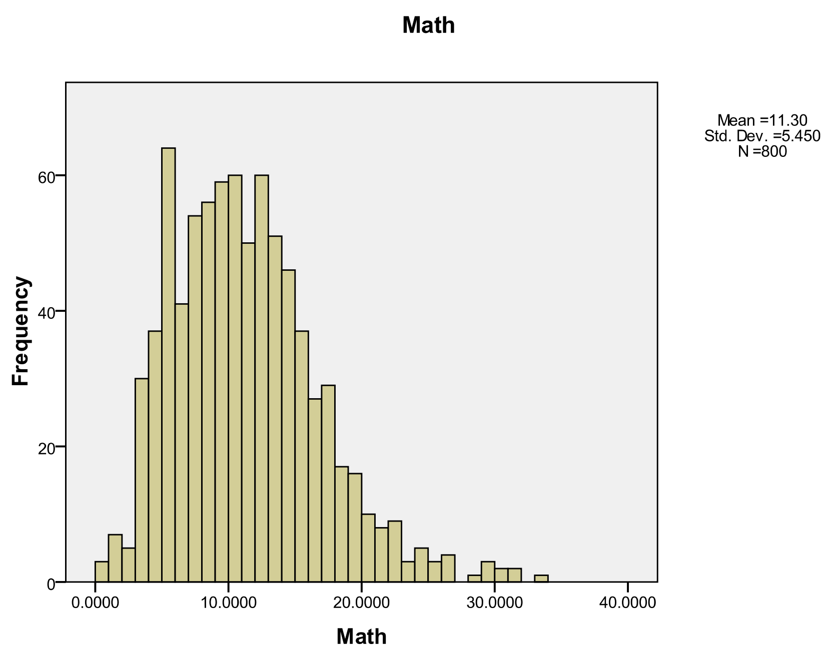
[14] See Appendix B.

[15] Many disaggregate occupations within the O*NET had the same level and importance scores. Therefore, for the missing occupations within those occupational groups, I was able to estimate with high confidence the appropriate skill scores. That is not to say that other estimates were any less significant. However, five occupations all with a level score of 5 would produce a mean of 5 and standard error of 0, alluding to a high significance estimation.

[16] A complete list of histograms can be found in Appendix D.

Figure 3.2 Frequency Dispersion of Science and Math Skill Indices





3.4.3 High skilled occupations

Occupations that require high degrees of training, education, and other learning activities could be assumed to have high requirements for the basic skills that facilitate knowledge accumulation. For instance, surgeons require vast amounts of experience, education, and on-the-job training at a very high level. Therefore, one could hypothesize that surgeons should have high degrees of basic skill such as reading, writing, listening, and active learning. The skill indices across skill domains confirm this by demonstrating that many of the same occupations have some of the highest skill requirements (see Appendix D for tables ranking occupations according to individual skill index scores). Physicians and surgeons, representing several core occupations, have high skill indices across Reading Comprehension, Active Learning, Critical Thinking, and Active Listening, in addition to high requirements in Math and Science.

The types of occupations that have higher skill indices in Science include those that could be expected to have higher levels, such as physical scientists. Those include astronomers and physicists, which had the highest Science skill index. Similarly, occupations with heavy reliance upon Math such as actuaries, statisticians, and computer scientists, engineers, math teachers, and other scientists, require higher degrees of this skill.

Many of the occupations with high basic skill requirements are those in the educational fields, including both secondary and post-secondary instructors, and healthcare practitioners; specifically those that diagnose and treat illness. This is especially true for the skill requirements for Learning Strategies, which is highly dominated by educators. Learning strategies refers to the ability to select appropriate means to train and educate people.

On the other end of the spectrum, occupations with the lowest skill requirements appear to be those generally not identified in the 'knowledge economy'. These include occupations such as Rail Yard Operators, Loggers, and Shuttle Car Operators.

Overall, the skill indices appear to be dominated by a core group of high skilled occupations including scientists, engineers, healthcare practitioners, and educators. While there are other occupations that have high skill requirements outside of these core groups, they are few and do not rank consistently across skill domains. However, by weighting skill based upon occupational composition, I am able to view how skill is distributed spatially and ultimately test the skill's relationship with productivity.

3.5 Calculating a Regional Skill Index

The regional skill index is constructed by calculating a weighted average for each MSA according to its occupational structure and the required skill levels of each occupation within that region. Therefore the skill index can be expressed by the equation:

$$SI^{ij} = \frac{\sum_j^i SK^{li} * EMP^{lj}}{TOTEMP^j}$$

Where SI is the skill index of *i* skill in MSA *j* calculated by the total weighted skill in MSA; which is derived by the sum of Skill Index 'SK' *i* of occupation *l,* times the employment total of occupation *l* in MSA *j*. This is divided by the total employment (TOTEMP) in MSA *j*. This has the effect of giving the proportional weight of each occupation's skill requirements within a region according to that region's occupational structure. For instance, a region concentrated with occupations requiring higher levels and importance of skill in 'Critical Problem Solving' will have a higher skill index for this particular skill. However, one problem with this is that a region could also have a high concentration of low skilled workers, thus diminishing the numeric influence of higher skill concentration.

In total, 10 skill indices are calculated for each of the 353 MSAs included in the BEA gross metropolitan product dataset, although only 289 of these are used in the regression analyses. A table of descriptive statistics is below (see Table 3-5). Skill scores are based off of the representative tasks for each skill; benchmarks that are different for each skill. Therefore, direct comparison of the index statistics would yield inaccurate assumptions about the data. Still the descriptive statistics are useful for understanding the distribution of the skill indices.

Table 3.4 Descriptive Statistics for Skill Indices Across All MSAs

	Content Skills						Process Skills			
	Reading Comp	Act List	Writing	Speaking	Math	Science	Critical Thinking	Active Learning	Learning Strategies	Monitoring
N	353	353	353	353	353	353	353	353	353	353
Mean	14.448	15.514	11.192	13.598	9.561	2.819	12.975	11.847	11.898	11.313
Median	14.397	15.471	11.158	13.605	9.579	2.820	12.914	11.806	11.948	11.316
Std. Deviation	.628	.525	.584	.516	.323	.335	.589	.586	.456	.543
Range	4.853	4.076	4.120	4.033	2.194	2.217	4.540	3.969	2.868	3.427
Minimum	12.265	13.603	9.470	11.501	8.659	2.010	11.075	10.283	10.401	9.730
Maximum	17.118	17.679	13.590	15.534	10.853	4.227	15.615	14.252	13.269	13.157

Source: US BLS, O*NET database, OES dataseries; Author's calculations

Histograms and MSA rankings (see Appendix E) show a much more evenly distributed range of frequency by skill score for Science and Math, compared to the individual skill indices across occupations presented in the previous section. Though there appear a few outliers, uncharacteristic of the remainder of the skill group. For instance, Durham-Chapel Hill, NC and San Jose-Sunnyvale-Santa Clara, CA have relatively higher skill indices for Science, indicative of the high amounts of research in Biotech and IT, which inhabit those regions.

Some regions rank consistently high across different skills. Those regions include Washington-Arlington-Alexandria DC, VA, WV, which ranks at the top of 9 out of 10 skills, all but Science, where it ranks third. San Jose-Sunnyvale-Santa Clara, CA (home to parts of Silicon Valley), Trenton-Ewing, NJ, Durham-Chapel Hill, NC, and Boston-Cambridge-Quincy, MA appear at the top of most skills in all but a few instances as well. These are all regions home to many importance facets of the 'knowledge economy'. A few others consistently rank high in many skills including Boulder, CO, Corvalis, OR, San Francisco, CA, and Bridgeport-Stanford-Norwalk, CT.

Thus, my hypothesis predicts a higher average GMP per capita as a result of the higher levels of human capital concentrated in these areas.

Some of the big differences appear within the Science, Math, and Learning Strategies skill indices. For example, within the Learning Strategies skill, McAllen-Edinburg-Mission, TX and Lawrence, KS both appear to be more concentrated with this skill than other MSAs. While in Science, Huntsville, AL, Bakersfield, CA and Kennewick-Pasco-Richmond, WA appeared within the top 10. It is no secret Hunstville, AL is home to NASA, while less well known is that Bakersfield MSA is home to Edwards Air Force Base, a central location of military and aeronautic research and testing facilities.

3.6 Control Variables

3.6.1 Educational attainment

One effect that may lead to higher levels of certain skills in a region is that of the approximate level of education. As mentioned in previous sections, educational attainment has been the traditional measure of human capital in occupational analyses seeking to explain economic gains from higher concentrations. It has been shown to explain higher productivity the higher the percentage of population with a college degree. By controlling for educational attainment, I am also able to capture the effects of college and university presence in a region, not tied to occupational requirements.

Using US Census Bureau estimates from the American Community Survey for the year 2005, I calculate the percentage of working age population over 25 who possess a Bachelor's degree or higher. These percentages are then used as independent variables in the regression analyses.

3.6.2 Population

Population estimates for year 2005 are used as an independent variable in the model to account for the effects of population size on productivity. Data from the US Census ACS one year estimates for year 2005 are used. We know that gross metropolitan product is directly correlated with population size, which is why the dependent variable is calculated on a per capita basis to obtain more comparable measures. However, population size may also influence productivity by the aggregate concentration of people due to such phenomena as economies of scale (Glaeser and Mare 2001).

3.6.3 Industry effects

GMP captures all final goods and services within a metropolitan statistical area. As a result, regions that have high production of natural resources or manufacturing activities will have a higher output less tied to a skilled workforce. This may not necessarily be reflective of the levels of human capital and occupational skill requirements within those regions.

In order to control for these industrial effects, I construct two variables based upon the concentration of each industries' contribution to GMP. Recalling that he

BEA reports GMP based upon the NAICS industrial codes, I use aggregate 2 digit NAICS reporting to calculate location quotients for the share of GMP devoted to manufacturing and natural resources and mining.[17]

3.6.4 Concentration of education occupations

I construct a control variable to measure regional concentration in occupations within the education SOC hierarchical category for a significant reason. Educators make up a substantial portion of regional employment, relative to others. These occupations are ubiquitous across regions, in that they are not highly concentrated in a few specific areas. This would not be a problem for it not educators having high levels of the basic skills for which I am measuring regional productivity. These occupations may potentially cloud the true contributions of certain skills exploited by other occupations. More importantly, educators have been found to have a negative impact on regional productivity (Abel and Gabe 2010). Abel and Gabe found a sizeable decrease in GMP per capita with increases in the number of occupations in the educator, writer, and librarian knowledge cluster. Therefore, I use the control variable to hold the influence of educators on regional productivity constant.

The variable is constructed by simply calculating the location quotients for total occupations in SOC 25-0000 “Educators, Training, and Library Occupations”

[17] I also calculated a similar measure for real estate concentration, which was left out of the analysis.

within each MSA relative to the nation. This variable is then used as a control within the regression models.[18]

3.7 Data Assumptions

This study makes an implicit assumption that workers are well matched to their specific occupation according to skill and other requirements. It should be recognized that in some instances workers may be over or under qualified for their particular position. However, on average we will maintain the assumption that most workers are best matched to their particular jobs according to their existing level of skill.

Secondly, this analysis assumes that occupations across regions require the same level of skill, educational and experience requirements. The O*NET makes no distinction of requirements based upon location; therefore it is assumed that occupational requirements are similar across regions. This also presents some challenges in the representation of a worker's true skill and requirement basis. For instance, teachers are governed by state level requirements, which of course differ from state to state. Requirements for teachers in Oklahoma may be much different than those in Massachusetts, although the O*NET scores are not based on regional requirements, but rather are taken from a national sample. Similarly, this study does not account for regional wage discrepancies across an occupation. Higher skilled workers may migrate to areas with higher pay, but enter jobs with similar skill

[18] Educational occupations have a statistically significant negative contribution to regional productivity. Detailed results are reported in Chapter 4.

requirements for positions across regions. Although this analysis is using the best available proxies, recognition of these constraints is appropriate.

CHAPTER 4

RESULTS OF REGRESSION ANALYSIS

In this chapter I present the results from the regression analysis in which I test the relationship between human capital, measured by basic skills, and productivity. I begin with a statistical descriptive analysis of the data and skill index variables in which I discuss the relationships between skills. This has important implications for running the multiple regression analysis and interpreting results. I continue with a presentation of four models testing skills in general, individual skills, and a final explanatory model. However, I first begin with a model using educational attainment, the traditional measure of human capital in the literature. Results and findings are discussed in detail in the following chapter.

4.1 Descriptive Analysis

In Table 4.1, I present a descriptive summary of the 10 skill indices and independent variables used in the regression analyses based on a sample of 289 observations. The mean values for the ten basic skill indices vary quite a bit. Active Listening and Reading Comprehension had the highest means at 15.6 and 14.5 respectively, while Science and Math scored much lower with 2.88 and 9.60, indicating a more specialized skill; skills less frequently required in a greater share of all occupations. Whereas other basic ‘communication skills’, such as speaking, reading, writing and listening, appear to be more common.

Table 4.1 Descriptive Statistics of Independent Variables

Variable	N	Min	Max	Mean	Std. Deviation
GMP per capita	289	17,653	87,385	39,302	10,720
Educaton Attainment	289	0.108	0.576	0.254	0.078
Population (000's)	289	121	18,351	800	1,677
Natural Resource	289	0.000	20.650	1.476	2.516
Manufacturing	289	0.000	4.480	1.250	0.841
Reading Comprehension	289	12.265	17.118	14.543	0.619
Active Listening	289	13.603	17.679	15.593	0.510
Writing	289	9.470	13.590	11.275	0.569
Speaking	289	11.501	15.534	13.667	0.503
Math	289	8.659	10.853	9.604	0.318
Science	289	2.017	4.227	2.877	0.316
Critical Thinking	289	11.075	15.615	13.073	0.575
Active Learning	289	10.283	14.252	11.956	0.559
Learning Strategies	289	10.401	13.269	11.968	0.420
Monitoring	289	9.73	13.157	11.411	0.511
TWSI	289	100.71	128.73	115.80	4.32

Source: US Bureau of Labor Statistics Occupational Information Network, Occupational Employment and Wage Series; Author's calculations

The O*NET breaks its 10 Basic Skills into two sets; content and process skills. To reiterate, content skills refer to skills that are ‘background structures needed to work with and acquire more specific skills in a variety of different domains’, whereas process skills ‘contribute to the more rapid acquisition of knowledge and skill across a variety of domains’. I break content skills down even further into communication skills and applied skills. Communication skills include Reading, Writing, Speaking and Active Listening, all of the most basic forms of how information and knowledge is received, retained, returned, transferred and redistributed. In general, we would expect to find these skill requirements to be higher in highly specialized areas, such as Writing in journalism or Active Listening for psychological fields. However, these skills may be highly complimentary on the whole. For instance, reading and writing are generally termed together as core basic skills everyone should learn as a child.

Math and science can be thought of more as applied skills, in that they are tools used to solve problems, questions, and generate answers. They are skills often used to think critically, in active learning, and as different approaches to learning and disseminating new information (Learning Strategies). In other words, Math and Science are more tools to be used in the process of interpreting and solving information. These fit well with the skills O*NET deems as process skills.

Higher skill requirements in the process skills should be expected to have higher skill requirements for the basic content skills, mainly those pertaining to how information is received and returned. This, I argue, is because skills that require higher levels of critical thinking and the processing of information must be able to communicate the approximate level of information processed. This is best demonstrated by the skill anchors provide by the O*NET as shown in Appendix F.

For instance, Critical Thinking explicitly references a content skill in anchor level 6 which states “Write a legal brief challenging a federal law.” Similarly, Learning Strategies level 6 which states “Apply principles of educational psychology to develop new teaching methods”. This undoubtedly would require higher levels of communicative skills such as Writing and Speaking in order to present the new methods. Both examples require high levels of basic content skills. It is therefore, that one should expect a high correlation between the 'communicative skills' themselves and also with process skills which are somewhat reliant upon content skills in order to facilitate their processes.

4.1.1 Variable correlations

In Table 4-2, I present a correlation matrix which shows Pearson coefficients for the 10 basic skills.[19] Lighter gray shades highlight moderate correlation between variables, while the next darkest shade signifies high levels of correlation. I use a Pearson coefficient of .600 to .799 to indicate moderate correlation and .800 or higher as a high indicator of correlation between variables.[20] Overall, the 10 basic skill indices are fairly well correlated with each other, both in moderation or to a high degree. As represented in the matrix, there is very high statistically significant correlation between the four communicative variables: Reading, Listening, Writing, and Speaking. This lends some confirmation to the theory that these skills are complementary and might typically be an indicator of overall communication requirements. The core four also appear to be highly correlated with most of the process skills, though there is moderate correlation with Learning Strategies.

