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Untangling the role of postsecondary education in economic success.

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UNTANGLING THE ROLE OF POSTSECONDARY EDUCATION IN ECONOMIC SUCCESS

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ABSTRACT

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This dissertation explored the relationship between postsecondary education and economic success through a person-centered lens. A sample of 365,315 employed individuals between the ages of 25 and 35 from the American Community Survey (ACS) were used in combination with data from three occupational databases (O*NET, the Occupational Outlook Handbook, the NORC occupational dataset) to examine this topic. The various sources of data were merged together by occupation to permit examination of occupational characteristics and creation of two measures of education and occupation match: 1) match in education level attained and required, and 2) match in field of study and field of work. To examine rates of education and occupation match, I conducted descriptive analyses. To identify latent classes of economic success and to understand the demographic, educational, and occupational characteristics that predict membership in those classes, I conducted latent class analyses (LCA).

Based on the results, I identified several findings of both practical and empirical interest. First, I identified relatively high rates of education and occupation match. Approximately 43.2% of the sample was overeducated for their occupation, 68.9% of the Bachelor's degree holders were working in fields unrelated to their degree, and 31.8% of

Bachelor's degree holders were both overeducated and working in unrelated fields. Second, the majority of non-traditional postsecondary students (who obtain more than a High School degree but less than a 4-year degree) experienced average to high levels of economic success that were similar to the levels experienced by traditional 4-year college graduates. Third, occupational characteristics contributed more to the understanding of economic success than educational (i.e., attained education and field of study) or demographic characteristics (i.e., age, race/ethnicity, and gender). Finally, several different pathways to economic success existed; including pathways to high levels of success among individuals in occupations with no education requirements and pathways to relatively low levels of success among traditional 4-year college graduates. As a whole, these results provide insight into the current value of a postsecondary education.

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CHAPTER ONE

OVERVIEW OF STUDY

In this dissertation, I explored the relationship between postsecondary education and economic success through a series of descriptive and latent class analyses (LCA). These analyses aimed to evaluate several trends and relationships that have not been examined previously. Over the past few decades, the US education system has been making systematic changes to promote college for all students (Brown & Schwartz, 2014; Schwartz, 2014); however, few studies have examined the ways in which such policies may negatively impact some individuals. The current study aimed to shed light on this issue by examining the topic through a person-centered lens. The study sought to decompose the average and understand pathways to economic success that contradict the norm. For example, the study identified pathways that result in high levels of economic success for non-traditional students and pathways that result in low levels of economic success for traditional 4-year college graduates. In this way, the study provides insight into the different postsecondary pathways to economic success, some of which may have been previously hidden. This information can help to further shape the direction of educational guidance and policy.

Specifically, the goals of this dissertation were to address three primary research questions: 1) How often do individuals' educational backgrounds misalign with the entry level requirements and field of their occupation? 2) Are there latent classes of individuals who succeed greater than or less than the group norm? and 3) Do demographic, educational, and occupational characteristics predict class membership? A sample of 365,315 employed individuals between the ages of 25 and 35 from the American Community Survey (ACS) was used in combination with data from three occupational databases (O*NET, the Occupational Outlook Handbook, the NORC occupational dataset) to address these questions. The various sources of data were merged together by occupation to permit examination of occupational characteristics and creation of two measures of education and occupation match. The methods used to address these questions and the main findings from each are summarized briefly below.

The first research question aimed to identify rates of misalignment between educational background and occupation. Two specific types of match or mismatch were examined: 1) match in educational level attained and the level generally required for an occupation; and 2) match in the field of study and field of work. Overall, the majority (43.2%) of the sample was found to be overeducated for their occupation and about a fifth (19.3%) were undereducated. Only 37.5% were adequately educated for their occupation. Among those who had Bachelor's degrees or higher, 58.9% worked in occupations unrelated to their field of study and 31.8% were also overeducated for their occupation, illustrating that nearly a third of the individuals who attained Bachelor's degrees experienced both field mismatch and overeducation.

The second research question aimed to identify and explore experiences of economic success that differ from the norm. Economic success was conceptualized as income, earnings potential, and occupational prestige. LCA was used to identify unique and naturally existing latent classes of economic success. To examine these trends at a finer level, the sample was separated into four different analytic groups: 1) Individuals in occupations that require a High School diploma or less; 2) Individuals with less than a Bachelor's degree and in occupations that require more than a High School diploma, or equivalent; 3) Individuals with a Bachelor's degree (or more) and experience field mismatch; and 4) Individuals with a Bachelor's degree (or more) and experience field match. Latent classes were identified separately within each analytic group as well as within the full sample. The research question then was addressed by identifying the class in each model that captured the largest portion of the sample. This class was identified as the "norm," and all others were identified as experiences of economic success that were less common.

The class representing the norm within each analytic group fell on either the high or the low end of the economic success spectrum, never in the middle. In the first model containing individuals in occupations that required a HS diploma or less, the majority fell into the uniformly low levels of economic success class. All other classes identified within the group captured relatively higher levels of economic success. Thus, although the majority who work in occupations with little to no education requirements experienced low levels of economic success, approximately 38% experience higher levels of economic success in some capacity. The opposite trend was seen among the other three analytic groups. The class representing the norm generally captured the highest levels of observed economic success and the other latent classes comparatively represented lower levels of economic success. These trends suggest that although higher levels of economic success may be the norm within these groups, approximately 32-67% experience relatively lower levels of success. Taken together, these results emphasize the existence and considerable size of groups who experience different levels of economic success than the norm.

The last research question aimed to identify predictors of class membership. A series of demographic, educational, and occupational measures were used to explore class membership. Because the focus of the study was to understand experiences outside of the norm, the norm classes were modeled as the reference classes. Thus, all comparisons aimed to predict membership in comparison to the norm. Separate models were run for each of the predictor variables in order to understand the overall relationship and reduce introduction of confounding variables.

Across the models, occupational characteristics and education level match contributed the most to the understanding of latent class membership. Most of the occupational characteristics and the education level match measure were associated with larger odds ratios than the demographic characteristics, educational characteristics, and field match measure. They also were associated with higher rates of identification as major predictors, a finding that indicates the higher odds ratios were generally experienced in a uniform manner and not as a result of one or two high ratios. Overall, this means that occupational characteristics and education level match were the most helpful in differentiating between different experiences of economic success.

The current study offers several implications for both research and practice. I found that a traditional 4-year college degree is not necessary for all and that a large portion of those who obtain a degree may not fully utilize it. Furthermore, the type of education and the field studied mattered less than occupational characteristics in understanding economic success. Based on these findings, K-12 schools may better serve their students through understanding of non-traditional pathways to success and preparation for college *OR* careers. Additionally, prior research on this topic has focused on the *average* relationship between postsecondary education and economic success. The current study demonstrates there are substantial subgroups that experience this relationship differently. Additional research should continue to approach this topic from a person-centered perspective and decompose the average to understand the underlying trends.

Several recommendations for future research also can be made based on the current study. First, the rates of field mismatch observed in the current study were much larger than those observed previously. Further research should aim to replicate these findings among other samples, using different measurements of match. Second, the LCA analyses were purely exploratory in nature and uncovered a number of interesting trends. Further research should expand upon these findings and work to understand: the predictive power of occupational and educational characteristics when modeled together; interactions among these characteristics; latent class composition when these characteristics are included in the modeling; and the non-traditional class of individuals who experienced average to high levels of economic success. Finally, the current study heavily relied on external occupational measures that were aggregated to represent the 539 occupations reported in the ACS dataset. Future research should examine the role of occupational characteristics in economic success using the richer SOC classification including 1110 detailed occupations.

The following five chapters present research conducted for this dissertation. Chapter two provides an introduction to the research topic, reviews theory and research related to the topic, and summarized the proposed study. Chapter three provides a detailed explanation of the data used and the analyses conducted. Chapter four presents the results for the study by research question. Chapter five provides a summary of the results. Finally, chapter six offers a discussion of the results, limitations of the current study, and implications for research and practice. The appendices provide several additional pieces of information from the current study. Appendices A through C present information about the data aggregation process, code lists, and the systematic method of evaluating field match. Finally, Appendix D offers supplementary results relevant to the current study.

CHAPTER TWO

INTRODUCTION

A college degree is commonly viewed as a ticket to a better job and larger income. This view is supported by research that finds the *majority* of college graduates earn more than the average high school graduate (e.g., Card, 1999; Grubb, 2002; Hout, 2012; Jepsen, Troske, & Coomes, 2014). However, the role of education in economic success can be more complex than this view permits. Bill Gates, Steve Jobs, and Ralph Lauren are all examples of college dropouts who went on to build thriving businesses and become billionaires. Although they earned much more money than most, their general experience is not all that uncommon. In 2011, 16% of male high school graduates earned as much or more than the median 4-year college graduate; and conversely, 20% of male 4-year college graduates earned less than the median high school graduate (Baum, Ma, & Payea, 2013). Together, these results suggest that although college may contribute to increased economic success for the majority, it does not for all; and the subgroup of the population for whom it does not work for is not trivial. Furthermore, a growing body of literature is finding that the value of a college degree may be diminishing and that a combination of other factors may matter just as much, or more, than simply having a degree (Bennett & Vedder, 2015; Oreopoulous & Petronijevic, 2013; Owen & Sawhill, 2013).

These findings contradict the current direction of the United States education system. Schools were built to prepare students for learning, employment, and future citizenship. Yet, for decades' academic policy has undergone systematic changes to increase the rigor of academic tracks and reduce vocational programs. High-stakes testing has increased exponentially, and in many states, graduation requirements have shifted to mirror the admissions requirements of 4-year public universities (Brown & Schwartz, 2014; Schwartz, 2014). There also has been a federal push in recent years to adopt K-12 curriculum standards that aim to make students "college-and-career ready" upon graduation. Although college-readiness is well researched, defined, and understood, career-readiness is not; thus, curriculum and assessments often are aligned to the former (Camara, 2013). Together, these systematic changes in schools are effectively preparing students for college, and not necessarily careers (Brown & Schwartz, 2014).

The current study aims to bridge the gap between research and practice by offering evidence of pathways to economic success that deviate from the norm of traditional 2- and 4-year college graduates. The study aspires to decompose the average that is emphasized in prior research and broaden the view to include pathways that incorporate direct entry into the workforce, participation in credentialing programs, and some college attendance but no degree. The study also seeks to understand and explain how different postsecondary pathways can contribute to different economic outcomes through exploration of several demographic, occupational, and educational factors (e.g., field of industry, occupational skills, overeducation). In this way, this study provides insight into the different postsecondary pathways to economic success, or lack of success, some of which may have been previously hidden. This information can help to further shape the direction of educational guidance and policy.

Theoretical Framework

The relationship between postsecondary education and occupational outcomes has traditionally been explained by human capital theory, job competition theory, and assignment theory. Human capital theory (Becker, 1962) views postsecondary education as an investment that will yield knowledge and skills that increase human capital. Investments are made by individuals and come at a cost of time, effort, and money (both from money not earned while in school and the cost of school), but they are rewarded through increased productivity in the market and subsequent earnings. Job competition theory (Thurow, 1975) highlights the role of the economy in evaluating the returns to postsecondary education. According to this theory, the number and types of jobs available are determined by the economy and there is competition between qualified workers to get those jobs. Those who obtain jobs, out of the pool of qualified workers, possess characteristics most desired by the employer (e.g., high levels of ability). Furthermore, characteristics of the job determine potential worker productivity and subsequent earnings. Finally, assignment theory (Sattinger, 1993) suggests earnings differ based on the match between an individual and an occupation. Workers have a choice in job or sector, and when they choose an occupation that aligns with their skills, they are more productive and subsequently earn more than they would in a less well-matched occupation.

Although these theories have been commonly pitted against one another (e.g., Hartog, 2000), they can be used together to build a more comprehensive view of the relationship between postsecondary education and earnings. Traditionally, the theories have attributed higher earnings to more human capital (e.g., education), employment in a highly-paid occupation, *or* skills match between an individual and an occupation. However, these rationales for earning differences do not need to be mutually exclusive. They can work together to form a more complete view of the many ways education can influence earnings. Education can impact earnings through a combination of the capital earned in the form of knowledge and skills, the match between the knowledge and skills and the occupation entered, and the availability of high-paying occupations in the economy. If an individual earns a degree and cannot find a job in the local market that matches their degree, they may not see the same returns as someone else with the same degree in another location. Similarly, if there are not enough qualified workers to fill a need in the market, some unqualified individuals may fill the need and experience greater returns than otherwise expected.

Two developmental theories, the bioecological theory and the person-centered approach, can serve to further complement the economic theories through consideration of individual differences and multiple pathways to economic success. The bioecological theory (Bronfenbrenner, 1977; Bronfenbrenner & Ceci, 1994) provides a framework for understanding the many inputs to development. It outlines the role of biology and the way it reciprocally interacts with the environment to influence and shape individual development. It proposes the existence of five nested levels of the environment (see Table 1) that can all work to influence the individual in different manners. Furthermore, the theory proposes that individuals have genetic potential for reaching certain levels of psychological functioning (e.g., cognitive abilities, motivation) and that they reach their actualized potential through repetitive interaction with the environment known as proximal processes. The person-centered approach shares many fundamental similarities with the bioecological theory (e.g., focus on the individual, emphasis on complex interactions, nature and nurture; Bergman & Trost, 2006). However, the person-centered approach adds to the theoretical base through its emphasis and understanding of unique pathways that may exist. The theoretical approach proposes that some pathways have similar beginnings but different endings (multifinality), other pathways have different beginnings but similar endings (equifinality), and yet others are rarely or never seen (antitypes/white-spots; Bergman & Trost, 2006; Roeser & Peck, 2003). The different types of pathways result from a set of unique interactions between the individual and the environment. Understanding of the patterns within individuals can then be aggregated up to understand groups of people.