[19] A full Correlation Matrix using Pearson coefficients including all independent variables is located in Appendix G.

[20] Traditionally, moderate correlation is indicated by a Pearson value of .5 up to .8, above which indicates a high degree of correlation between variables. I use .6 as a barometer here for comparison purposes across all variables to distinguish where correlation is concentrated and where it is less so. Variables with high correlation make it hard for the model to distinguish between which of the highly correlated independent variables is explaining variation in the dependent variable. Thus, it may lead to inaccurate model interpretation and collinearity.

Math and Science show moderate correlation between both communicative skills and process skills. While I would expect some correlation between math, science, and other basic skills, there should be some variation in the level between skill requirements; this is confirmed by my correlation coefficients.

Table 4.2 Pearson Coefficients of Basic Skill Indices, non-standardized variables

	Reading	Listening	Writing	Speaking	Math	Science	Critical Thinking	Active Learn	Learn Strategies	Monitor-ing
Reading	1.00	.967**	.963**	.929**	.657**	.673**	.982**	.950**	.783**	.899**
Active Listening	.967**	1.00	.969**	.979**	.580**	.583**	.952**	.886**	.733**	.852**
Writing	.963**	.969**	1.00	.946**	.589**	.657**	.957**	.905**	.744**	.870**
Speaking	.929**	.979**	.946**	1.00	.550**	.531**	.925**	.835**	.697**	.807**
Math	.657**	.580**	.589**	.550**	1.00	.746**	.703**	.750**	.509**	.576**
Science	.673**	.583**	.657**	.531**	.746**	1.00	.710**	.809**	.671**	.717**
Critical Thinking	.982**	.952**	.957**	.925**	.703**	.710**	1.00	.962**	.767**	.905**
Active Learning	.950**	.886**	.905**	.835**	.750**	.809**	.962**	1.00	.846**	.938**
Learn Strategies	.783**	.733**	.744**	.697**	.509**	.671**	.767**	.846**	1.00	.911**
Monitoring	.899**	.852**	.870**	.807**	.576**	.717**	.905**	.938**	.911**	1.00

** and * denote significant at the .01 percent and .05 percent level respectively. Based on 353 observations. Source: US Bureau of Labor Statistics Occupational Information Network, Occupational Employment and Wage Series; Author's calculations

The potential implications for the regression models are significant. Such a high degree or correlation across basic skill variables, specifically the communicative skills and process skills, does not allow sufficient variation for the model to distinguish explanatory power between variables. Alternatively, the variables could be representing identical relative skill level. The result will be a high degree of collinearity across the basic skill variables. In light of this, I construct an additional measure of total skill to regress against GMP per capita, simply to provide a general indicator of basic skill explanatory power. The Total Weighted Skill Index (TWSI) is simply the sum of all ten weighted skills by MSA, divided by total employment of those occupations by MSA. Thus, the new variable captures the total skill requirements across all Basic Skill variables in a region. It does not distinguish between different skills, but rather measures the average weighted skill for an occupation within each MSA. However, by combining all skills into one variable, the dimensionality and importance of each skill is washed out, leaving this variable weak in explaining individual skill importance or interpreting results. The regression results for the TWSI are presented in the next section of this chapter.

4.2 Regression Model Results

4.2.1 Base model – educational attainment

I first test whether human capital, measured by educational attainment, has an impact on regional productivity. Traditionally, educational attainment has been the main proxy variable for human capital in the literature. The effect of human capital on productivity and economic activity has been confirmed in numerous studies including Moretti (2004), Barro (1991), Rauch (1993), and Lucas (1988), among others. Most recently it has been used by Abel and Gabe (2010) to explain domestic aggregate productivity, which measures the relationship across metropolitan areas, a method I follow closely here. My results are similar to those of previous studies.

The results of the base model are presented in Table 4-3. I first run the model with just the variables for education attainment and population. Overall this model performs quite well, explaining approximately 46 percent of the variation in GMP per capita across regions. Both variables are significantly different from zero, thus concluding educational attainment does have a positive effect on productivity. Since the coefficients are reflective of the natural log of the dependent variable, I translate the impacts of human capital on GMP per capita into percentages, by calculating the exponent of the variable and subtracting 1 [exp(b1)-1]. For every one percent increase in the amount of the population with a bachelor's degree or higher, the base model predicts a 1.7 percent increase average GMP per capita.

Table 4.3 Base model regression results

Variable	Estimated Coefficient	t-stat	Exp(B)-1	Adj. R^2
Base model				
Educational Attain	1.636***	10.37	0.016	0.461
Population (Ln)	0.088***	7.278	0.092	
Controlling for industry and occupational effects				
Intercept (constant)	9.358***	62.72		0.676
Educational Attain	2.263***	15.96	0.023	
Population (Ln)	0.072***	7.088	0.075	
Natural Resource	0.026***	6.255	0.026	
Manufacturing	0.041***	3.154	0.042	
Edu Occ Concentration	-0.397***	-9.994	-0.328	

*** denotes significant at the .01 percent level. Source: US Bureau of Labor Statistics Occupational Information Network, Occupational Employment and Wage Series; Author's calculations. Based on sample of 289 observations.

I next add control variables to this model including industry and occupational effects that are largely influential for the variations in GMP per capita. The results show a substantial boost in the explanatory power of the model, increasing the model R-squared from .451 to .676. All variables prove statistically significant at the .01 (99 percent) level. The coefficient for educational attainment closely mirrors the results in Abel and Gabe's analysis,[21] after controlling for population and industry effects. The model predicts that for a one percent increase in educational attainment of the total population, GMP per capita should increase by approximately 2 percent. When the variable for education occupational concentration in controlled for, the variation can be

[21] Abel and Gabe (2010) use the same measure of educational attainment as I, in there model to explain variation in average GDPPC for years 2001 through 2005. They use slightly different control variables including variables for capital equipment and capital structure, proxied by regional investment in each category. The study uses population as well, while also controlling for regional effects. The resulting coefficient for education reflects a 2.3% increase in GDPPC for every 1 unit increase in educational attainment.

explained by a 2.3 percent increase in GMP per capita for every percentage increase in the population with a bachelor's degree or higher. This is not surprising in that most education occupations require at least a bachelor's degree for certification. Furthermore, the coefficient is negative for Education Occupation concentration, suggesting that the more concentrated a region with these types of educational occupations, there will be a negative effect on GMP per capita. This is not to suggest that these occupations hurt regional productivity, but rather their value may not directly contribute to total output of goods and services, the measure of GMP.

Similarly, the model suggests that an increase in population of 1,000,000 people explains an increase of approximately 7.5 percent in GMP per capita. This suggests that there are gains to be had by larger concentration of people and human capital due to economies of scale and knowledge spillovers (Audretsch and Feldman 1996). While the variable does not consider density, it does lend some confirmation to productivity gains from economies of scale. The variables for natural resources and manufacturing also suggest a positive effect on GMP per capita. These results are not surprising considering they are generally more capital and resource intensive industries, whose output is more heavily influenced by the capital stock rather than human capital in the workforce. Nonetheless, higher concentrations of manufacturing output and natural resource activity reflect higher average GMP per capita measures.

4.3 Modeling Human Capital as Skill

The crux of this analysis attempts to employ alternative measures of human capital in seeking to explain variation in regional productivity across US metropolitan regions. Specifically, I attempt to determine the role of basic skills (communicative, applied, and process) possessed by the workforce and the contribution they make to GMP per capita. As discussed in the descriptive analysis, there is a substantial amount of correlation among the skill variables. I first test each individual skill index by regressing against GMP per capita, both with and without additional controls to assess their individual impact.

The previous model uses educational attainment as a proxy for human capital. I now use variables constructed from the O*NET and OES dataseries as measures of average skill in a region held by its workforce. To reiterate, these measures capture experience entry requirements across occupations, and are not necessarily representative of the full skill and potential of a region's workforce. Nevertheless, the aggregate level of skill will provide a good measure for the purposes of this study.

This section proceeds as follows. I begin with a model incorporating all ten basic skill measures discussed in the previous section, the Total Weighted Skill Index. I then move to exploring the impacts of each skill individually in the model, keeping in mind the high level of correlation between many of the skills. The purposes of this sequence is to first analyze skill broadly and then moving to identify the impacts of each individual skill on productivity. I then conclude with a reduced skill explanatory model using three skill variables in this final model to explain variation in average GMP per capita.

4.3.1 Total Weighted Skill Index

I first run the model without controlling for industry effects but I include a variable for the concentration of education occupations in a region (see Model A in Table 4.4 below). The TWSI is not statistically significant at conventional levels, though it is significant at the .10 level. All other variables are significant, showing positive coefficients for both population and educational attainment and a negative affect for higher concentrations of education occupations.

Model B controls for industry effects of both natural resources and manufacturing. As a result the TWSI variable appears statistically significant at the .01 level. However, the effects on GMP per capita appear minimal. This index measure is not used as a predictive value, but rather to obtain a general indicator of the influence of basic skill. As such, the model suggests that regions with higher overall basic skill requirements of their workforce appear to have higher productive capacity.

Table 4.4 Total Weighted Skill Index (TWSI) Regression Results

	Variable	Coefficient	T-stat	Tolerance	Adj. R^2
Model A	(Constant)	9.028***	25.584		0.629
	Population (Ln)	0.054***	4.478	0.627	
	Educational Attain	1.722***	9.853	0.534	
	Ed Occupations	-0.391***	-9.429	0.907	
	TWSI	0.007*	1.846	0.420	
	Controlling for industry effects and educ occ concentration				
Model B	(Constant)	8.523***	25.149		0.683
	Population (Ln)	0.059***	5.175	0.604	
	Educational Attain	2.009***	12.009	0.498	
	Natural Resource	0.027***	6.591	0.788	
	Manufacturing	0.042***	3.325	0.765	
	Ed Occupations	-0.417***	-10.383	0.823	
	TWSI	0.009***	2.748	0.415	

***and * denote significant at the .01 percent and .10 percent level respectively. Based on 289 observations.
Source: US Bureau of Labor Statistics Occupational Information Network, Occupational Employment and Wage Series; Author's calculations.

4.3.2 Individual basic skill regression results

To allow for comparisons across skills and their contribution to productivity, I standardized variables by calculating the relative Z-score for each metropolitan area and its corresponding skill indices (for 10 basic skills). Standardized values represent the number of standard deviations a value is above or below the average proportion of skill index (measuring average skill concentration) for each metropolitan area.

I first run a model including all ten basic skills included as independent variables. As anticipated, there is a high degree of collinearity among the communication skills and process skills. Tolerance values appeared below .10, a standard threshold for distinguishing the level of variation among variables. This presents problems interpreting coefficients as the variables of skill are largely explaining the variations in one another, rather than the dependent variable.

I next test the model with each individual skill indices as an independent variable in the model. I run three different scenarios, using different control variables to highlight the differences in results among variables. Table 4.5 presents the results from a sample of 289 observations, controlling first for population and educational attainment. A majority of the skills presented do not return significant results. In fact, only Math and Active Learning appear significantly different from zero, according to conventional levels (.05). The models on average offer good explanatory power in the R-squared, however conclusive results from these models are weak.

Math skills, holding all population and educational attainment constant are statistically significant at the .01 level and have a positive impact on regional productivity. A one standard deviation from the mean increase in the level of math skills used contributes to a 6.9 percent increase in GMP per capita. It appears from these results that math skills provide a substantial boast to regional productivity, even more so than educational attainment. In the same model, the coefficient for population assumes a 6.7 percent increase in GMP per capita for every additional one million people in each region, all other variables held constant.

Active Learning is the only other basic skill that is statistically significant in the first model. Defined as being able to digest and understand new information to make decisions in the present and in the future, a one standard deviation increase (.56 units of average skill) from the mean predicts a 4.3 percent increase in GMP per capita, holding all other variables constant. Put another way, a one unit increase in average active learning skill predicts an increase of 7.1 percent in GMP per capita.[22]

[22] See Appendix X for full results of both standardized and non-standardized regression results.

Table 4.5 Individual Skill Indices Regression Results

Variable	Estimated Coefficient	T-Statistic	Adj. R^2
With education and population controls			
Reading Comprehension	0.015	0.825	0.46
Active Listening	-0.028	-1.526	0.463
Writing	-0.019	-1.119	0.461
Speaking	-0.031*	-1.752	0.464
Math	0.067***	4.717	0.498
Science	0.023	1.481	0.463
Critical Thinking	0.036*	1.885	0.465
Active Learning	0.042**	2.14	0.467
Learning Strategies	-0.023	-1.534	0.463
Monitoring	0.012	0.738	0.46
Controlling for industry effects natural resource and manufacturing			
Reading Comprehension	0.025	0.153	0.514
Active Listening	-0.006	-0.309	0.511
Writing	-0.007	-0.44	0.511
Speaking	-0.004	-0.211	0.511
Math	0.051***	3.596	0.532
Science	-0.012	-0.787	0.512
Critical Thinking	0.04**	2.218	0.519
Active Learning	0.027	1.41	0.514
Learning Strategies	-0.037**	-2.573	0.522
Monitoring	0	-0.008	0.511
Controlling for occupational share in education			
Reading Comprehension	0.058***	3.673	0.691
Active Listening	0.038***	2.372	0.682
Writing	0.041***	2.668	0.684
Speaking	0.035**	2.249	0.681
Math	0.036**	2.491	0.551
Science	-0.012	-0.809	0.543
Critical Thinking	0.058***	3.668	0.691
Active Learning	0.06***	3.517	0.69
Learning Strategies	0.036**	2.283	0.681
Monitoring	0.053***	3.462	0.689

***, **, and * denote significant at the .01 percent, .05 percent, and .10 percent level respectively. Based on 289 observations. Based on 30 regression runs for each skill and with varying control variables.
Source: US Bureau of Labor Statistics Occupational Information Network, Occupational Employment and Wage Series; Author's calculations. Based on 30 regression runs for each skill and with varying control variables.

4.3.3 Controlling for industry effects and occupational concentration of educators

The same regression models are run again, first controlling for industry effects and then adding a variable to control for the amount of concentration in educator occupations (a variable discussed in Chapter 3).

Similar to the results of the last set of basic skill regressions (refer to Table 4.5), very few basic skills appear to be significantly different than zero, although the explanatory power of the model increases on average for all skills. Math remains significant, although the coefficient has decreased slightly to .051, indicating a 5.1 percent increase in GMP per capita for every one standard deviation increase from the mean in the math skill index. Critical thinking also appears statistically significant when controlling for natural resources and manufacturing. A one standard deviation increase from the mean average skill index explains a 4.1 percent increase in GMP per capita, or also translated as a one unit increase in the average skill of critical thinking in a region equates to a 6.9 percent increase in GMP per capita.

When I then control for education occupational concentration in the models, most all variables become statistically significant within each regression run. Interestingly, the only variable to not appear significant is that of the skill Science. This is a skill and area of knowledge generally considered synonymous with the new economy. However, science in the model by itself does not appear to influence regional productivity either way.

All other skills are statistically significant when controlling for occupation concentration in educators. This lends some confirmation that education occupations, which tend to have high basic skill requirements, cloud the influence of the skills in other occupations which have a more direct contribution to productivity, as measured by final goods and services. By teasing out these skills and holding them constant, I am able to allow for a better picture of the influence these skills in other occupations have upon the productive process. Furthermore, the coefficients for this control variable are statistically significant and negatively correlated with GMP per capita to a substantial degree. These impacts are discussed within the next section.

4.4 Final Model Regression Results – Combing Basic Skills

A regression model using all ten basic skill indices returned results with high degrees of collinearity as indicated by tolerance scores between communicative and process skills. Math and science were not as affected. This was a result anticipated by the high and moderate levels of correlation between independent skill index variables covered in the descriptive analysis. This suggests that much of the variation in GMP per capita cannot be explained by the other skill variables in the model when attempting to account for all basic skills. Therefore, in order to distinguish and identify the variables that do explain variation in GMP per capita I construct a model which attempts to capture math, science, and a skill representative of all other basic skills. I choose to include a process skill rather than a communicative because communicative skills are internalized in process skills. One could think of an example as if an occupation required a high level of critical thinking, that skill in turn would require a high level of communicative skill to receive and transfer the high level of knowledge developed in thinking critically. Therefore, reading, writing, listening, and speaking are not directly entered in this model, but rather are captured in the process skill index Critical Thinking.