Table 1

Levels of the Environment in the Bioecological Model

Level	Description
Microsystem	encompasses the immediate environment such as the school and home
Mesosystem	includes interactions between different microsystems, such as interactions between family, school and peer group
Exosystem	can be viewed as an extension of the mesosystem that includes interactions and links with settings that are not a direct part of an individual's environment, but are a part of their larger context, such as parents' occupation and characteristics of a neighborhood
Macrosystem	includes the system of cultural norms, beliefs, and laws that structure society
Chronosystem	includes elements of exposure to various aspects of the previous levels, such as the duration, frequency, timing, and intensity of the exposure

The two developmental theories are broad in nature, but offer a context to begin understanding the relationships between postsecondary education and economic success. According to bioecological theory, individuals make different decisions as a result of unique and diverse experiences that interact with biological predispositions. For example, the child of a mathematician that attends a magnet school for mathematics may be more likely to attend college and major in a mathematics-related field than another child who attends a vocational school and is expected to work in order to help support their family. In addition, the person-centered approach suggests that the two children discussed above could end up experiencing similar levels of economic success through different mechanisms (equifinality), and that two very similar children could end up experiencing very different levels of economic success through unique interactions (multifinality). In this way, the bioecological theory offers a framework for understanding the various inputs to human decisions, feelings, and behaviors and the person-centered approach offers insight into the formation of pathways that may transcend individuals. Furthermore, these theories allow and actually expect individuals to deviate from the norm. Therefore, when patterns occur that cannot be explained by the three economic theories, the developmental theories can be used to begin to understand the trends.

Together, these five theories offer a theoretical base to begin exploring the relationship between postsecondary education and economic success. Figure 1 provides an overview of the theories and the proposed intersection and interaction amongst them. In general, the bioecological theory offers a framework to begin understanding postsecondary education decisions and outcomes. The three economically-centered theories can be situated within this framework to provide insight on the collective manner in which human capital, the economy, and worker-job match can impact economic success—operationalized as income, earnings potential, and occupational prestige. Finally, the person-centered approach offers conceptual guidance on the formation of pathways to economic success. This approach is not represented within the figure because it is used to understand the aggregation of results and relationships, not specific relationships. Taken together, the economically-centered theories provide guidance on the relationships between postsecondary education and earnings; whereas the developmental theories offer a structure to explain decisions and explore alternative pathways.

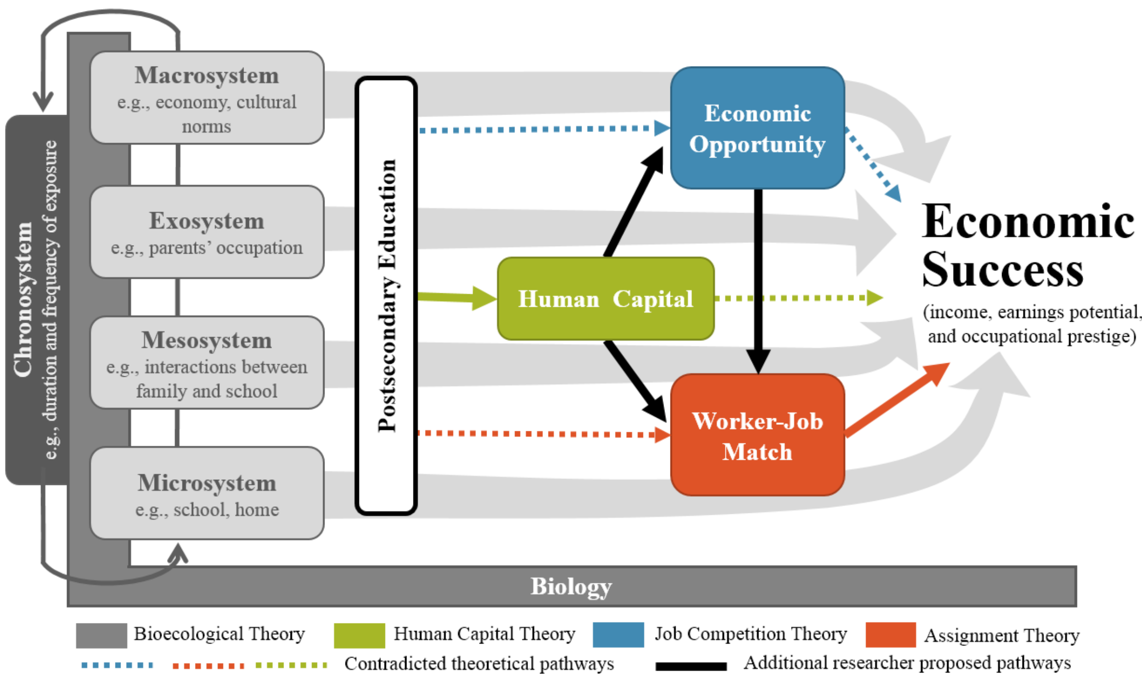

Figure 1. *Theoretical framework.*

Literature Review

The Growth of the American Postsecondary Education System

The United States postsecondary system has experienced marked growth over the past half century. Starting with the GI Bill of 1944, a college education became accessible to many through federal funding. Over the years, additional funding (e.g., the Higher Education Act of 1965, the 1978 Middle Income Student Assistance Act) continued to increase college opportunities and contribute to a progressively more diverse undergraduate student body (Baum, Kurose, & McPherson, 2013; Bennett & Vedder, 2015). For example, in 1960 45% of all high school completers, including 38% of women completers, attended college the fall after graduating. By 2015, the overall attendance rate had risen to 69% of high school completers, including 73% of women completers. Similarly, in 1972, 45% of Black and Hispanic high school completers attended college the following fall. By 2015, their enrollment numbers had increased to 56% and 69%, respectively (Snyder, de Brey, & Dillow, 2016).

Increased interest and funding for a college education has opened the door for an education industry. The number of postsecondary degree-granting institutions has more than doubled since 1950, but the largest increases have been seen in the number of community colleges and private for-profit institutes. Since 1950, the number of community colleges has more than tripled, and since 1975, the number of private for-profit institutes has increased from 55 to 1,334 (Snyder et al., 2016). The growth in community colleges can be attributed primarily to their use as the state- and federally-funded means of bringing accessible and affordable education to all. By the 1970's, all states had set up a community college system that anyone could attend, regardless of previous academic ability, and most could get government grants to help defray the cost (Baum, Kurose, et al., 2013; Cohen, Brawer, & Kisker, 2013). In contrast, private for-profit colleges and universities expanded as a market response to an increased need for education, offering everything from certificates to doctoral degrees (Deming, Goldin, &

Katz, 2013; Gilpin, Saunders, & Stoddard, 2015). Although there is great variation among for-profit institutes, as a whole they have been associated with higher tuition (Deming et al., 2013; Iloh & Tierney, 2013), highly structured and streamlined curricula (Deming, Goldin, & Katz, 2012; Tierney & Hentschke, 2007), and fewer post-graduation opportunities for students (Deming et al., 2013) when compared to community colleges and other similar schools. In addition, both types of schools provide an option for many who would not meet traditional college admissions requirements by offering open enrollment procedures, (Baum, Kurose, et al., 2013; Deming et al., 2013; Seiden, 2009).