I bring attention to Model 2 in Table 4.6 below, which presents these three skills; math, science, and critical thinking in the final model. All variables in the model are statistically significant with moderately high collinearity[23] among the skill variables, but still at conventionally acceptable levels. Most surprising in the model, is the negative correlation of Science to average GMP per capita. Again using the same calculation to translate the effects of skill on the natural log of GMP per capita [exp(B1)-1], I find that a one standard deviation from the mean increase in the average level of the skill science predicts a decline of approximately 7.9 percent, all else held constant. This is a substantial effect on overall economic activity, considering the skill's perceived role in today's economy.

Alternatively, math again appears statistically significant and has a positive effect on GMP per capita. A one standard deviation increase from the mean in average math skills explains a 7.9 percent increase in GMP per capita. Likewise, Critical Thinking has a positive impact as well, accounting for a 4.8 percent increase in GMP per capita for every one standard deviation above the mean skill concentration. Overall, this model has good explanatory power, accounting for approximately 56 percent of the variation in GMP per capita.

[23] This is indicated by the Tolerance scores in Table 4-6. A value of .2 or below indicates a high level of collinearity, while .5 indicates moderate levels. The higher the value the more variation explained across variables.

Table 4.6 Final Basic Skill Model, standardized coefficients

	Variable	Coefficient	T-stat	Tolerance	Adj. R^2
Model 2	Intercept (Constant)	8.847***	45.572		0.556
	Educational Attain	1.634***	8.431	0.473	
	Population (Ln)	0.089***	6.591	0.564	
	Natural Resource	0.026***	5.364	0.712	
	Manufacturing	0.074***	4.980	0.686	
	Math	0.076***	4.376	0.374	
	Science	-0.082***	-4.095	0.304	
	Critical Thinking	0.047**	2.185	0.249	

*** and ** denote significant at the .01 percent and .05 percent level respectively. Based on 289 observations.

Source: US Bureau of Labor Statistics Occupational Information Network, Occupational Employment and Wage Series; Author's calculations.

CHAPTER 5

FINDINGS AND DISCUSSION

The results of the regression models suggest that concentrations of skill in general have a positive effect on regional productivity. While some skills have a more significant affect than others, some do not appear to have any particular influence at all, or conversely the relationship appears negative. There is a high degree of correlation between many of these basic skills, particularly between skills which communicate information and skills which process information. This can be interpreted as a high interdependence and complementary nature of basic skills themselves. Math skills required for problem solving have a significant and positive relationship to productivity, more so than any other basic skill. Science, on the other hand, has a negative correlation with productivity; a finding not consistent with popular views.

When one considers the dynamics of basic skills they often are linked together in a complementary manner. If an occupation is required to interpret and translate with a high degree of skill, they must also be able to collect and distribute high level information as well. Conversely, it could also be true that low skill requirements for processing information will have lower requirements for the skills needed in communicating information. The applied skills, math and science used in problem solving, are also moderately correlated with the other basic skills. However, applied skills are not as dependent upon other basic skills. Still, one could expect that a higher skill requirement for math should be accompanied with a higher level of process skill.

5.1 Key Findings

The key findings of this research are presented as follows:

1. Basic skills are complementary and dependent upon each other.
2. Level of basic skill explains some of the variation in GMP per capita.
3. Math has a significant and positive effect on productivity and economic activity.
4. Science appears to have a negative impact on productivity, though not statistically significant.
5. Critical thinking positively explains some of the variation in average GMP per capita.
6. Educational attainment has a positive effect on regional productivity.
7. Higher metropolitan population explains some of the variation in GMP per capita.
8. Industry effects explain some of the variation in GMP per capita.
9. Higher concentrations of occupations relating to education have a negative correlation with regional productivity.

5.2 Discussion of Key Findings

Basic skills are complementary and dependent upon each other

Correlation coefficients suggest a high level of correlation among the variables for basic skill indices. There may be several explanations for this. First, obvious questions can be directed at the measuring and scoring of these skills within the O*NET dataset and my own estimations. Data is collected through surveys of occupational analysts and from incumbent workers. The average sample across all occupations reported in the O*NET is 31, while the standard deviation is almost 23. This suggests some room for sampling error.

However, a more likely explanation is that these skills are complementary and dependent upon each other. Let's assume that the samples from the O*NET dataset accurately reflect the average skill in relative occupations. An occupation requiring a high level of Active Listening should also expect to have a similar requirement for Speaking, both being forms of verbal communication. Very few occupations could be expected to have an extremely high requirement of Reading Comprehension, but a very low requirement for Writing. There would have to be some correlate level between the skills. Furthermore, as noted previously, process skills are dependent upon subsequent basic communication skills in order to give and receive information. They should expect to have relative levels of basic skills as well. Therefore, these measures of skill are perhaps more reflective of the level of average skill.

Level of basic skill explains some of the variation in GMP per capita

In developing this research, I hypothesize that basic skills have a positive influence on economic activity and productivity in urban areas. My results suggest that basic skill levels in general, explain at least part of the variation in GMP per capita across US urban areas. Therefore, I am able to reject the null hypothesis and confirm that basic skill does have a positive influence on economic productivity in US metropolitan areas.

However, this finding is not to suggest that this is a clear picture of the magnitude general skill has on regional productivity, but rather confirms that skill does explain productivity and that the relationship is positive. Future research resulting from this finding should target ways to distinguish between the different skill levels or to construct additional estimations of approximate skill level in regions. Furthermore, there may be other variables not considered which need to be controlled for in modeling general skill in regional economies.

Math has a significant and positive effect on productivity and economic activity

Math has the most clear and significant impact on economic activity comparable to other types of basic skill. Models show a statistically significant and positive correlation with productivity, holding all else equal. Math is not as common a skill required across occupations as others, such as communication or process skills. However, when considering the occupations that have higher requirements in math, these findings make sense.

Math is a skill required by occupations that range from financial services and accounting to manufacturing production based jobs. Machine workers, for instance, have an above average requirement for math skills and work in an industry which has a high contribution to GMP. Therefore, when considering the basic dispersion of math requirements across occupations, it is easy to see how this skill not required everywhere, has specific and significant value in contributing to worker productivity.

Science appears to have a negative impact on productivity, though not statistically significant

In all regression models, the coefficients for Science showed a negative correlation with GMP per capita. However, these results can not be confirmed as statistically significant. Nonetheless, it deserves discussion due to perceptions that science is often deemed an important aspect of the knowledge based economy which has come to dominant present day economic development policy. Science, a skill defined as using scientific methods and theory to solve problems, is not a typical skill required for the majority of the workforce; a finding demonstrated in the descriptive analysis in Chapter 4.

One could imagine that the use of science would be concentrated in those specific occupations of the physical, life, and natural sciences, such as astronomy or biologists. In general, scientists such as these are research and development based occupations. GMP measures final goods and services of a metropolitan area and does not necessarily capture the total degree of innovative activity, which ultimately contributes to long-term productivity. In research and development, a lot of capital goes in, but what exits are ideas, not necessarily sold goods and services which contribute to GMP. Therefore, it could be concluded that it may not be science has no significant relationship with productivity, but rather that the gains from these types of skills cannot directly be measured by final goods and services. Furthermore, the knowledge spillovers generated by these types of occupations and research are not geographically bound. Therefore, a future area of research might be to examine exactly where in the productive process science skills contribute, such as innovative activity measured by patents or how knowledge spillovers generated from these types of occupation influence economic growth.

Critical thinking positively explains some of the variation in average GMP per capita

The regression results suggest a positive correlation between critical thinking and GMP per capita, explaining some of the variation in productivity levels. Critical thinking is defined by the O*NET as “Using logic and reasoning to identify the strengths and weaknesses of alternative solutions, conclusions or approaches to problems.” By this definition, it is quite clear that this skill is essential to problem solving; something which bears new information and knowledge. Therefore, it is no surprise that such a skill has a positive impact on productivity.

Educational attainment has a positive effect on regional productivity

In line with past studies, my model substantiates that education plays a significant role in explaining variations in regional productivity. My findings closely resemble those of Able and Gabe (2010) who used data for average GMP per capita for the years 2001 through 2005. Therefore, my findings lend good verification to their results, since I measure average GMP per capita for 2005 and the three years following, 2006 through 2008. My model finds a 2.3 percent increase in GMP per capita for every one percent increase in the percent of population with a bachelor’s degree or higher.

Able and Gabe (2010) found a 2.3 percent increase as well, controlling for population and capital inputs (which I use industry concentration variables as similar controls).

Higher metropolitan population explains some of the variation in GMP per capita.

Much of the variation in GMP per capita can be explained by the total population of a region. Population has a statistically significant effect on average GMP per capita, varying by controls and other variable explanation. This of course, does not allude to the role of population density on the production process; that is the number of people per square mile in metropolitan region which may provide a more meaningful measure of the impacts of knowledge spillovers. Nonetheless, population does play a role in explaining variation in productivity. This allows me to conclude that there are productivity gains to economies of scale found in urban areas, echoing the findings of Glaser and Mare (2001) and Abel and Gabe (2010).

High concentrations of occupations relating to education have a negative correlation with regional productivity

In their analysis, Abel and Gabe (2010) found that knowledge associated with 'education' had a negative influence on metrics of regional productivity. I use a variable to control for these impacts, under the premise that these occupations require a high level of basic skill. My models predict a very similar conclusion. Higher concentrations of educating, writing, and library occupations have a negative correlation and influence on regional productivity. This is not to say that educators do not facilitate a significant role in developing the skills and types of human capital I am measuring in this research, but rather their influence on final goods and services is negative in relation to other forces and occupations. However, these occupations have high levels of basic skill requirements relative to other workers in the economy. Therefore, it was necessary to include in the analysis to account for the influence on aggregate skill across MSAs.

Industry effects explain some of the variation in GMP per capita

It is here which I will recognize that the model and the measure of GMP could simply be more reflective of regional industry composition. Simon and Nardinelli (2002) and Koo (2005) identified similar conclusions in their respective studies. Koo in particular, found that within the Rubber Manufacturing industry, firm operations take place in different regions of the United States. Innovative activities associated with research and development take place in northern states, while manufacturing actually takes place in the southern states. Therefore, one could conclude that the characteristics, knowledge, and skill of the workforces vary significantly between firm operations; therefore differ spatially. Likewise, it could be assumed that regions which capture the manufacturing end of business operations have a much larger contribution to final goods and services compared to the innovative activities in the northern states. This may explain that knowledge spillovers produced in one region, may not be reflective in measures of productivity.

While it is a difficult task to account for the wide range of agglomerative industrial structure that exist across the US economy, I attempt to control for two industries which

I deem to have obvious exaggerative effects on GMP per capita which may be less a result of human capital than physical capital outputs in the productive process. My regression results confirm that concentration of industry in natural resource extraction and mining, and manufacturing (production based) industry explain some of the variation in average GMP per capita. A higher regional concentration (relative to the nation) in these industries has a positive effect on GMP per capita.

CHAPTER 6

CONCLUSION

This thesis finds that the level of human capital possessed in a region's workforce, explains variations in productivity across regions. The relationship is positive showing that a higher concentration of human capital in more urban areas, at least partially explains higher levels of average GMP per capita. Therefore, higher skilled people are located in areas that have greater productive capacity, controlling for outside forces. These findings advance the existing literature concerned with urban economics, human capital, and regional economic development, while directly contributing to the understanding of what makes cities and regional economies tick.

Countless has been the number of studies over the past several decades which have demonstrated the economic returns of education, particularly college level. These studies have influenced policy at the federal level resulting in a massive jump in college enrollment throughout the 80's and 90's. However, these studies have influenced policy which is directed at the proxies for measuring human capital. They do not address the actual knowledge, skills, and abilities which contribute to knowledge creation and economic growth. While a college education undoubtedly contributes to productivity, it is an umbrella estimate of the real skills and abilities which contribute to economic activity.

These findings, and the work of this thesis, attempt to provide policy makers and economic development planners with a better understanding of some of the driving forces which contribute to greater well-being, reflected in my measure of GMP per capita. As such, policies and initiatives can be targeted at developing those core skills which contribute to regional productivity. This would have the effect of enhancing worker efficiency and productivity, as well as building one of the most significant regional economic assets, the workforce.

6.1 Implications for Policy and Planners

These findings lend confirmation to the existing literature that suggests human capital has a positive influence on economic activity in US metropolitan regions. These findings extend the literature by constructing new measures for the approximation of human capital levels which are held by the workforce. It also confirms that basic skills, such as math and critical thinking, are important contributors to increasing economic activity.

By identifying and confirming that these basic skills and tacit knowledge can explain some of the variation in productivity across regions, it suggests that programs and policies targeting skill building will have positive impacts on regional economies. While I am careful to suggest that policies directed at workforce development will undoubtedly increase regional productivity, I do conclude that there are economic benefits to be gained from a more skilled workforce, particularly in today's economy which so heavily depends upon knowledge creation.

These results may also inform education policy, specifically at early development stages. If we conclude that basic skills such as reading, writing, speaking, and math are vital to the acquisition and accumulation of more knowledge, it is critical to ensure early development of these basic skills, which have a cumulative effect as human capital is built throughout one's life. Therefore, this research suggests that policies should direct significant focus towards early and middle stage skill development and education.

6.2 Limitations of this Research

While this study contributes to the understanding of the relationship between basic skill and productivity, the findings and results do have limitations which warrant discussion and may also help inform areas of future research.

6.2.1 Skills may be under or overestimated

The measures used for skills are entry requirements for particular occupations and cannot be assumed to be the actual level of skills possessed by individual workers. By using entry requirements, I am invariably underestimating the potential true level of skill held by the workforce. We can assume that some of the workforce may actually possess less of the required skill, particularly in regions with less occupational supply (where demand for workers is inelastic) and corresponding wages are lower. Similarly, highly urban areas have larger labor supplies and may have elastic demands for workers, choosing those with skills higher than entry requirements. Furthermore, cities and urban areas attract higher skilled workers in general (Glaeser et al 1995) and therefore these regions might have higher entry requirements. However, these higher requirements are not reflective of the population as a whole reported in the O*NET dataset. Therefore, these proxies may not capture the full contributions of skill on productivity and leaves more detailed or better approximations to be desired.

Coinciding are the regional applications of the O*NET skill estimates. O*NET occupational data is collected from a survey of incumbent workers and occupational analysts from a national pool. In this study these values are applied to regional labor pools, which may have different specialized occupational skill requirements that are not reflected in the national estimates. For instance, a Computer Programmer in Silicon Valley may have higher occupational skill entry requirements than a programmer in Charleston, South Carolina, though equal weight is given by the national skill requirement estimates. This is another case where skill levels may be over or under accounted for in the regional data.

6.2.2 Measure productivity at an aggregate level rather than at the individual

This study tests whether aggregate levels of skill influence regional and urban productivity and does not examine how these basic skills influence individual productivity. Going even further, this study is unable to conclude which skills are most influential in specific occupations or industries. This perhaps may have the benefit as to more specialized policy decisions, such as workforce development programs within a certain industry.

6.2.3 The study only considers basic cognitive abilities and tacit knowledge

In attempts to focus attention on certain knowledge accumulating and acquiring skills, this study invariably ignores physical and technical skills that undoubtedly influence productivity. As such, researchers are cautioned not to falsely conclude that the findings here represent the most important skills for productivity. This study is not an exhaustive analysis of all skills. It focuses solely on the most basic forms of knowledge to better understand which of these may be most significant to productivity. The analysis could benefit much from an equally informed understanding of the types of technical and physical skills that compliment and drive economic activity.

6.3 Future Areas for Research

Part of the study was to explore new measures of human capital, such as the basic skills reported in the ONET. Building upon this, other research should expand upon the other types of skill requirements, such as technical skill requirements and physical requirements to examine other dimensions of human capital. Furthermore, research could be done to identify occupational skill clusters, such as was done by Feser (2003) and Abel and Gabe (2010).

In addition, all occupations have and require some minimum level of skill. Another potential avenue for future research could be to identify some minimum threshold of skill possessed in regions, and consider the levels above and beyond as a more direct explanation for differences in productivity across cities.

6.3.1 Measuring wage differences for skills and changes in requirements

The skill indices I developed in this study could be used in conjunction with occupational wage data to determine an estimation of how the labor market might value these types of basic skills. Likewise, skill indices could also be used to look at the change in skill requirements over time, both nationally and in analyzing regional economies. Such analysis could shed light on the changing dynamics of the workforce and economy to find out what skills are in demand and what skills are becoming less important.

6.3.2 Other measures of innovation and productivity

Furthermore, it appears that some of the tacit skills that I explore here contribute more to innovative activity and knowledge creation which might not necessarily be accounted for in my measures of productivity, GMP per capita. Future research should consider other more direct proxies for innovation, such as patent, entrepreneurship, and research and development activity to test whether these skills contribute to those knowledge creating activities.

APPENDIX A

BASIC SKILL REQUIREMENTS DEFINITIONS

O*NET Definitions – The definitions below are taken directly from the descriptions offered in the O*NET Content Model, verbatim.

WORKER REQUIREMENTS – "Worker requirements represent developed or acquired attributes of an individual that may be related to work performance such as work-related knowledge and skill. Knowledge represents the acquisition of facts and principles about a domain of information. Experience lays the foundation for establishing procedures to work with given knowledge. These procedures are more commonly known as skills. Skills may be further divided into basic skills and cross-functional skills. Basic skills, such as reading, facilitate the acquisition of new knowledge. Cross-functional skills, such as problem solving, extend across several domains of activities."

Reading Comprehension — Understanding written sentences and paragraphs in work related documents.

Active Listening — Giving full attention to what other people are saying, taking time to understand the points being made, asking questions as appropriate, and not interrupting at inappropriate times.

Writing — Communicating effectively in writing as appropriate for the needs of the audience.

Mathematics — Using mathematics to solve problems.

Science — Using scientific rules and methods to solve problems.

Critical Thinking — Using logic and reasoning to identify the strengths and weaknesses of alternative solutions, conclusions or approaches to problems.

Active Learning — Understanding the implications of new information for both current and future problem-solving and decision-making.

Learning Strategies — Selecting and using training/instructional methods and procedures appropriate for the situation when learning or teaching new things.

Monitoring — Monitoring/Assessing performance of yourself, other individuals, or organizations to make improvements or take corrective action.

Source: BLS, O*NET dataset

APPENDIX B

EXAMPLE 2000 SOC OCCUPATIONAL HIERARCHY

SOC Structure

11-0000 Management Occupations
- 11-1000 Top Executives
  - 11-1010 Chief Executives
    - 11-1011 Chief Executives
  - 11-1020 General and Operations Managers
    - 11-1021 General and Operations Managers
  - 11-1030 Legislators
    - 11-1031 Legislators
- 11-2000 Advertising, Marketing, Promotions, Public Relations, and Sales Managers
  - 11-2010 Advertising and Promotions Managers
    - 11-2011 Advertising and Promotions Managers
  - 11-2020 Marketing and Sales Managers
    - 11-2021 Marketing Managers
    - 11-2022 Sales Managers
  - 11-2030 Public Relations Managers
    - 11-2031 Public Relations Managers
- 11-3000 Operations Specialties Managers
  - 11-3010 Administrative Services Managers
    - 11-3011 Administrative Services Managers
  - 11-3020 Computer and Information Systems Managers
    - 11-3021 Computer and Information Systems Managers
  - 11-3030 Financial Managers
    - 11-3031 Financial Managers
  - 11-3040 Human Resources Managers
    - 11-3041 Compensation and Benefits Managers
    - 11-3042 Training and Development Managers
    - 11-3049 Human Resources Managers, All Other
  - 11-3050 Industrial Production Managers
    - 11-3051 Industrial Production Managers
  - 11-3060 Purchasing Managers
    - 11-3061 Purchasing Managers
  - 11-3070 Transportation, Storage, and Distribution Managers
    - 11-3071 Transportation, Storage, and Distribution Managers
- 11-9000 Other Management Occupations
  - 11-9010 Agricultural Managers
    - 11-9011 Farm, Ranch, and Other Agricultural Managers
    - 11-9012 Farmers and Ranchers
  - 11-9020 Construction Managers
    - 11-9021 Construction Managers
  - 11-9030 Education Administrators
    - 11-9031 Education Administrators, Preschool and Child Care Center/Program
    - 11-9032 Education Administrators, Elementary and Secondary School
    - 11-9033 Education Administrators, Postsecondary
    - 11-9039 Education Administrators, All Other
  - 11-9040 Engineering Managers
    - 11-9041 Engineering Managers
  - 11-9050 Food Service Managers
    - 11-9051 Food Service Managers
  - 11-9060 Funeral Directors
    - 11-9061 Funeral Directors
  - 11-9070 Gaming Managers
    - 11-9071 Gaming Managers

11-9080 Lodging Managers
11-9081 Lodging Managers
11-9110 Medical and Health Services Managers
11-9111 Medical and Health Services Managers
11-9120 Natural Sciences Managers
11-9121 Natural Sciences Managers
11-9130 Postmasters and Mail Superintendents
11-9131 Postmasters and Mail Superintendents
11-9140 Property, Real Estate, and Community Association Managers
11-9141 Property, Real Estate, and Community Association Managers
11-9150 Social and Community Service Managers
11-9151 Social and Community Service Managers
11-9190 Miscellaneous Managers
11-9199 Managers, All Other

13-0000 Business and Financial Operations Occupations

13-1000 Business Operations Specialists
13-1010 Agents and Business Managers of Artists, Performers, and Athletes
13-1011 Agents and Business Managers of Artists, Performers, and Athletes
13-1020 Buyers and Purchasing Agents
13-1021 Purchasing Agents and Buyers, Farm Products
13-1022 Wholesale and Retail Buyers, Except Farm Products
13-1023 Purchasing Agents, Except Wholesale, Retail, and Farm Products
13-1030 Claims Adjusters, Appraisers, Examiners, and Investigators
13-1031 Claims Adjusters, Examiners, and Investigators
13-1032 Insurance Appraisers, Auto Damage
13-1040 Compliance Officers, Except Agriculture, Construction, Health and Safety, and Transportation
13-1041 Compliance Officers, Except Agriculture, Construction, Health and Safety, and Transportation
13-1050 Cost Estimators
13-1051 Cost Estimators
13-1060 Emergency Management Specialists
13-1061 Emergency Management Specialists
13-1070 Human Resources, Training, and Labor Relations Specialists
13-1071 Employment, Recruitment, and Placement Specialists
13-1072 Compensation, Benefits, and Job Analysis Specialists
13-1073 Training and Development Specialists
13-1079 Human Resources, Training, and Labor Relations Specialists, All Other
13-1080 Logisticians
13-1081 Logisticians
13-1110 Management Analysts
13-1111 Management Analysts
13-1120 Meeting and Convention Planners
13-1121 Meeting and Convention Planners
13-1190 Miscellaneous Business Operations Specialists
13-1199 Business Operations Specialists, All Other
13-2000 Financial Specialists
13-2010 Accountants and Auditors
13-2011 Accountants and Auditors
13-2020 Appraisers and Assessors of Real Estate
13-2021 Appraisers and Assessors of Real Estate
13-2030 Budget Analysts
13-2031 Budget Analysts
13-2040 Credit Analysts
13-2041 Credit Analysts
13-2050 Financial Analysts and Advisors
13-2051 Financial Analysts
13-2052 Personal Financial Advisors

Source: US Bureau of Labor Statistics, Standard Occupational Classification System

APPENDIX C

ESTIMATION METHODOLOGY FOR O*NET AND OES

*Differences between OES and O*NET occupational data*

There are differences between the O*NET and the SOC system. At times, O*NET provides more detailed occupational information than the SOC. For example, SOC code 27-2012 is broken down into 5 disaggregate occupations by the O*NET (see Table C.1). In this case the base SOC occupation is broken into five more detailed occupations. While Producers and Directors are reported under SOC 27-2012, the O*NET reports data values for the five more detailed occupations.

Table C.1 Disaggregate O*NET-SOC reporting structure

O*NET - SOC	Title
27-2012.00	Producers and Directors
27-2012.01	Producers
27-2012.02	Directors- Stage, Motion Pictures, Television, and Radio
27-2012.03	Program Directors
27-2012.04	Talent Directors
27-2012.05	Technical Directors/Managers

*Source: US Bureau of Labor Statistics, O*NET*

The OES dataset, which reports occupations under the SOC classification system, reports occupations at the aggregate level of 27-2012. However, the O*NET does not report data values at the aggregate level, but rather the more detailed occupational codes. Although more detailed occupational information would be welcomed, it would undoubtedly present further data problems, such as suppression at the more detailed levels within the OES dataset. Therefore, O*NET data values are averaged and aggregated up to the reported SOC level; in this case 27-2012.

Skill requirement estimates

As a result of the differences, some of the biggest challenges in working with the O*NET is the lack of scoring for several SOC codes within the O*NET dataset. This includes the 'All Other' categories which group occupations not easily assigned to one particular occupational category. In certain metropolitan areas and occupational hierarchies of the SOC system, the 'All Other' categories employ a substantial number of people. So much so, that to exclude them completely from analysis would risk having significant impacts on the results. Therefore, dealing with the 'All Other' categories is necessary in this model in order to estimate accurate levels of human capital for each MSA and occupation.

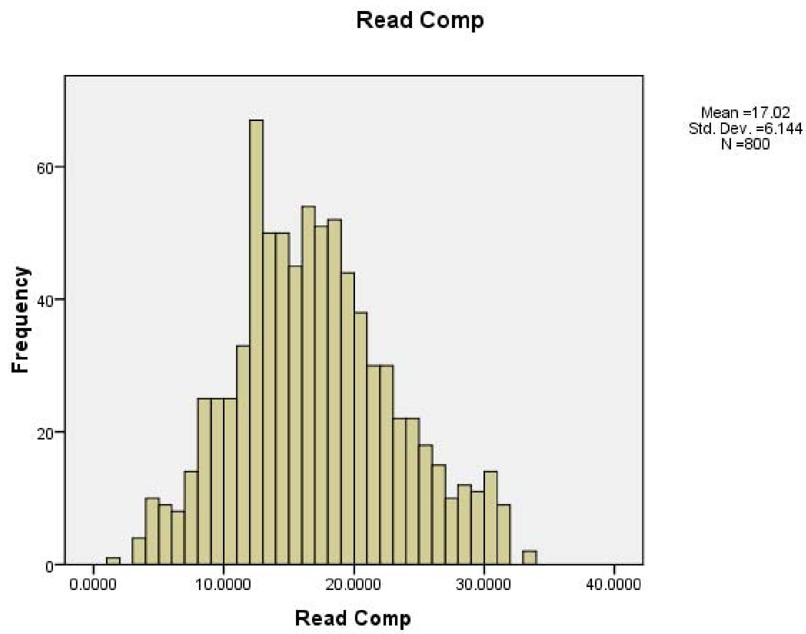
In many cases, the O*NET provides even more detailed occupational information and are denoted using decimals to indicate a more detailed hierarchy than what the OES and traditional SOC system provides. These occupations are typically considered the new and emerging occupations as updated by the O*NET database and include such occupations as 'Chief Sustainability Officers' (SOC 11-1011.03, which is affiliated under 'Chief Operating Officer' (SOC 11-1011). Most of these new and emerging occupations are grouped under the standard SOC (such as the Chief Sustainability Officer), for which there is no need to distinguish between the two when merging with OES data because the OES does not report these new and emerging occupations.

However, there are instances where the O*NET breaks off the main SOC and reports two or more detailed occupations only within the Skills Domain. For instance, SOC 43-3021 – Billing and Posting Clerks and Machine Operators does not specifically have skill scores consigned to it, but rather O*NET reports skill scores for 3 disaggregate occupations; 43-3021.01 (Statement Clerks), 43-3021.02 (Billing, Cost and Rate Clerks), and 43-3021.03 (Billing, Posting and Calculating Machine Clerks). Therefore, in order to derive an approximate score for the aggregate occupational codes able to be linked with OES data, an average score was taken for the disaggregate occupations. For example, a skill score for SOC 43-3021 is estimated by averaging the skill scores for 43-3021.01, 43-3021.02, and 43-3021.03. This is done for both the level and importance scores for each skill variable.

A total of 116 occupations required some sort of O*NET skill estimate out of 800 occupations used in the OES. Most disaggregate O*NET scores within a certain SOC code exhibited very similar skill scores, thereby capturing vastly different skill scores than what might be characteristic is not a large concern. In fact, some O*NET disaggregate SOC scores are the same across disaggregate occupations. Therefore, I was able to estimate several skill scores with high confidence.

APPENDIX D

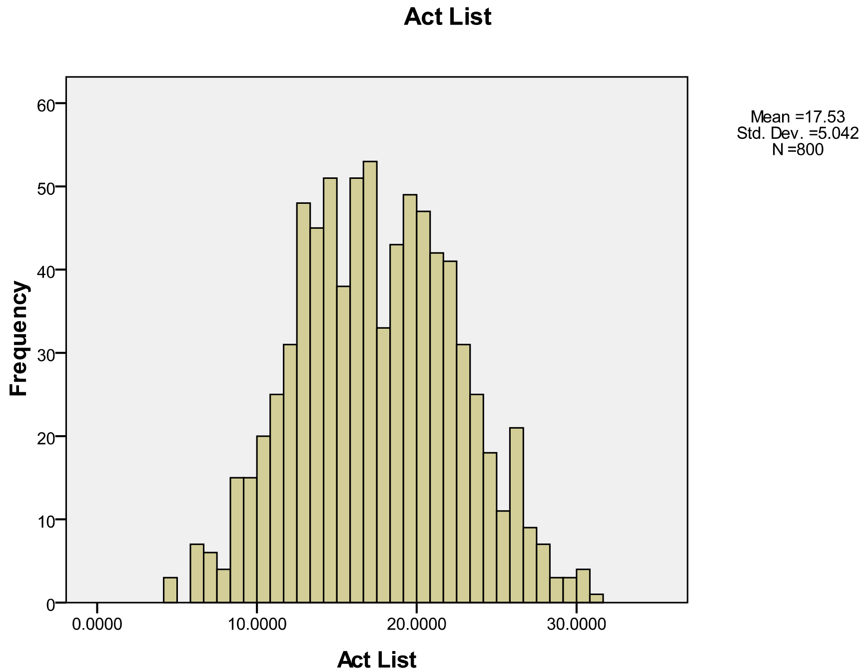
ANALYSIS OF SKILL INDEX SCORES BY OCCUPATION



Top 20 Skill Occupations for Reading Comprehension

Rank	SOC Code	SOC Occupational Title	Reading
1	25-1061	Anthropology and archeology teachers, postsecondary	33.25
2	19-1042	Medical scientists, except epidemiologists	33.08
3	29-1061	Anesthesiologists	31.97
4	29-1062	Family and general practitioners	31.78
5	19-3094	Political scientists	31.59
6	29-1067	Surgeons	31.48
7	25-1053	Environmental science teachers, postsecondary	31.39
8	25-1071	Health specialties teachers, postsecondary	31.35
9	25-1072	Nursing instructors and teachers, postsecondary	31.34
10	29-1064	Obstetricians and gynecologists	31.16
11	19-3041	Sociologists	31.01
12	19-2012	Physicists	30.94
13	25-1065	Political science teachers, postsecondary	30.83
14	25-1123	English language and literature teachers, postsecondary	30.80
15	25-1112	Law teachers, postsecondary	30.78
16	25-1126	Philosophy and religion teachers, postsecondary	30.60
17	19-2011	Astronomers	30.59
18	29-1022	Oral and maxillofacial surgeons	30.56
19	25-1051	Atmospheric, earth, marine, and space sciences teachers, postsecondar	30.50
20	43-9081	Proofreaders and copy markers	30.31