As a result of the increases in postsecondary options with less rigorous requirements, a growing number of underprepared students may be enrolling in postsecondary institutes. The increased enrollment observed over the past 50 years suggests a widening of the ability pool in postsecondary institutes. With 69% of high school completers currently going on to attend college (Snyder et al., 2016), at least some must be of lower average ability, particularly when comparing them to earlier cohorts that were much smaller (Bennett & Vedder, 2015). Additionally, the growing number of institutes with open enrollment policies suggest more students are enrolling who would have previously been turned away. Some research provides support of this theory. Among the cohort of postsecondary students matriculating during the 2011-2012 academic year, a third had to take a remedial class during their studies (Snyder et al., 2016). Although this only captures a snapshot of postsecondary preparation, other studies have found evidence of longitudinal trends. Bound, Lovenheim, and Turner (2010) used a nationally representative dataset to examine college completion rates and found rates were 5% higher among the 1972 cohort as compared to the 1992 cohort (45% vs 40%

respectively). The authors attributed this decrease in graduation rates to less prepared students entering college and fewer college resources offered to the 1992 cohort. Another study conducted by the National Center for Education Statistics (NCES) found that the average literacy of college graduates significantly decreased from 1992 to 2003 (Kutner, Greenburg, & Baer, 2005). Overall, these findings suggest that the changing context of the postsecondary education system may contribute to a changing and increasingly diverse student body; a student body that might not uniformly benefit from a particular credential or degree.

Returns to Postsecondary Education

Postsecondary education programs provide education with an unstated promise of a career and a means of making a living. On average, this promise is kept. Four-year college graduates have been found to have better jobs and make more money than those with sub-baccalaureate credentials or no postsecondary education (Baum, Ma, et al., 2013; Carnevale, Rose, & Cheah, 2011; Hout, 2012) and to be more socio-economically mobile than non-college graduates (Baum, Ma, et al., 2013). They also have been found to be healthier, happier, and more civically active and to even have longer lives (Baum, Ma, et al., 2013; Hout, 2012; Lawrence, Rogers, & Zajacova, 2016; Mirowski & Ross, 2003). Although fewer studies have investigated outcomes for sub-baccalaureate certificates and degrees; the studies that have been conducted have found higher average earnings and/or wages among those with some college (but no degree), a certificate, or an associate's degree when compared with those who only received a high school diploma (Carnevale, Rose, & Hanson, 2012; Dadgar & Weiss, 2014; Jepsen et al., 2014; Kerckhoff & Bell, 1998). Together, these findings support the expectations of human capital theory with participation in postsecondary education contributing to greater economic success than no participation. However, as bioecological theory, job competition theory and assignment theory would suggest, a series of additional factors can, and have been found to, moderate the relationship between postsecondary education and economic success. The research and theory behind each of these factors is further explored below.

Race and gender. Racial and gender wage gaps have been studied extensively and documented in the United States (e.g., Black, Haviland, Sanders, & Taylor, 2006; Blau & Kahn, 2006; Reimers, 1983; Sites & Parks, 2011; Stanley & Jarrell, 1998; U.S. Bureau of Labor Statistics, 2016b). According to 2014 Census data, females earned 88% of what males earned, and Blacks and Hispanics earned 72% and 70% respectively of what whites earned (Snyder et al., 2016). Studies examining the returns to a postsecondary credential have found similar wage gaps by race and gender across the levels of educational achievement (e.g., Baum, Ma, et al., 2013; Carnevale et al., 2011). For example, in a study examining predicted life-time earnings using the 2006-2008 American Community Survey data, Julian and Kominski (2011) found median life-time earnings consistently increased with education across the full population and when examined separately by gender and race. However, there was considerable variations between individuals based on race and gender. Men experienced the greatest range in earnings based on race, but women consistently earned less than the average white, Black, or Hispanic man. These differences in income by gender and race generally have been attributed to amount of work experience, educational choices/opportunities, types of occupation/industry entered, and discrimination (Antecol & Bedard, 2004; Blau & Kahn, 2007; CONSAD Research Corporation, 2009; Fan, Wei, & Zhang, 2016).

Disparities in earnings among different races and genders may be attributable to differences in educational choices and opportunities. Starting in the 1970's, more women began to attend college than men. In 2015, there were approximately 14.7 million more women than men in two- and four-year schools (Snyder et al., 2016). Blacks and Hispanics also have experienced growth in enrollment rates, with 10% more Blacks and 25% more Hispanics enrolling in 2015 than in 1972; however, whites and Asians have continued to have the highest enrollment rates (Snyder et al., 2016). The increase in enrollment rates of women, Blacks, and Hispanics has been attributed to more educational opportunities for these groups (Baum, Kurose, et al., 2013). Despite these trends, women and minorities are underrepresented in a particular set of fields collectively referred to as science, technology, engineering, and mathematics (STEM; Glass & Minnotte, 2010; NSF, 2015). These fields often are associated with higher-paying occupations (Oh & Kim, 2015); thus, systematic differences in the choice of field to study can further perpetuate earnings differences between gender and racial groups.

Race and gender differences in earnings and educational choices and opportunities can primarily be explained through bioecological theory. Gender and racial stereotypes permeate our society at the Macrosystem level and they trickle-down to influence everyday experiences through entertainment (e.g., books, television), social interactions (e.g., with teachers and peers), and observations (e.g., discrimination in public places). In this way, these stereotypes are then passed on to younger generations (Macrae, Stangor, & Hewstone, 1996). They work to silently shape perceptions about the capabilities and capacities of individuals by race and gender, even among those who belong to a marginalized group (e.g., Evans, Copping, Rowley, & Kurtz-Costes, 2011; Grossman & Porche, 2014). These stereotypes may then serve as an explanation for observed differences in educational choices and opportunities as well as labor market outcomes by race and gender. Furthermore, differences in the perceived value of education by race and gender would contribute to different experiences in the market as proposed by human capital theory, job competition theory, and assignment theory. For example, white males might be perceived as having obtained greater human capital (e.g., knowledge and skills) from a postsecondary education program than white females, which could lead to greater economic opportunity for white males, and greater likelihood of worker-job match among white males; all of which contribute to differential returns of education.