Source: US BLS, O*NET dataset, OES dataseries; Author's calculations

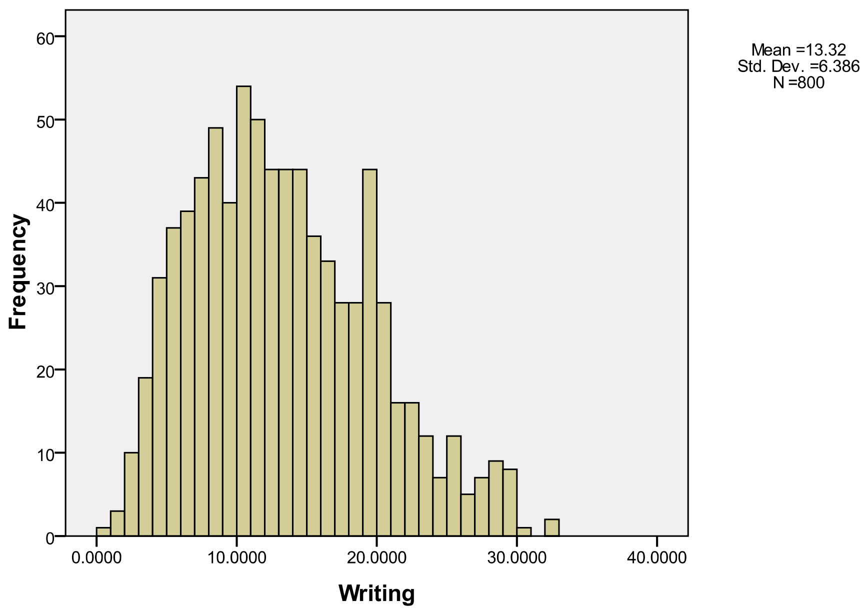


Top 20 Skill Occupations for Active Listening

Rank	SOC Code	SOC Occupational Title	Listening
1	29-1081	Podiatrists	31.56
2	21-1013	Marriage and family therapists	30.81
3	23-1022	Arbitrators, mediators, and conciliators	30.69
4	53-2021	Air traffic controllers	30.27
5	23-1023	Judges, magistrate judges, and magistrates	30.15
6	29-1063	Internists, general	29.91
7	19-1042	Medical scientists, except epidemiologists	29.77
8	19-3031	Clinical, counseling, and school psychologists	29.20
9	29-1064	Obstetricians and gynecologists	29.00
10	25-1113	Social work teachers, postsecondary	28.85
11	29-1067	Surgeons	28.45
12	21-1012	Educational, vocational, and school counselors	28.24
13	29-1062	Family and general practitioners	28.02
14	25-1123	English language and literature teachers, postsecondary	28.00
15	29-1065	Pediatricians, general	27.87
16	21-1023	Mental health and substance abuse social workers	27.86
17	29-9091	Athletic trainers	27.72
18	29-1061	Anesthesiologists	27.51
19	25-1061	Anthropology and archeology teachers, postsecondary	27.44
20	23-1011	Lawyers	27.35

Source: US BLS, O*NET dataset, OES dataseries; Author's calculations

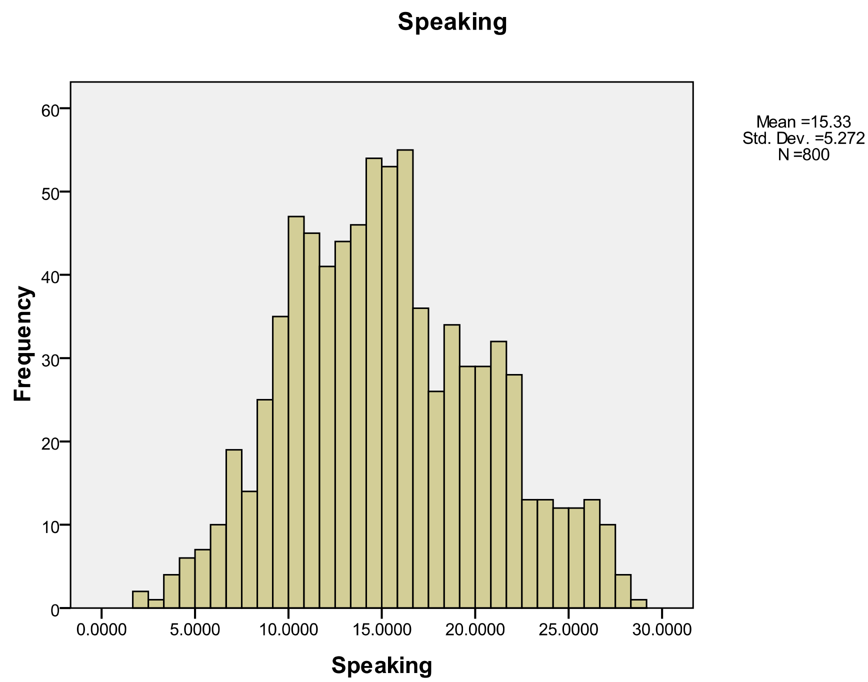
Writing



Top 20 Skill Occupations for Writing

Rank	SOC Code	SOC Occupational Title	Writing
1	25-1062	Area, ethnic, and cultural studies teachers, postsecondary	32.74
2	25-1061	Anthropology and archeology teachers, postsecondary	32.57
3	19-3041	Sociologists	30.43
4	25-1123	English language and literature teachers, postsecondary	29.94
5	19-3094	Political scientists	29.91
6	25-1125	History teachers, postsecondary	29.81
7	25-1053	Environmental science teachers, postsecondary	29.70
8	25-1111	Criminal justice and law enforcement teachers, postsecondary	29.69
9	25-1072	Nursing instructors and teachers, postsecondary	29.57
10	27-3022	Reporters and correspondents	29.42
11	19-3091	Anthropologists and archeologists	29.42
12	25-1043	Forestry and conservation science teachers, postsecondary	28.93
13	25-1082	Library science teachers, postsecondary	28.76
14	25-1071	Health specialties teachers, postsecondary	28.62
15	25-1065	Political science teachers, postsecondary	28.37
16	25-1069	Social sciences teachers, postsecondary, all other	28.33
17	25-1192	Home economics teachers, postsecondary	28.30
18	19-1042	Medical scientists, except epidemiologists	28.18
19	25-1113	Social work teachers, postsecondary	28.13
20	25-1051	Atmospheric, earth, marine, and space sciences teachers, postsecondar	28.04

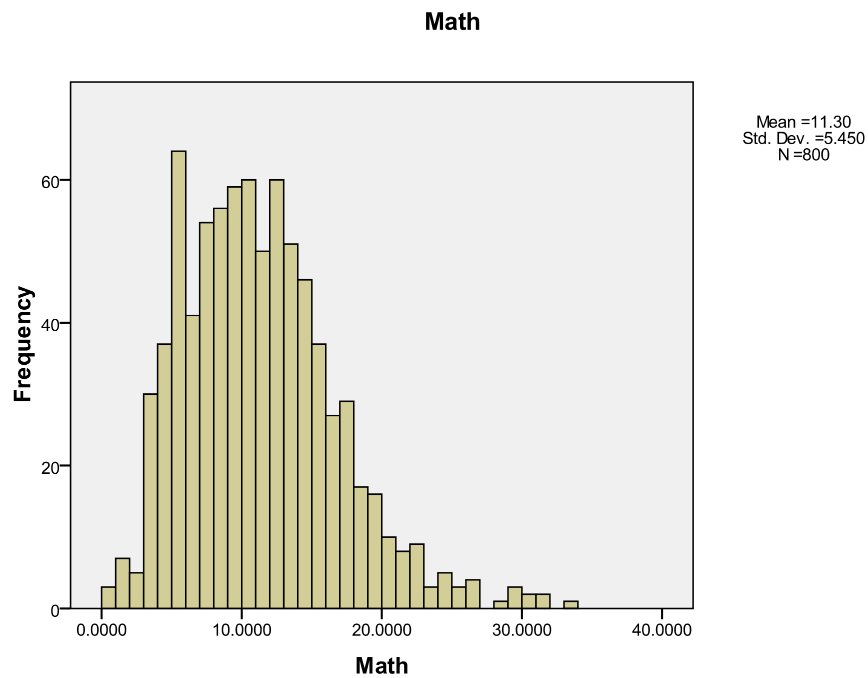
Source: US BLS, O*NET dataset, OES dataseries; Author's calculations



Top 20 Skill Occupations for Speaking

Rank	SOC Code	SOC Occupational Title	Speaking
1	27-3011	Radio and television announcers	28.94
2	25-1126	Philosophy and religion teachers, postsecondary	27.97
3	25-1065	Political science teachers, postsecondary	27.73
4	25-1112	Law teachers, postsecondary	27.65
5	25-1042	Biological science teachers, postsecondary	27.61
6	25-1125	History teachers, postsecondary	27.44
7	21-2011	Clergy	27.24
8	25-1111	Criminal justice and law enforcement teachers, postsecondary	27.21
9	27-2011	Actors	27.19
10	25-1121	Art, drama, and music teachers, postsecondary	27.05
11	25-1192	Home economics teachers, postsecondary	27.05
12	25-1123	English language and literature teachers, postsecondary	26.94
13	25-1067	Sociology teachers, postsecondary	26.79
14	25-1071	Health specialties teachers, postsecondary	26.76
15	25-1113	Social work teachers, postsecondary	26.73
16	25-1072	Nursing instructors and teachers, postsecondary	26.62
17	25-1069	Social sciences teachers, postsecondary, all other	26.58
18	25-1062	Area, ethnic, and cultural studies teachers, postsecondary	26.57
19	25-1066	Psychology teachers, postsecondary	26.55
20	25-1032	Engineering teachers, postsecondary	26.38

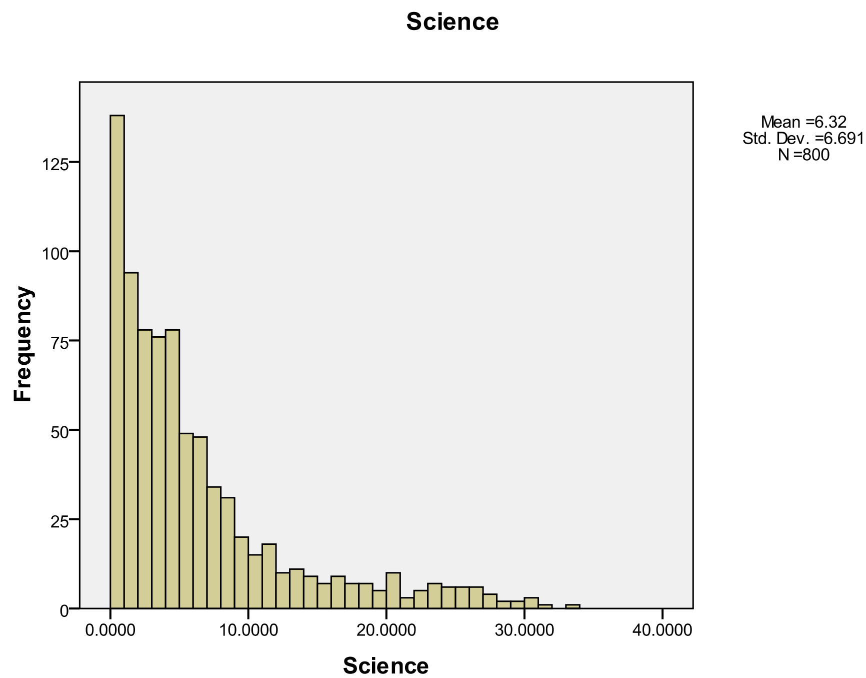
Source: US BLS, O*NET dataset, OES dataseries; Author's calculations



Top 20 Skill Occupations for Math

Rank	SOC Code	SOC Occupational Title	Math
1	15-2021	Mathematicians	33.90
2	15-2031	Operations research analysts	31.59
3	19-2011	Astronomers	31.02
4	19-2012	Physicists	30.64
5	25-1022	Mathematical science teachers, postsecondary	30.64
6	15-2011	Actuaries	29.90
7	25-1032	Engineering teachers, postsecondary	29.83
8	15-2099	Mathematical scientists, all other	29.17
9	17-2021	Agricultural engineers	28.38
10	15-2091	Mathematical technicians	26.38
11	19-2032	Materials scientists	26.29
12	25-1054	Physics teachers, postsecondary	26.20
13	25-1051	Atmospheric, earth, marine, and space sciences teachers, postsecondar	26.18
14	17-2121	Marine engineers and naval architects	25.25
15	25-1052	Chemistry teachers, postsecondary	25.24
16	47-2081	Drywall and ceiling tile installers	25.13
17	17-2141	Mechanical engineers	24.72
18	41-9031	Sales engineers	24.69
19	19-2043	Hydrologists	24.67
20	15-2041	Statisticians	24.53

Source: US BLS, O*NET dataset, OES dataseries; Author's calculations

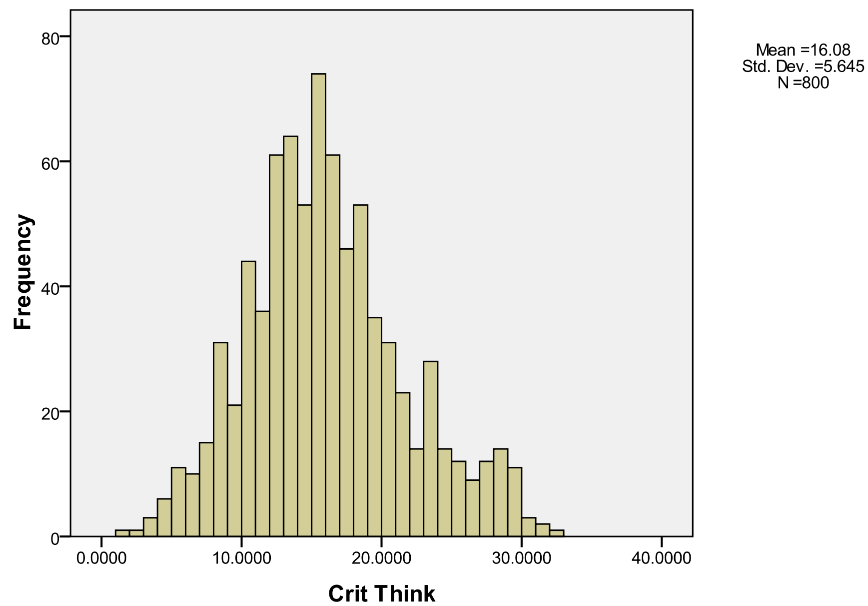


Top 20 Skill Occupations for Science

Rank	SOC Code	SOC Occupational Title	Science
1	19-2011	Astronomers	33.64
2	25-1051	Atmospheric, earth, marine, and space sciences teachers, postsecondar	31.40
3	19-2012	Physicists	30.75
4	19-2032	Materials scientists	30.18
5	25-1052	Chemistry teachers, postsecondary	30.16
6	25-1042	Biological science teachers, postsecondary	29.82
7	25-1032	Engineering teachers, postsecondary	29.28
8	19-1042	Medical scientists, except epidemiologists	28.99
9	25-1071	Health specialties teachers, postsecondary	28.24
10	25-1043	Forestry and conservation science teachers, postsecondary	27.68
11	19-1021	Biochemists and biophysicists	27.50
12	29-1064	Obstetricians and gynecologists	27.07
13	17-2041	Chemical engineers	27.01
14	25-1054	Physics teachers, postsecondary	26.97
15	25-1041	Agricultural sciences teachers, postsecondary	26.85
16	17-2021	Agricultural engineers	26.47
17	19-1013	Soil and plant scientists	26.29
18	25-1053	Environmental science teachers, postsecondary	26.08
19	19-2043	Hydrologists	26.03
20	19-1020		25.99

Source: US BLS, O*NET dataset, OES dataseries; Author's calculations

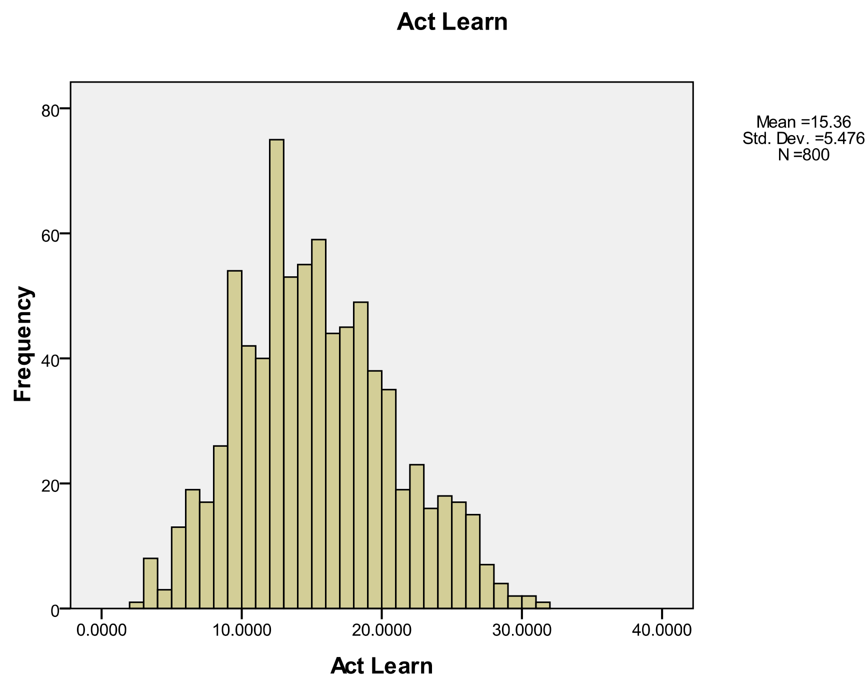
Crit Think



Top 20 Skill Occupations for Critical Thinking

Rank	SOC Code	SOC Occupational Title	CritThink
1	25-1061	Anthropology and archeology teachers, postsecondary	32.45
2	25-1062	Area, ethnic, and cultural studies teachers, postsecondary	31.80
3	19-2011	Astronomers	31.43
4	25-1032	Engineering teachers, postsecondary	30.82
5	25-1111	Criminal justice and law enforcement teachers, postsecondary	30.62
6	15-2021	Mathematicians	30.11
7	29-1061	Anesthesiologists	29.99
8	19-3041	Sociologists	29.99
9	19-2012	Physicists	29.94
10	25-1053	Environmental science teachers, postsecondary	29.57
11	25-1112	Law teachers, postsecondary	29.39
12	25-1126	Philosophy and religion teachers, postsecondary	29.36
13	25-1113	Social work teachers, postsecondary	29.36
14	17-2011	Aerospace engineers	29.23
15	29-1064	Obstetricians and gynecologists	29.22
16	29-1067	Surgeons	29.14
17	25-1065	Political science teachers, postsecondary	29.05
18	29-1065	Pediatricians, general	28.95
19	23-1011	Lawyers	28.95
20	25-1051	Atmospheric, earth, marine, and space sciences teachers, postsecondar	28.88

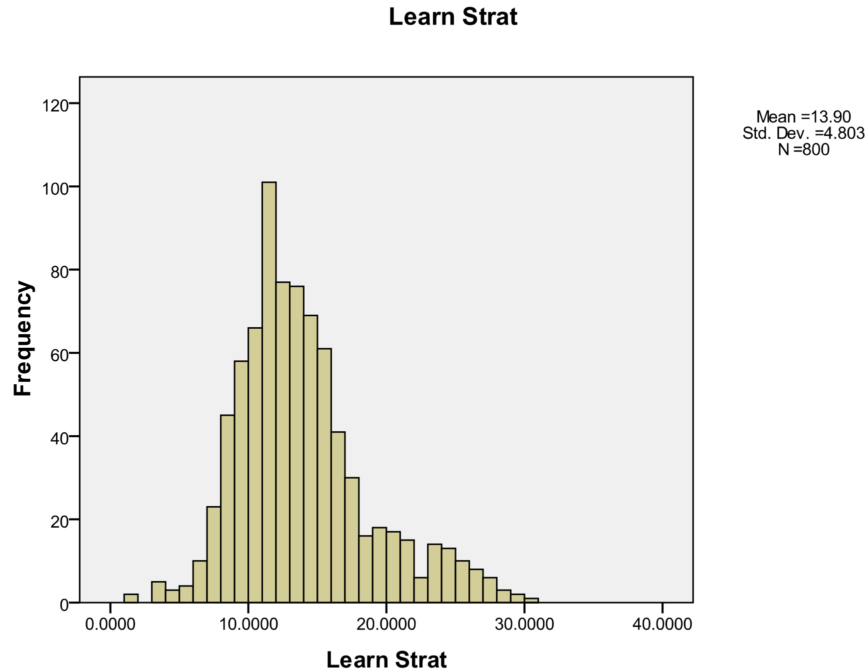
Source: US BLS, O*NET dataset, OES dataseries; Author's calculations



Top 20 Skill Occupations for Active Learning

Rank	SOC Code	SOC Occupational Title	ActLearn
1	15-1011	Computer and information scientists, research	31.45
2	25-1061	Anthropology and archeology teachers, postsecondary	30.46
3	25-1032	Engineering teachers, postsecondary	30.05
4	19-2011	Astronomers	29.68
5	29-1022	Oral and maxillofacial surgeons	29.24
6	25-1051	Atmospheric, earth, marine, and space sciences teachers, postsecondar	28.57
7	29-1064	Obstetricians and gynecologists	28.42
8	25-1053	Environmental science teachers, postsecondary	28.29
9	15-2021	Mathematicians	28.23
10	19-2012	Physicists	27.96
11	25-1113	Social work teachers, postsecondary	27.92
12	25-1043	Forestry and conservation science teachers, postsecondary	27.66
13	19-1042	Medical scientists, except epidemiologists	27.55
14	25-1192	Home economics teachers, postsecondary	27.42
15	25-1111	Criminal justice and law enforcement teachers, postsecondary	27.36
16	29-1065	Pediatricians, general	27.01
17	25-1066	Psychology teachers, postsecondary	26.95
18	25-1067	Sociology teachers, postsecondary	26.82
19	29-1063	Internists, general	26.81
20	25-1123	English language and literature teachers, postsecondary	26.75

Source: US BLS, O*NET dataset, OES dataseries; Author's calculations

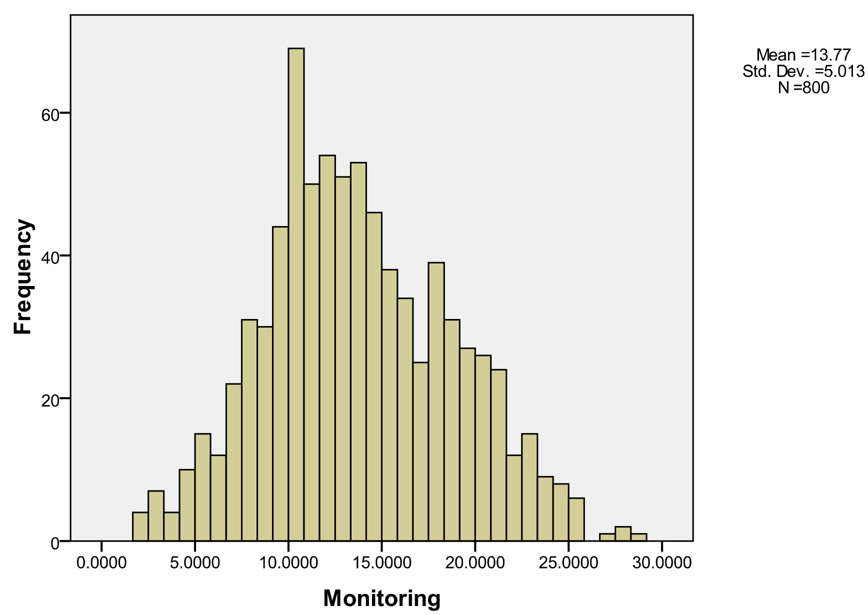


Top 20 Skill Occupations for Learning Strategies

Rank	SOC Code	SOC Occupational Title	LearnStrat
1	25-1081	Education teachers, postsecondary	30.16
2	25-2031	Secondary school teachers, except special and vocational education	29.57
3	25-1123	English language and literature teachers, postsecondary	29.02
4	25-1113	Social work teachers, postsecondary	28.32
5	25-2022	Middle school teachers, except special and vocational education	28.17
6	25-1066	Psychology teachers, postsecondary	28.02
7	25-1082	Library science teachers, postsecondary	27.84
8	25-2043	Special education teachers, secondary school	27.47
9	11-9032	Education administrators, elementary and secondary school	27.45
10	25-1067	Sociology teachers, postsecondary	27.29
11	25-1192	Home economics teachers, postsecondary	27.11
12	25-1072	Nursing instructors and teachers, postsecondary	27.01
13	25-9031	Instructional coordinators	26.88
14	25-1065	Political science teachers, postsecondary	26.85
15	25-2042	Special education teachers, middle school	26.68
16	25-1042	Biological science teachers, postsecondary	26.42
17	25-1071	Health specialties teachers, postsecondary	26.40
18	25-1122	Communications teachers, postsecondary	26.20
19	25-2021	Elementary school teachers, except special education	26.03
20	25-2041	Special education teachers, preschool, kindergarten, and elementary sc	26.01

Source: US BLS, O*NET dataset, OES dataseries; Author's calculations

Monitoring



Top 20 Skill Occupations for Monitoring

Rank	SOC Code	SOC Occupational Title	Monitoring
1	29-1061	Anesthesiologists	28.61
2	11-9032	Education administrators, elementary and secondary school	27.55
3	25-2031	Secondary school teachers, except special and vocational education	27.53
4	11-1011	Chief executives	26.75
5	29-1022	Oral and maxillofacial surgeons	25.79
6	21-1091	Health educators	25.73
7	53-2011	Airline pilots, copilots, and flight engineers	25.63
8	25-2022	Middle school teachers, except special and vocational education	25.40
9	25-1072	Nursing instructors and teachers, postsecondary	25.37
10	11-9039	Education administrators, all other	25.34
11	11-9033	Education administrators, postsecondary	24.95
12	39-6022	Travel guides	24.75
13	25-1122	Communications teachers, postsecondary	24.72
14	25-9031	Instructional coordinators	24.56
15	25-1113	Social work teachers, postsecondary	24.38
16	13-1111	Management analysts	24.31
17	29-1023	Orthodontists	24.18
18	25-2021	Elementary school teachers, except special education	24.17
19	17-2011	Aerospace engineers	24.09
20	11-9151	Social and community service managers	23.85

Source: US BLS, O*NET dataset, OES dataseries; Author's calculations

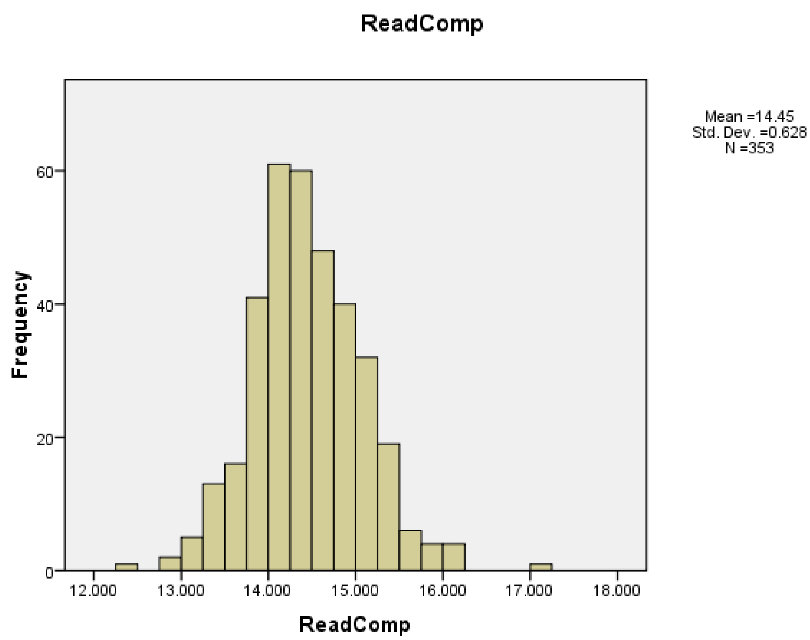
Descriptive Statistics of Basic Skills Indices

	Content Skills						Process Skills			
	Reading Comp	Act List	Writing	Speaking	Math	Science	Critical Thinking	Active Learning	Learning Strategies	Monitoring
N	800	800	800	800	800	800	800	800	800	800
Mean	17.017	17.528	13.320	15.328	11.303	6.320	16.080	15.359	13.898	13.769
Median	16.534	17.288	12.510	14.996	10.705	4.148	15.621	14.903	13.078	13.256
Std. Deviation	6.144	5.042	6.386	5.272	5.450	6.691	5.645	5.476	4.803	5.013
Range	31.335	27.238	32.103	26.500	33.425	33.641	31.305	28.517	28.760	26.884
Minimum	1.915	4.320	.632	2.439	.475	.000	1.147	2.936	1.402	1.728
Maximum	33.250	31.558	32.735	28.939	33.900	33.641	32.452	31.452	30.163	28.612

Source: US BLS, O*NET database

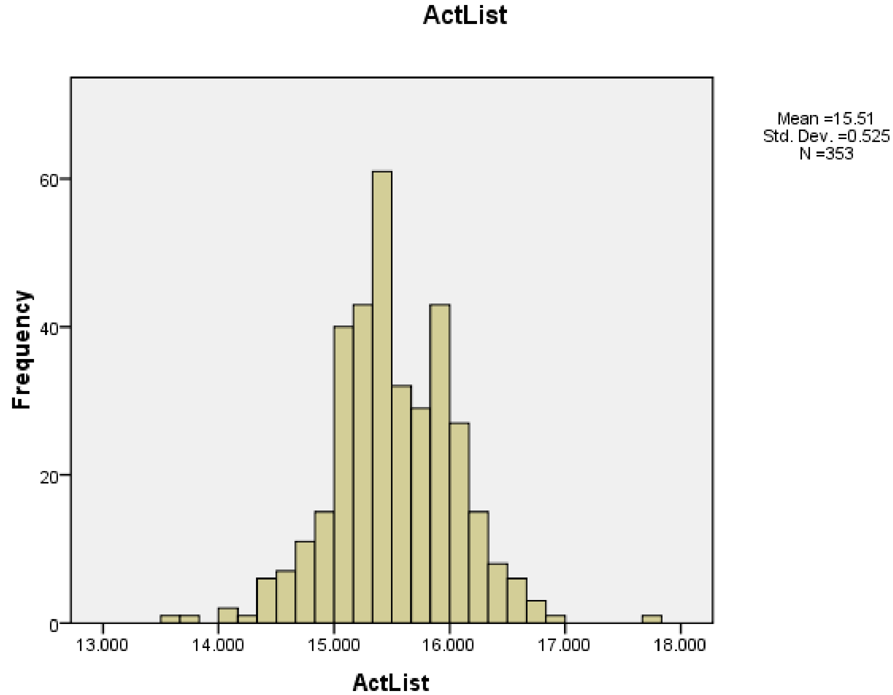
APPENDIX E

FREQUENCY HISTOGRAMS AND RANKINGS FOR SKILL INDICES BY MSA



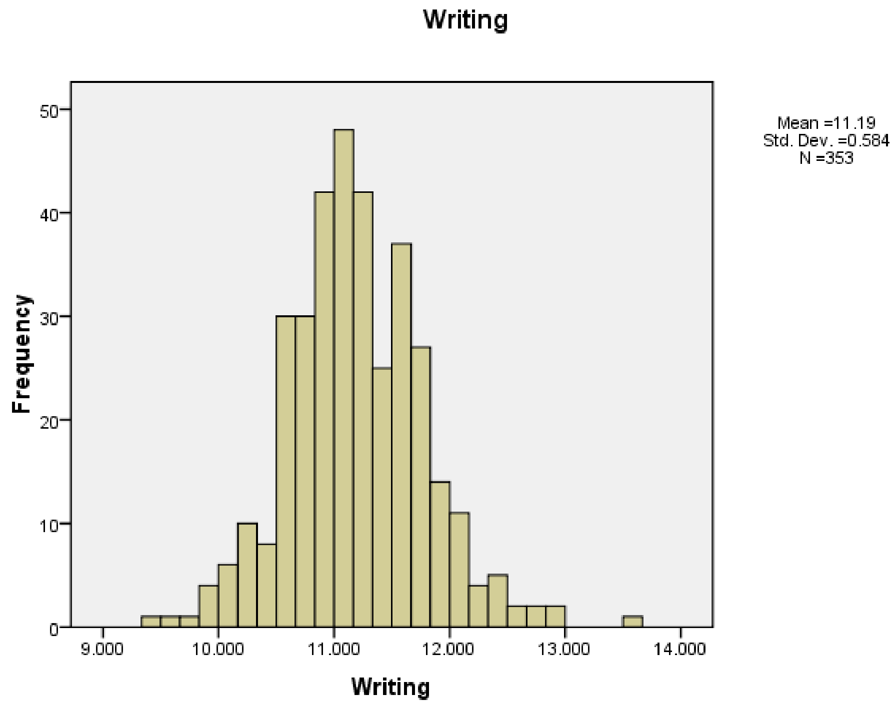
Rank	MSA	Read Comp
1	Washington-Arlington-Alexandria, DC-VA-MD-WV (MSA)	17.12
2	San Jose-Sunnyvale-Santa Clara, CA (MSA)	16.16
3	Boston-Cambridge-Quincy, MA-NH (MSA)	16.15
4	Durham-Chapel Hill, NC (MSA)	16.14
5	Trenton-Ewing, NJ (MSA)	16.09
6	Boulder, CO (MSA)	15.90
7	Bridgeport-Stamford-Norwalk, CT (MSA)	15.89
8	Corvallis, OR (MSA)	15.87
9	New York-Northern New Jersey-Long Island, NY-NJ-PA (MSA)	15.77
10	Hartford-West Hartford-East Hartford, CT (MSA)	15.73
	Lower 10	
344	Salinas, CA (MSA)	13.28
345	Danville, VA (MSA)	13.27
346	Cleveland, TN (MSA)	13.24
347	Elkhart-Goshen, IN (MSA)	13.22
348	Myrtle Beach-North Myrtle Beach-Conway, SC (MSA)	13.19
349	Jacksonville, NC (MSA)	13.12
350	Yuma, AZ (MSA)	13.11
351	Elizabethtown, KY (MSA)	13.00
352	Dalton, GA (MSA)	12.88
353	Madera-Chowchilla, CA (MSA)	12.27