Skills and abilities. Although skills and abilities are routinely studied, operational definitions of the terms have proven elusive. The literature in the field of educational psychology has not used specific definitions of these terms. Instead, theorists and researchers frequently have conceptualized ability as overall cognitive ability or general intelligence and have conceptualized skills as another term for ability or as ability in a specific domain (e.g., reading, math). However, the literature in the field of industrial and organizational (IO) psychology has employed more uniform meanings due to federal definitions for the field published in the *Uniform Guidelines on Employee Selection Procedures* (1978). Skills were defined as the capacity to "perform a learned psychomotor act" (p. 30) and abilities were defined as the capacity to "perform an observable behavior which results in an observable product" (p. 29). According to these definitions, abilities focus on underlying capacities to do something, whereas skills tend to emphasize the application of learning and the proficiencies developed (Myers, 2004). These definitions offer a broader view of abilities, as something that includes non-cognitive components as well as cognitive components, and a more distinct definition of skills, as something that focuses on the application of learning and is distinct from abilities. These definitions of skills and abilities are necessary for reviewing the literature as the terms are frequently used interchangeably.

Skills and abilities influence educational and occupational outcomes. Individuals with higher cognitive abilities are more likely to attend a postsecondary institution (e.g., Belley & Lochner, 2007; Kutner et al., 2005), complete the program (e.g., Bound et al., 2010; Calcagno, Crosta, Bailey, & Jenkins, 2007), receive promotions in shorter time(e.g., Furnham, Crump, & Ritchie, 2013), and receive higher compensation (e.g., Barone & van de Werfhorst, 2011; Heckman, Stixrud, & Urzua, 2006). These types of findings illustrate ability bias or sorting, in which individuals self-select or sort themselves based on their ability. Research on non-cognitive abilities is not as well developed but has found non-cognitive abilities such as persistence, initiative, and self-esteem to be associated with higher levels of postsecondary education (Heckman et al., 2006), lower rates of unemployment (Lindqvist & Vestman, 2011), and higher income (after controlling for participant cognitive ability; Eren & Ozbeklik, 2013; Heckman et al., 2006; Lindqvist & Vestman, 2011). Finally, researchers studying the relationships between skills (using the IO definition) and fields of study have found postsecondary education fosters development of general and occupation-specific skills and the amount and type of skill development varies by program and field of study (Kraebber & Greenan, 2012; Robst, 2007a). Additionally, higher levels of soft skills (e.g., cooperation, leadership)[1], cognitive skills (e.g., critical thinking, reading comprehension), and linguistic skills are associated with significantly higher wage returns (often after controlling for participant cognitive ability; Bacolod, 2016; Balcar, 2014; Barone & van de Werfhorst, 2011). Together, this literature suggests that abilities can help individuals attain higher levels of education and make more money; meanwhile skills are acquired through postsecondary education, can be field specific, and successful mastery can contribute to higher earnings.

Bioecological theory and human capital theory can be used to understand the role of skills and abilities on the relationship between postsecondary education and economic success. As mentioned previously, abilities are viewed as the underlying capacity of an individual to do something. Bioecological theory proposes that abilities interact with and are shaped by the environment; and that they may also interact with the environment and shape subsequent experiences and opportunities through proximal processes (Bronfenbrenner, 1977; Bronfenbrenner & Ceci, 1994). For example, high levels of cognitive abilities may lead to college scholarships and acceptance at a selective postsecondary institute. Human capital theory then proposes that skills and learned aspects of abilities are further developed and honed through investment (e.g., time, effort) in education. This theory views human capital as the knowledge, skills, and abilities that an individual has that are valued in the labor market (Becker, 1962). Thus, education increases human capital, and human capital leads to greater earnings in the labor market.

[1] Balcar (2014) defines these as "intangible skills which are hard to measure and are closely connected with [individual's] attributes" and contrasts them to hard skills, which are "skills which re easily observable and/or measured, easily trained and closely connected with [individual's] knowledge (e.g., surgical skills or typing skills; p. 4).

In this way, these theories support the findings from the literature: that abilities can assist people in attaining higher levels of education, education fosters greater levels of skills and abilities, and skills and abilities are rewarded in the labor market.

Field of study. Researchers have found considerable differences in economic returns to education, depending on the field of study. Postsecondary credentials (including certificates) in health and STEM fields have been associated with larger returns than average for each level of education, after controlling for participant cognitive ability (Dadgar & Weiss, 2014; Finnie & Frenette, 2003; Grubb, 2002; Jepsen et al., 2014; Rumberger & Thomas, 1993). In contrast, degrees in the social sciences, humanities, and education have been associated with lower returns (Finnie & Frenette, 2003; Grubb, 2002; Jepsen et al., 2014; Rumberger & Thomas, 1993). These studies provide further support of findings that STEM fields are associated with higher pay than social sciences and humanities fields (Oh & Kim, 2015). However, not all fields yield similar returns across education levels. For example, sub-baccalaureate credentials and degrees in business are associated with lower earnings than average across sub-baccalaureate graduates, whereas baccalaureate credentials in business are associated with higher earnings than average for baccalaureates (Grubb, 2002; Jepsen et al., 2014; Rumberger & Thomas, 1993). Some researchers studying the effect of sub-baccalaureate education on earnings have found greater variation in earnings by field of study than by credential or degree (Dadgar & Weiss, 2014; Jepsen et al., 2014; Kerckhoff & Bell, 1998). These researchers suggest that field of study can have a larger impact on earnings than credential or degree type, particularly at lower levels of education. Certificate holders in certain fields can and do make more money than the average associate degree holders. Overall, the available literature indicates that the differential returns across educational levels is field-specific.

Differences in economic returns by field of study can be explained by human capital theory and job competition theory. Human capital theory suggests that postsecondary education fosters the development of skills, knowledge, and abilities, which can be viewed as a form of human capital (Becker, 1962). This human capital is valued in the labor market and subsequently increases an individual's value in that market. However, different educational options foster different types and levels of human capital, and this varying capital can be associated with different values and returns in the market. Thus, different fields of study can have different returns associated with postsecondary education. Additionally, job competition theory proposes that the availability of jobs within a market sector further influences the returns in a particular field (Thurow, 1975). For example, if there are limited jobs within a sector of the market the average returns for a field of study may be lower because many individuals may not be able to find employment in their field. Together, these theories support and explain the findings in the research. Some skills and abilities fostered within particular fields of study (e.g., STEM fields) are associated with consistently higher returns, and others (e.g., business fields) have varying returns by education level. Varying returns by education level can be due to the different level of skills and abilities fostered in the programs or varying amounts of market opportunities associated with those skills and abilities. Finally, the skills and abilities learned over the course of a shorter period of time (i.e., within a lower degree/credential program) in a particular field can be of more value and in higher demand than the skills and abilities learned over a longer period of time in another field.