Source: US BLS, O*NET dataset, OES dataseries; Author's calculations



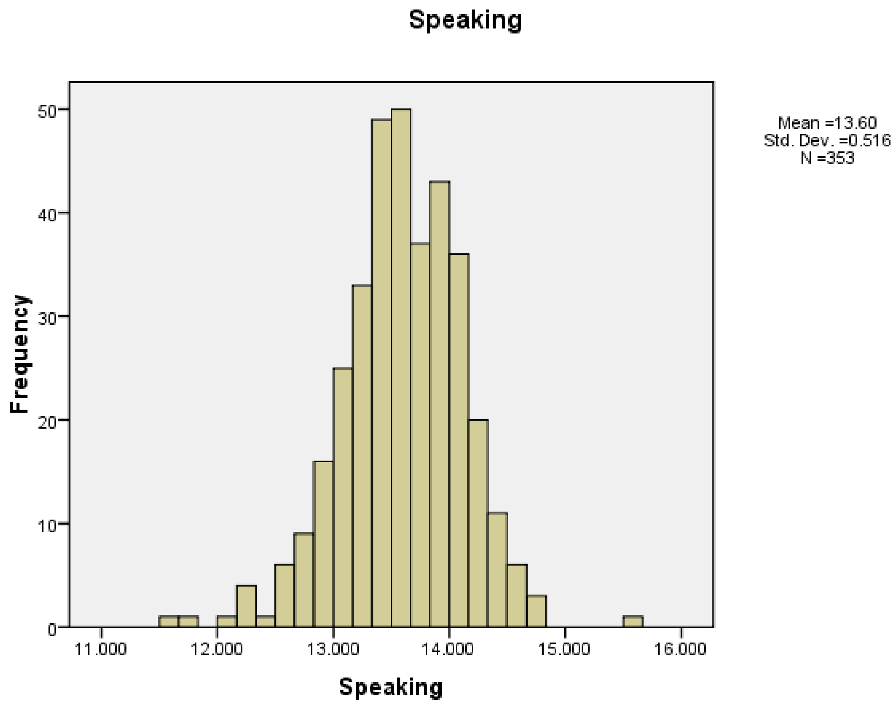
Rank	MSA	Act List
1	Washington-Arlington-Alexandria, DC-VA-MD-WV (MSA)	17.68
2	Trenton-Ewing, NJ (MSA)	16.91
3	Boston-Cambridge-Quincy, MA-NH (MSA)	16.81
4	Corvallis, OR (MSA)	16.73
5	New York-Northern New Jersey-Long Island, NY-NJ-PA (MSA)	16.68
6	Bridgeport-Stamford-Norwalk, CT (MSA)	16.63
7	Durham-Chapel Hill, NC (MSA)	16.59
8	Boulder, CO (MSA)	16.55
9	Albany-Schenectady-Troy, NY (MSA)	16.54
10	Hartford-West Hartford-East Hartford, CT (MSA)	16.52
	Lower 10	
344	Columbus, IN (MSA)	14.46
345	Jackson, TN (MSA)	14.46
346	Clarksville, TN-KY (MSA)	14.45
347	Burlington, NC (MSA)	14.42
348	Morristown, TN (MSA)	14.40
349	Elizabethtown, KY (MSA)	14.25
350	Elkhart-Goshen, IN (MSA)	14.10
351	Cleveland, TN (MSA)	14.09
352	Madera-Chowchilla, CA (MSA)	13.78
353	Dalton, GA (MSA)	13.60

Source: US BLS, O*NET dataset, OES dataseries; Author's calculations



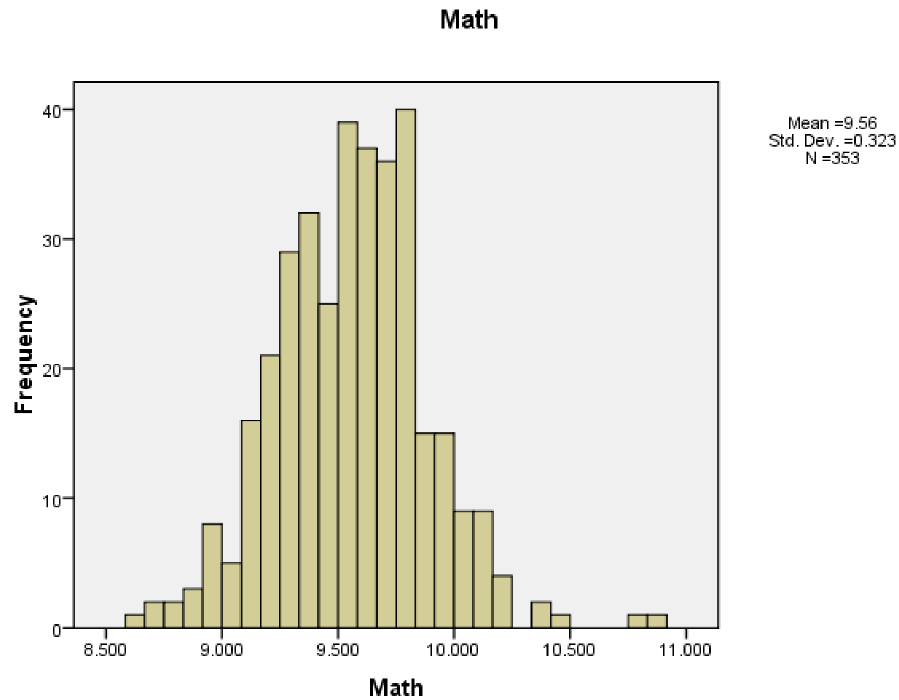
Rank	MSA	Writing
1	Washington-Arlington-Alexandria, DC-VA-MD-WV (MSA)	13.59
2	Trenton-Ewing, NJ (MSA)	12.90
3	Durham-Chapel Hill, NC (MSA)	12.87
4	Corvallis, OR (MSA)	12.80
5	Boston-Cambridge-Quincy, MA-NH (MSA)	12.79
6	San Jose-Sunnyvale-Santa Clara, CA (MSA)	12.55
7	Bridgeport-Stamford-Norwalk, CT (MSA)	12.53
8	New York-Northern New Jersey-Long Island, NY-NJ-PA (MSA)	12.49
9	Albany-Schenectady-Troy, NY (MSA)	12.49
10	Boulder, CO (MSA)	12.45
	Lower 10	
344	Jackson, TN (MSA)	10.12
345	Harrisonburg, VA (MSA)	10.04
346	Morristown, TN (MSA)	10.02
347	Burlington, NC (MSA)	9.97
348	Danville, VA (MSA)	9.95
349	Elizabethtown, KY (MSA)	9.90
350	Cleveland, TN (MSA)	9.89
351	Madera-Chowchilla, CA (MSA)	9.74
352	Elkhart-Goshen, IN (MSA)	9.60
353	Dalton, GA (MSA)	9.47

Source: US BLS, O*NET dataset, OES dataseries; Author's calculations



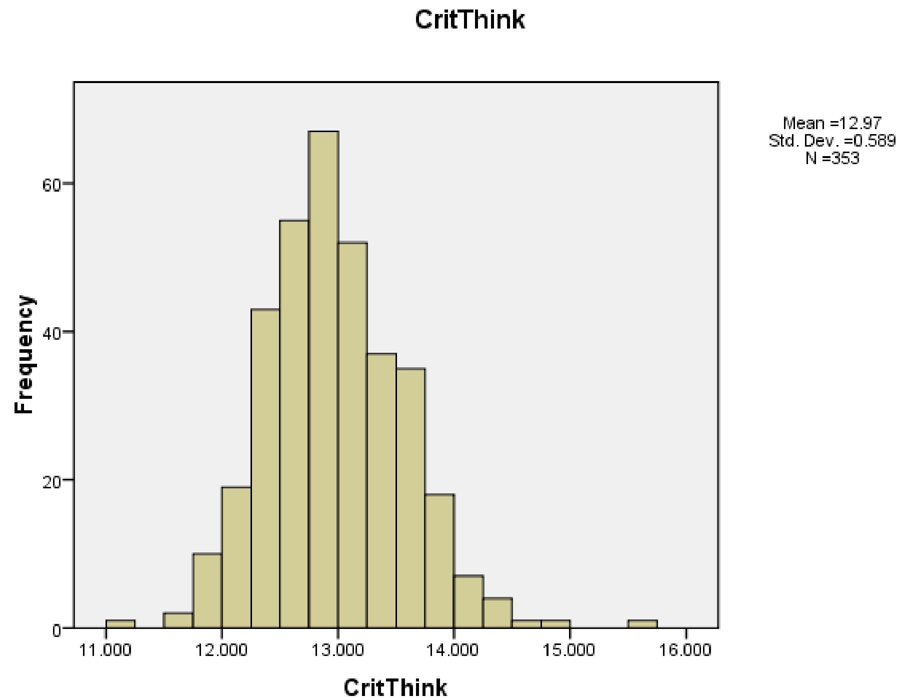
Rank	MSA	Speaking
1	Washington-Arlington-Alexandria, DC-VA-MD-WV (MSA)	15.53
2	Trenton-Ewing, NJ (MSA)	14.83
3	Boston-Cambridge-Quincy, MA-NH (MSA)	14.83
4	Durham-Chapel Hill, NC (MSA)	14.73
5	Bridgeport-Stamford-Norwalk, CT (MSA)	14.67
6	Boulder, CO (MSA)	14.65
7	Corvallis, OR (MSA)	14.64
8	New York-Northern New Jersey-Long Island, NY-NJ-PA (MSA)	14.59
9	San Jose-Sunnyvale-Santa Clara, CA (MSA)	14.57
10	Albany-Schenectady-Troy, NY (MSA)	14.51
	Lower 10	
344	Elizabethtown, KY (MSA)	12.56
345	Harrisonburg, VA (MSA)	12.51
346	Yuma, AZ (MSA)	12.48
347	Morristown, TN (MSA)	12.33
348	Danville, VA (MSA)	12.30
349	Cleveland, TN (MSA)	12.25
350	Burlington, NC (MSA)	12.24
351	Elkhart-Goshen, IN (MSA)	12.05
352	Madera-Chowchilla, CA (MSA)	11.70
353	Dalton, GA (MSA)	11.50

Source: US BLS, O*NET dataset, OES dataseries; Author's calculations



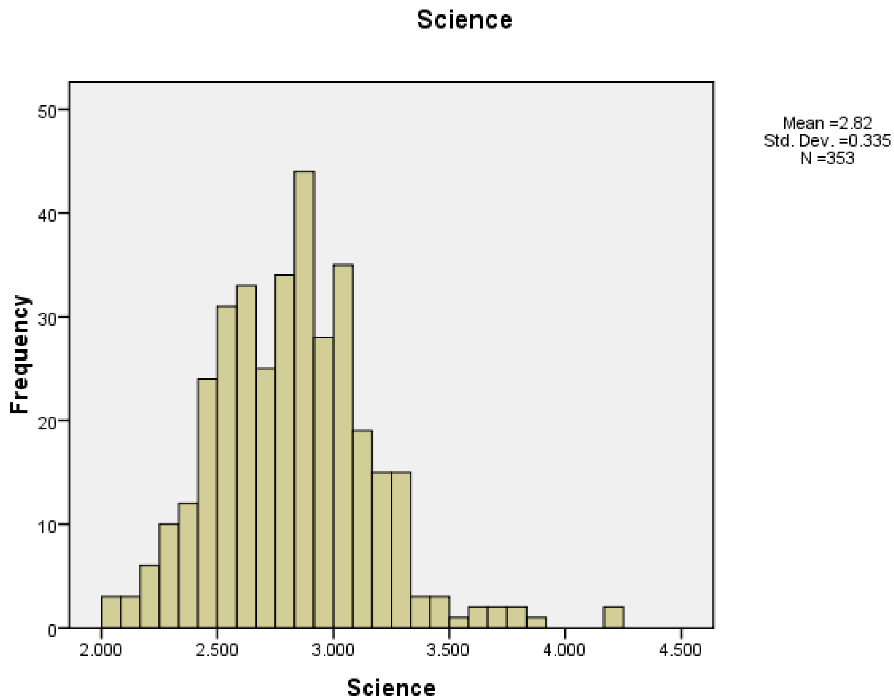
Rank	MSA	Math
1	Washington-Arlington-Alexandria, DC-VA-MD-WV (MSA)	10.85
2	San Jose-Sunnyvale-Santa Clara, CA (MSA)	10.77
3	Warner Robins, GA (MSA)	10.42
4	Boulder, CO (MSA)	10.42
5	Huntsville, AL (MSA)	10.37
6	Sacramento-Arden-Arcade-Roseville, CA (MSA)	10.22
7	Ogden-Clearfield, UT (MSA)	10.21
8	San Francisco-Oakland-Fremont, CA (MSA)	10.19
9	Bridgeport-Stamford-Norwalk, CT (MSA)	10.17
10	Holland-Grand Haven, MI (MSA)	10.16
	Lower 10	
344	Cumberland, MD-WV (MSA)	8.94
345	Ocean City, NJ (MSA)	8.94
346	Abilene, TX (MSA)	8.90
347	Brunswick, GA (MSA)	8.88
348	Madera-Chowchilla, CA (MSA)	8.86
349	McAllen-Edinburg-Mission, TX (MSA)	8.83
350	Dalton, GA (MSA)	8.82
351	Rome, GA (MSA)	8.73
352	Laredo, TX (MSA)	8.70
353	Brownsville-Harlingen, TX (MSA)	8.66