Match between education and occupation: Educational level. Finally, a growing body of research finds that economic returns vary based on the match between an individual's occupation and their training or education. The proportion of the American workforce that is overeducated for their job has been estimated to be as low as 1 in 10 and as high as 1 in 2 (McGuinness, 2006). These estimates vary considerably based on the sample, the definition of overeducation, and the time period during which the study was conducted. In general, over- or undereducation is determined using the degree or credential obtained and the degree or credential that is required for an occupation. The required education for an occupation is derived in one of three ways: 1) job analysis, a systematic evaluation by occupational experts or industrial-organizational psychologists to identify education; 2) worker self-assessment, a rating of the education level required for the job that is provided by workers in the job; and 3) realized matches, an average or mode of the education level that workers actually have in the occupation (Hartog, 2000). Thus, the measurements used to capture overeducation can vary widely.

A large number of studies have examined the economic returns associated with overeducation and undereducation. A systematic review of 15 studies containing 27 independent samples found individuals that were overeducated for a particular occupation received approximately 4% lower returns than those who were adequately educated for the occupation (Hartog, 2000). Those who were undereducated earned 9% less than those who were overeducated. Additionally, although an undereducated individual earned less than those who were adequately or overeducated, they earned more than an individual with a similar educational background who was employed in an occupation for which they were adequately educated. Two other systematic reviews containing 34 unique studies in total (including the 15 studies reviewed by Hartog, 2000) generally yielded similar conclusions (McGuinness, 2006; Rubb, 2003). However, Rubb (2003) did find evidence of a larger earnings gap between the overeducated and undereducated, with the undereducated receiving approximately 14% lower earnings than the overeducated and 20% lower than the adequately educated. Finally, a recent study has critiqued previous research for not controlling for participant ability and called into question some of their findings. Using a large longitudinal dataset, Tsai (2010) found no difference in earnings between the adequately educated and overeducated after controlling for participant ability. These results suggest that that the overeducated may have lower abilities and not be able to obtain jobs that match their education level.

The different returns associated with overeducation and undereducation can be understood through job competition theory and assignment theory. According to job competition theory, individuals may accept a job for which they are overeducated due to a limited availability of jobs that they are qualified for in the market. Furthermore, individuals who are able to obtain these highly competitive jobs may have more skills, abilities and knowledge than others in their field. In contrast, individuals may also find themselves in a job for which they are undereducated if there is a large demand in the market for the particular type of work and not enough skilled workers to meet the demand. In this way, the availability of jobs in the economy can influence whether or not an individual is able to find a job that matches their education. As has been previously discussed, jobs that require more education tend to pay more (e.g., Baum, Ma, et al., 2013), and thus overeducation and undereducation can lead to the returns identified in the literature. Assignment theory offers further understanding of these varying returns through examination of skill match. Assignment theory suggests that individuals with skills that match those required by their job are more productive and earn more money than they would in a less well-matched occupation (Sattinger, 1993). Based on graduation requirements for different credential and degree programs, it can be argued that higher levels of education are associated with more specific skills (as opposed to general skills) and increased critical thinking skills. Thus, different levels of education may foster varying levels and types of skill development. Skill mismatch that reduces the productivity of an individual, such as when an individual is overeducated and performing tasks below their potential, can reduce the individual's potential earnings. Similarly, undereducated individuals that have greater skill mismatch than their adequately educated peers may receive lower earnings than their peers.

Match between education and occupation: Field of study and work. Another type of match between educational background and occupation can be called field match/mismatch. This type of match concerns the relatedness of a training or education program to the skills, knowledge and ability associated with an occupation. It is often more difficult to evaluate because it requires a targeted question about the relatedness of an individual's education or training to their occupation (often not included in nationally-collected datasets) or the ability to systematically evaluate the relatedness of degree programs to occupations. Robst (2007a) briefly summarizes the two methods, acknowledging the potential bias introduced by self-reporting educational relevance to occupation but also outlining the difficulty of systematically matching fields of study to occupations. Fortunately, the National Center for Education Statistics (NCES; 2000) has built a crosswalk to link 2,846 specific fields of study with related occupations that are represented within several common occupational coding systems. However, the current review could only identify an undergraduate honors thesis (Hampton, 2013) that had used this resource. Additionally, only two studies were identified that have attempted to systematically evaluate field match based on information about education and occupations. One study (Nordin, Persson, & Rooth, 2010) employed a frequency-based approach that determined matched based on common match in the data; and the other (Yakusheva, 2010) used a human coder to evaluate match for each observation based on the knowledge, skills and abilities associated with an occupation. Although both methods are creative in using available information to address their research questions, the first suffers from bias in the form of available jobs in the labor market and the second is not feasible in large datasets. The current study proposes a systematic method of identifying field match using the NCES crosswalk.

Although fewer studies have investigated field match, poor field match has generally been associated with a significant income penalty. Using a nationally representative sample of individuals with some form of postsecondary education (e.g., a certificate, vocational license, bachelor's degree), Yakusheva (2010) found those employed in an occupation unrelated to their field of study earned 30% less than those working in an occupation that was related, after controlling for participant cognitive and non-cognitive ability and a series of education factors. Other studies have found slight lower estimates. A study of Swedish young adults found field mismatch was associated with a 20% income penalty for men and 12% income penalty for women (Nordin et al., 2010). Another study of a nationally representative sample of American college graduates found an 11% income penalty for those working outside their field of study (Robst, 2007a). The study also examined the income penalty associated with field mismatch by degree field and found large differences by field. For example, mismatch was associated with more than a 20% income penalty for those who majored in business management, engineering, health professions, computer science and law and less than a 6% income penalty for those who majored in liberal arts, English, social sciences and education. Other studies have found field mismatch to account for approximately 22% of the return to a bachelor's degree, with individuals in unrelated occupations experiencing a smaller returns (Lemieux, 2014) and to contribute to differences in earnings above and beyond overeducation (Robst, 2008). Furthermore, one study found that there are different reasons for taking a job in an unrelated field and only some of those reasons are associated with an income penalty (Robst, 2007b).

Job competition theory and assignment theory can be used to understand the differences in the returns to education based on field match and mismatch. In general, these theories are applied in similar ways to field match and mismatch as they were to overeducation and undereducation. Job competition theory proposes that field mismatch occurs due to economic factors that control the number of jobs available in the market (Thurow, 1975). It is difficult to obtain a job in a particular field if there are limited jobs available. Those that work in other fields not related to their degree field may have less relevant skills for that occupation and loose the value associated with their field-specific skills. Assignment theory suggests that this skill mismatch is associated with lower productivity and earnings compared to others in their field who are working in a field related to their degree (Sattinger, 1993).

Summary of the Literature

The American postsecondary education system has changed over the past half a century. The educational market is expanding to offer more postsecondary options and students are attending in increasing numbers. On average, students receive returns on their investments in education, but there are many factors that influence those returns. Race, gender, skills, abilities, field of study, and match between educational background and occupation matter when evaluating economic returns. Women and racial/ethnic minorities tend to have lower earnings than white men (e.g., Carnevale et al., 2011). Furthermore, higher levels of certain skills (e.g., linguistic, critical thinking) and abilities (e.g., cognitive, persistence; e.g., Barone & van de Werfhorst, 2011), a degree in a STEM field (Oh & Kim, 2015), and an educational background that matches the occupation (e.g., field and required education level; Robst, 2008) are associated with larger returns. However, there are a number of gaps in the current literature reviewed. These gaps concern the methodology and datasets used as well as the examination and measurement of field match.

Research approach. The studies in the current review have examined the returns to education using a variable-centered research approach. They used descriptive analyses to summarize the mean and range of earnings for groups of interest to the researcher (e.g., by gender, race, education level) and they used regression analyses to predict average earnings for groups of interest to the researcher (see Table 2). A few of the studies reviewed used more sophisticated regression models than the basic ordinary least squares

(OLS) regression (e.g., fixed effects models that impose time independent effects, quantile regression), but all aimed to uncover the average experience for a predefined group. These variable-centered types of analyses are good for determining the relationship between variables of interest and the average experience of participants, but they do not permit in-depth exploration of individual differences and unique pathways. Instead, person-centered methods that examine patterns within individuals are necessary to identify such relationships. Person-centered methods are a tool of the person-centered theoretical approach used in the current study and encompass methods such as latent class analysis, cluster analysis, and configural frequency analysis (Bergman & Magnusson, 1997). This approach to the current issue could offer greater understanding of the many pathways to economic success.

Age of datasets. The postsecondary education system has experienced rapid growth, but much of the research examining trends in postsecondary education has used datasets from decades past. For example, the previous section of this paper references 19 original research articles that explore the economic returns to postsecondary education and were published in 2007 or later (not including reviews, meta-analyses, or annually updated government reports; see Table 2). Of these articles, only seven use data collected in the past decade including only one study using data collected after 2010. This is partially due to the limited availability of large quality datasets that collect variables of interest to this research topic (e.g., income, education, occupation, relevance of degree, required education for occupation) as well as the longitudinal nature of the topic. Regardless, with the increased push for a college education, the changing postsecondary demographic, the growth in technology-related jobs, and the reduction in blue-collar jobs, the education and labor markets are changing. Thus, the current literature reviewed here may not adequately capture the nuances of the current relationship between education and economic returns. Instead, the trends reviewed could be more representative of societies of the past.

Examination and measurement of field match. Few studies have examined field match between postsecondary education and occupation. Of the studies identified for the current review, the majority used self-reports of field match, which are subjective and can suffer from reporting bias. Although Robst (2007a) suggests that subjective measures of participant education are commonly used in the field and there may be no reason to expect more bias in reports of field match, match between field of education and occupation may involve more interpretation than reciting a degree or occupation. Participants who are not happy with their current occupation or perceived returns may be more inclined to report a lower degree of match. Additionally, self-report measures of field match are not commonly included on federal surveys, thus relying on such a measure limits the data that can be used to examine this topic. The other studies reviewed attempted to systematically evaluate field match, but the methods used were biased by the higher rates of certain jobs in the labor market or were not feasible in large datasets. No studies were identified that used a crosswalk provided by the NCES (2000) for linking fields of study to related occupations. Overall, more research examining the returns to field match is needed, particularly research that identifies a systematic method for examining field match.

Table 2

Summary of References on the Economic Returns to Education

Study	Type [a]				Dataset	Method(s)
	R	SR	AR	OR		
Antecol & Bedard (2004)				X	1979-1998 National Longitudinal Survey of Youth	Fixed effects regression
Bacolod (2016)				X	2000 Census Data	OLS regression
Balcar (2014)		X				
Barone & van de Werfhorst (2011)				X	1994-1998 International Adult Literacy Survey	Interval regression (linear)
Baum, Ma & Payea (2013)				X	1971-2012 Census Data	Descriptive
Blau & Kahn (2006)				X	1979, 1989, & 1998 data from the Michigan Panel Study of Income Dynamics	OLS regression
Blau & Kahn (2007)	X					
Carnevale, Rose & Cheah (2011)				X	2009 Census Data	Descriptive
Carnevale, Rose & Handson (2012)				X	2004 & 2008 Survey of Income and Program Participation; 1997 National Longitudinal Survey of Youth	Descriptive & OLS regression
CONSAD Research Corporation (2009)				X	2007 Current Population Survey	OLS regression
Dadgar & Weiss (2014)				X	2001-2002 Washington State Board of Community & Technical Colleges Institutional Records	Fixed effects regression

Study	Type [a]				Dataset	Method(s)
	R	SR	AR	OR		
Eren & Ozbeklik (2013)				X	1988 National Education Longitudinal Study	OLS regression, quantile regression & instrumental quantile regression
Fan, Wei & Zhang (2016)				X	1982-2000 waves of the National Longitudinal Survey of Youth	OLS regression
Finnie & Frenette (2003)				X	1982,1986 & 1990 National Graduate Survey	OLS regression
Grubb (2002)		X				
Hartog (2000)		X				
Heckman, Stixrud & Urzua (2006)				X	1979 National Longitudinal Survey of Youth	OLS regression
Hout (2012)	X					
Jepsen, Troske & Coomes (2014)				X	2000-2008 Kentucky Community & Technical College System Student Records; 2002-2006 National Student Clearinghouse transfer information	OLS regression
Julian & Kominski (2011)			X		1940-2000 & 2006-2008 American Community Survey	Descriptive & OLS regression
Kerckhoff & Bell (1998)				X	1980, 1982, 1984 & 1986 High School & Beyond	OLS regression
Lemieux (2014)				X	2005 Canadian National Graduates Survey; 2006 Census Data	OLS regression
Lindqvist & Vestman (2011)				X	1968-2007 Swedish Longitudinal Individual Database (LINDA)	OLS regression & quantile regression
McGuiness (2006)		X				

Study	Type [a]				Dataset	Method(s)
	R	SR	AR	OR		
Nordin, Persson & Rooth (2010)				X	2003 Swedish Register of Education; 2003 National Tax Board; 2003 Register of the Total Population	OLS regression
Oh & Kim (2015)				X	1983, 1996 & 2009 Central Personnel Data File	OLS regression
Robst (2007a)				X	1993 National Survey of College Graduates	Ordered logistic regression & OLS regression
Robst (2007b)				X	1993 National Survey of College Graduates	Logistic regression & OLS regression
Robst (2008)				X	1993 National Survey of College Graduates	Ordered logistic regression & OLS regression
Rubb (2003)		X				
Rumberger & Thomas (1993)				X	1987 Survey of Recent College Graduates; 1985-1986 Annual Survey of Colleges	OLS regression & HLM
Snyder, de Brey & Dillow (2016)			X		1947-2015 Census Data	Descriptive
Tsai (2010)				X	1979-2005 Michigan Panel Study of Income Dynamics	OLS regression
U.S. Bureau of Labor Statistics (2016)			X		1979-2015 Current Population Survey Data	Descriptive
Yakusheva (2010)				X	1992 High School and Beyond	OLS regression

[a] R=Review; SR=Systematic Review; AR=Annual Report; OR=Original Research.