Source: US BLS, O*NET dataset, OES dataseries; Author's calculations

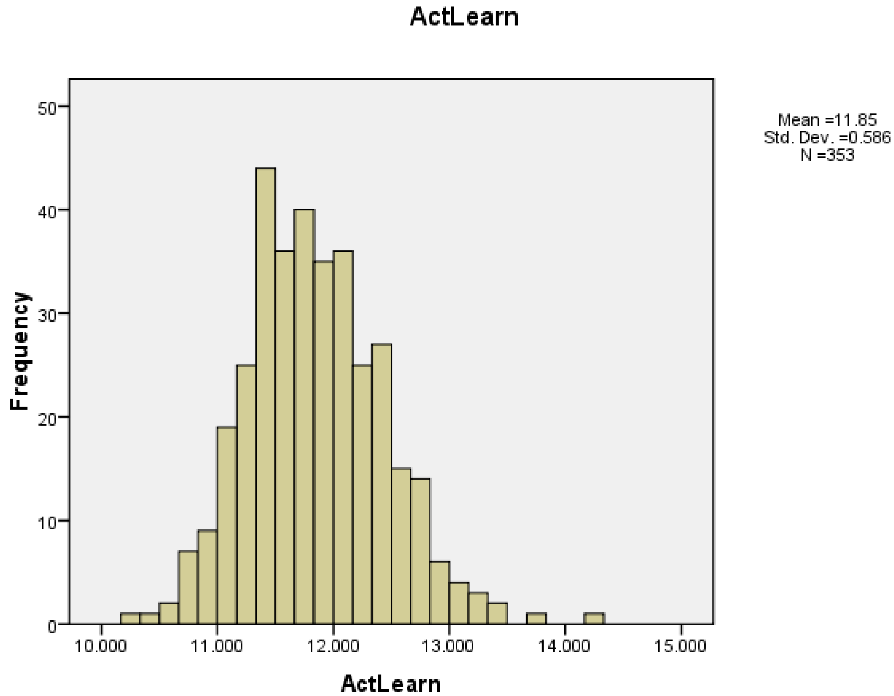


Rank	MSA	Crit Think
1	Washington-Arlington-Alexandria, DC-VA-MD-WV (MSA)	15.62
2	San Jose-Sunnyvale-Santa Clara, CA (MSA)	14.81
3	Boston-Cambridge-Quincy, MA-NH (MSA)	14.64
4	Trenton-Ewing, NJ (MSA)	14.48
5	Boulder, CO (MSA)	14.46
6	Durham-Chapel Hill, NC (MSA)	14.46
7	Bridgeport-Stamford-Norwalk, CT (MSA)	14.42
8	Hartford-West Hartford-East Hartford, CT (MSA)	14.19
9	Austin-Round Rock, TX (MSA)	14.17
10	San Francisco-Oakland-Fremont, CA (MSA)	14.16
	Lower 10	
344	Yuma, AZ (MSA)	11.84
345	Burlington, NC (MSA)	11.83
346	Harrisonburg, VA (MSA)	11.82
347	Wenatchee-East Wenatchee, WA (MSA)	11.81
348	Dalton, GA (MSA)	11.81
349	Elizabethtown, KY (MSA)	11.81
350	Jacksonville, NC (MSA)	11.80
351	Danville, VA (MSA)	11.74
352	Cleveland, TN (MSA)	11.67
353	Madera-Chowchilla, CA (MSA)	11.08

Source: US BLS, O*NET dataset, OES dataseries; Author's calculations



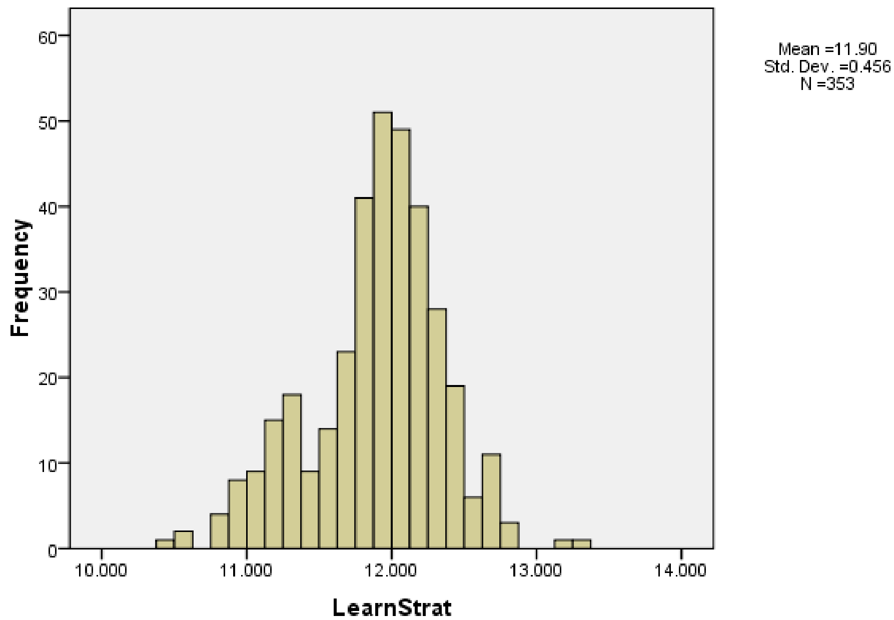
Rank	MSA	Skill Index
1	Durham-Chapel Hill, NC (MSA)	4.23
2	San Jose-Sunnyvale-Santa Clara, CA (MSA)	4.17
3	Washington-Arlington-Alexandria, DC-VA-MD-WV (MSA)	3.87
4	Huntsville, AL (MSA)	3.83
5	Boulder, CO (MSA)	3.75
6	Corvallis, OR (MSA)	3.73
7	Boston-Cambridge-Quincy, MA-NH (MSA)	3.69
8	Bridgeport-Stamford-Norwalk, CT (MSA)	3.65
9	Bakersfield, CA (MSA)	3.60
10	Kennewick-Pasco-Richland, WA (MSA)	3.54
	Lower 10	
344	Pocatello, ID (MSA)	2.24
345	Cleveland, TN (MSA)	2.22
346	Lawton, OK (MSA)	2.20
347	Bend, OR (MSA)	2.18
348	San Angelo, TX (MSA)	2.15
349	Jacksonville, NC (MSA)	2.14
350	Myrtle Beach-North Myrtle Beach-Conway, SC (MSA)	2.14
351	Punta Gorda, FL (MSA)	2.05
352	Laredo, TX (MSA)	2.02
353	Brunswick, GA (MSA)	2.01



Rank	MSA	Act Learn
1	Washington-Arlington-Alexandria, DC-VA-MD-WV (MSA)	14.25
2	San Jose-Sunnyvale-Santa Clara, CA (MSA)	13.75
3	Boston-Cambridge-Quincy, MA-NH (MSA)	13.46
4	Durham-Chapel Hill, NC (MSA)	13.34
5	Boulder, CO (MSA)	13.27
6	Bridgeport-Stamford-Norwalk, CT (MSA)	13.27
7	Trenton-Ewing, NJ (MSA)	13.20
8	Corvallis, OR (MSA)	13.11
9	Hartford-West Hartford-East Hartford, CT (MSA)	13.06
10	Austin-Round Rock, TX (MSA)	13.02
	Lower 10	
344	Columbus, IN (MSA)	10.83
345	Jackson, TN (MSA)	10.75
346	Cleveland, TN (MSA)	10.73
347	Brunswick, GA (MSA)	10.69
348	Elizabethtown, KY (MSA)	10.68
349	Harrisonburg, VA (MSA)	10.67
350	Myrtle Beach-North Myrtle Beach-Conway, SC (MSA)	10.54
351	Danville, VA (MSA)	10.53
352	Jacksonville, NC (MSA)	10.47
353	Madera-Chowchilla, CA (MSA)	10.28

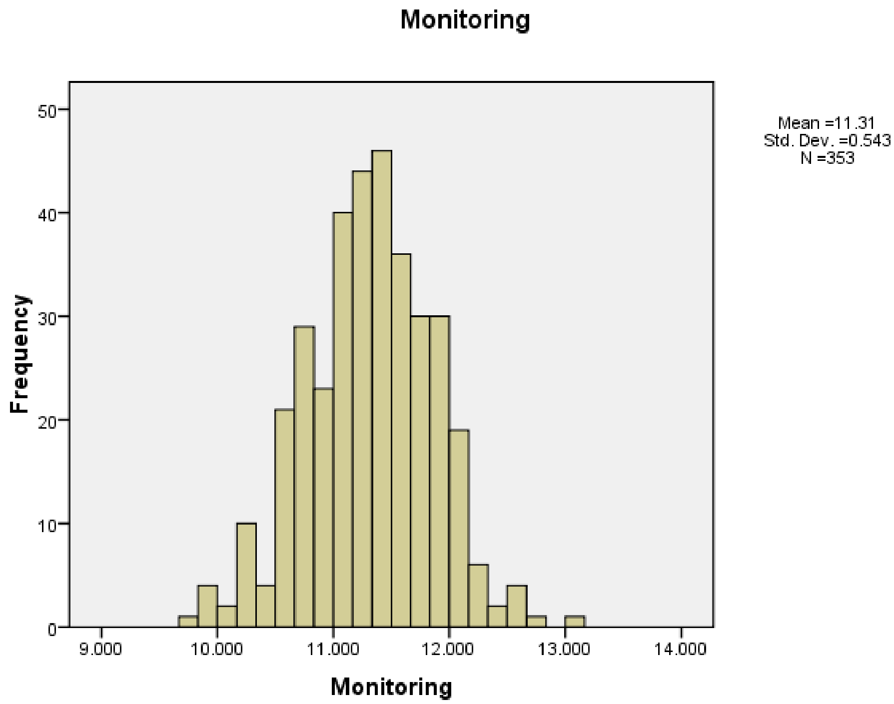
Source: US BLS, O*NET dataset, OES dataseries; Author's calculations

LearnStrat



Rank	MSA	Learn Strat
1	Washington-Arlington-Alexandria, DC-VA-MD-WV (MSA)	13.27
2	Corvallis, OR (MSA)	13.25
3	Rochester, NY (MSA)	12.81
4	Durham-Chapel Hill, NC (MSA)	12.79
5	Boston-Cambridge-Quincy, MA-NH (MSA)	12.75
6	McAllen-Edinburg-Mission, TX (MSA)	12.74
7	Syracuse, NY (MSA)	12.72
8	Bridgeport-Stamford-Norwalk, CT (MSA)	12.71
9	Lawrence, KS (MSA)	12.71
10	San Jose-Sunnyvale-Santa Clara, CA (MSA)	12.68
	Lower 10	
344	St. George, UT (MSA)	10.93
345	Columbus, IN (MSA)	10.92
346	Danville, VA (MSA)	10.91
347	Yuma, AZ (MSA)	10.85
348	Brunswick, GA (MSA)	10.81
349	Naples-Marco Island, FL (MSA)	10.79
350	Jacksonville, NC (MSA)	10.78
351	Punta Gorda, FL (MSA)	10.62
352	Myrtle Beach-North Myrtle Beach-Conway, SC (MSA)	10.61
353	Madera-Chowchilla, CA (MSA)	10.40

Source: US BLS, O*NET dataset, OES dataseries; Author's calculations



Rank	MSA	Monitoring
1	Washington-Arlington-Alexandria, DC-VA-MD-WV (MSA)	13.16
2	Boston-Cambridge-Quincy, MA-NH (MSA)	12.68
3	Trenton-Ewing, NJ (MSA)	12.65
4	Durham-Chapel Hill, NC (MSA)	12.59
5	Bridgeport-Stamford-Norwalk, CT (MSA)	12.52
6	San Jose-Sunnyvale-Santa Clara, CA (MSA)	12.51
7	Hartford-West Hartford-East Hartford, CT (MSA)	12.46
8	Austin-Round Rock, TX (MSA)	12.34
9	New York-Northern New Jersey-Long Island, NY-NJ-PA (MSA)	12.31
10	Albany-Schenectady-Troy, NY (MSA)	12.20
	Lower 10	
344	Wenatchee-East Wenatchee, WA (MSA)	10.24
345	Elizabethtown, KY (MSA)	10.22
346	Brunswick, GA (MSA)	10.17
347	St. George, UT (MSA)	10.16
348	Punta Gorda, FL (MSA)	10.13
349	Danville, VA (MSA)	9.99
350	Harrisonburg, VA (MSA)	9.90
351	Jacksonville, NC (MSA)	9.89
352	Myrtle Beach-North Myrtle Beach-Conway, SC (MSA)	9.87
353	Madera-Chowchilla, CA (MSA)	9.73

Source: US BLS, O*NET dataset, OES dataseries; Author's calculations

APPENDIX F

BASIC SKILL LEVEL ANCHORS REPORTED IN THE O*NET

Reading Comprehension	LV	2	Read step-by-step instructions for completing a form
Reading Comprehension	LV	4	Read a memo from management describing new personnel policies
Reading Comprehension	LV	6	Read a scientific journal article describing surgical procedures
Active Listening	LV	2	Take a customer's order
Active Listening	LV	4	Answer inquiries regarding credit references
Active Listening	LV	6	Preside as judge in a complex legal disagreement
Writing	LV	2	Take a telephone message
Writing	LV	4	Write a memo to staff outlining new directives
Writing	LV	6	Write a novel for publication
Speaking	LV	2	Greet tourists and explain tourist attractions
Speaking	LV	4	Interview applicants to obtain personal and work history
Speaking	LV	6	Argue a legal case before the Supreme Court
Mathematics	LV	2	Count the amount of change to be given to a customer
Mathematics	LV	4	Calculate the square footage of a new home under construction
Mathematics	LV	6	Develop a mathematical model to simulate and resolve an engineering problem
Science	LV	2	Conduct standard tests to determine soil quality
Science	LV	4	Conduct product tests to ensure safety standards are met, following written instructions
Science	LV	6	Conduct analyses of aerodynamic systems to determine the practicality of an aircraft design
Critical Thinking	LV	2	Determine whether a subordinate has a good excuse for being late
Critical Thinking	LV	4	Evaluate customer complaints and determine appropriate responses
Critical Thinking	LV	6	Write legal brief challenging a federal law
Active Learning	LV	2	Think about the implications of a newspaper article for job opportunities
Active Learning	LV	4	Determine the impact of new menu changes on a restaurant's purchasing requirements
Active Learning	LV	6	Identify the implications of a new scientific theory for product design
Learning Strategies	LV	2	Learn a different method of completing a task from a coworker
Learning Strategies	LV	4	Identify an alternative approach that might help trainees who are having difficulties
Learning Strategies	LV	6	Apply principles of educational psychology to develop new teaching methods
Monitoring	LV	2	Proofread and correct a letter
Monitoring	LV	4	Monitor a meeting's progress and revise the agenda to ensure that important topics are discussed
Monitoring	LV	6	Review corporate productivity and develop a plan to increase productivity

Source: US Bureau of Labor Statistics, Occupational Information Network Content Model

APPENDIX G

CORRELATION MATRIX

	Reading	Listening	Writing	Speaking	Math	Science	Critical Thinking	Active Learn	Learn Strategies	Monitor-ing	Pop-ulation	Educ Attainme	Nat Resource	Manu-facturing	Ed Occ Concent
Reading	1.000	.967**	.963**	.929**	.657**	.673**	.982**	.950**	.783**	.899**	.601**	.684**	-.296**	-.219**	0.034
Active Listening	.967**	1.000	.969**	.979**	.580**	.583**	.952**	.886**	.733**	.852**	.591**	.665**	-.245**	-.361**	.123*
Writing	.963**	.969**	1.000	.946**	.589**	.657**	.957**	.905**	.744**	.870**	.546**	.657**	-.193**	-.333**	.181**
Speaking	.929**	.979**	.946**	1.000	.550**	.531**	.925**	.835**	.697**	.807**	.544**	.669**	-.241**	-.409**	.148*
Math	.657**	.580**	.589**	.550**	1.000	.746**	.703**	.750**	.509**	.576**	.492**	.524**	-0.112	-0.020	-.203**
Science	.673**	.583**	.657**	.531**	.746**	1.000	.710**	.809**	.671**	.717**	.537**	.464**	-0.010	0.040	0.016
Critical Thinking	.982**	.952**	.957**	.925**	.703**	.710**	1.000	.962**	.767**	.905**	.611**	.686**	-.245**	-.233**	0.007
Active Learning	.950**	.886**	.905**	.835**	.750**	.809**	.962**	1.000	.846**	.938**	.645**	.657**	-.245**	-0.091	-0.023
Learn Strategies	.783**	.733**	.744**	.697**	.509**	.671**	.767**	.846**	1.000	.911**	.484**	.399**	-.229**	0.083	.186**
Monitoring	.899**	.852**	.870**	.807**	.576**	.717**	.905**	.938**	.911**	1.000	.595**	.497**	-.201**	-0.039	0.053
Population (Ln)	.601**	.591**	.546**	.544**	.492**	.537**	.611**	.645**	.484**	.595**	1.000	.363**	-.172**	-.213**	-.193**
Ed Attainment	.684**	.665**	.657**	.669**	.524**	.464**	.686**	.657**	.399**	.497**	.363**	1.000	-.297**	-.245**	0.076
Nat Resources	-.296**	-.245**	-.193**	-.241**	-0.112	-0.010	-.245**	-.245**	-.229**	-.201**	-.172**	-.297**	1.000	-.180**	.190**
Manufacturing	-.219**	-.361**	-.333**	-.409**	-0.020	0.040	-.233**	-0.091	0.083	-0.039	-.213**	-.245**	-.180**	1.000	-.227**
Education Occs Concentration	0.034	.123*	.181**	.148*	-.203**	0.016	0.007	-0.023	.186**	0.053	-.193**	0.076	.190**	-.227**	1.000

** and * denote significant at the .01 percent and .05 percent level respectively. Based on 353 observations. Source: US Bureau of Labor Statistics Occupational Information Network, Occupational Employment and Wage Series; Author's calculations

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