The Present Study

The current study aims to examine the relationship between education and economic success. More specifically, the study aims to identify postsecondary pathways to success, or lack of success, and increase understanding about pathways that contradict the idea that college is *the pathway* to economic success. A nationally-representative census dataset was used to examine this issue. The sample was divided into the four groups outlined in Table 3, and then latent classes of economic success were identified within each group. The latent classes represent naturally occurring subgroups of individuals who experience different levels of economic success (e.g., high prestige and low earning potential and income). Analyses then sought to understand the predictors of latent class membership. In this way, the analysis first identified the outcome of interest—varying levels of economic success—and then worked to understand the occupational, educational, and demographic characteristics that might contribute to the outcomes. This information was then used to identify and understand pathways to economic success. The resulting pathways that are identified may be similar to others that have been found in previous research (e.g., higher education is associated with in higher earnings), or they may highlight pathways that are less often taken and have not yet been studied. Regardless, this study seeks to provide additional understanding about the complex role of education in determining economic success.

It is important to note that the current examination of pathways is different from the approach commonly used in the literature. Most studies that are interested in understanding pathways to some outcome use longitudinal data to examine changes or decisions across time. The current study uses a cross-sectional dataset that includes information about educational and occupational decisions that individuals have already made (e.g., decisions about postsecondary education, field of study, field of industry). The study examines pathways by using information about individuals to predict membership in latent classes of economic success.

The four groups outlined in Table 3 were created to combine individuals with some similarities in occupational and educational characteristics. The groups were created and used in the analysis to allow further understanding of potential pathways that may exist within each larger group. This approach focuses the analysis to a more specific level within the sample, so that analyses identify meaningful classes that are not solely driven by a specific educational or occupational variable alone (e.g., education level, required level of education). In this way, this approach allows a more detailed understanding of the pathways that exist among individuals who have some common experiences.

Table 3

Researcher Defined Groups

Groups	Description
1. No required education	Individuals in occupations that do not generally require a college degree.
2. Education required, has less than Bachelor's	Individuals with less than a Bachelor's degree and in occupations that require more than a High School diploma.
3. Education required, field mismatch	Individuals with a Bachelor's degree or more in occupations unrelated to their field of study.
4. Education required, field match	Individuals with a Bachelor's degree or more in occupations related to their field of study.

Three gaps in the literature will be addressed by the current study. First, the study uses a person-centered methodology known as latent class analysis (LCA), which is designed to identify unobserved classes in the data. This methodology will add to the literature by exploring pathways that may have been previously ignored by variable-centered descriptive and regression analyses. Second, the study uses data from the 2014

American Community Survey (ACS). This will provide a recent, nationally representative sample on which to explore the relationship between education and economic success and understand current trends. Finally, the study uses the NCES (2000) crosswalk to construct a systematic method for examining field match. Although the crosswalk does not perfectly align with field of study codes in the ACS data, a relatively simple and straightforward matching of the field of study codes is proposed. This method will permit systematic determination of field match in large datasets with minimal effort.

Research Questions

This study aims to address the following research questions:

1) How often do individuals' educational background (level of education and/or field of study) misalign with the entry level requirements and field of their occupation?
2) Within each of four groups based on participants' educational background and characteristics of their occupation, are there latent classes of individuals who succeed greater than or less than the group norm, as determined through income, earnings potential, and occupational prestige?
3) Do the following demographic, educational, and occupational characteristics predict class membership in the classes identified in research question 2?
    a. Race/Ethnicity
    b. Gender
    c. Attained education
    d. Bachelor field of study
    e. Major occupational group
    f. Required level of education
    g. Required work experience
    h. Level of on-the-job-training
    i. Occupational abilities
    j. Occupational skills
    k. Education level match/mismatch
    l. Field match/mismatch

Theoretical Underpinnings

The potential relationship between postsecondary education, economic success, and each variable in the current study can be explained through the proposed theoretical framework. Table 4 provides a summary of each variable included in the current study along with the associated theoretical models that is primary used to explain the relationship. Eight of the variables presented in the table summarize variables and theoretical models that were already discussed in detail in the literature review. To briefly summarize, economic success may be influence by: race/ethnicity and gender (1 & 2) through gender and racial stereotypes (bioecological theory); attained education level (3) through varying levels of knowledge and skill accumulation (human capital theory); field of study (4) through varying levels of human capital and market factors (human capital theory and job competition theory); abilities and skills (9 & 10) through different genetic-environment interactions, yielding different levels of capital (bioecological theory and human capital theory); and educational and occupational match (11 & 12) through inevitable discord in supply and demand and skill mismatch (job competition theory and assignment theory).

Table 4

Variables Linked to Theoretical Models

Variable	Primary theoretical models to explain different levels of economic success
1. Race/Ethnicity	BT
2. Gender	BT
3. Attained education	HCT
4. Bachelor field of study	HCT, JCT
5. Major occupational group	HCT, JCT

Variable	Primary theoretical models to explain different levels of economic success
6. Required level of education	HCT
7. Required work experience	HCT
8. Level of on-the-job training	HCT
9. Occupational abilities	HCT, BT
10. Occupational skills	HCT, BT
11. Education level match/mismatch	JCT, AT
12. Field match/mismatch	JCT, AT

Note. BT=Bioecological Theory; HCT=Human Capital Theory; JCT=Job Competition Theory; and AT=Assignment Theory.

Four of the variables presented in Table 4 have not commonly been examined in previous research on this topic. However, they are similar in many ways to other variables that have been studied and are included in the current literature review. Required level of education (6), required work experience (7), and level of on-the-job training (8) are variables that can be thought of in a similar manner as level of attained education. Education, experience, and training all increase the knowledge and skills of an individual, which yields increased earnings according to human capital theory. In addition, major occupational group (5) can be thought of in a similar manner as field of study. Different levels of knowledge and skills are associated with different industries. These knowledge and skills are then associated with different levels of value (human capital theory) and supply/demand (job competition theory) in the market. Lower levels of value, higher levels of supply, and lower levels of demand are all associated with lower earnings.

Note that the person-centered theoretical approach is not used to explain the potential influence of any of the variables presented in Table 4. It is not meant to. Instead, the person-centered approach focuses on the individual rather than specific variables. It aims to understand the relationships amongst these variables within the person and identify patterns that may exist across groups of individuals. In this way, the approach can yield understanding of pathways that incorporate a number of variables. It does not offer conceptual guidance for any of the individual variables but instead offers direction for how they may fit together within individuals to form pathways.

Replicability and Class Expectations

Person-centered methods, such as LCA, have commonly been criticized for lack of replicability (Sterba & Bauer, 2010). The current study addresses this concern through a priori consideration of potential latent classes and inclusion of a cross-validation approach to examine model replicability. The consideration of a priori latent classes offers guidance during the model identification phase and helps to ensure that theory drives the modeling process and not data alone. Overreliance on model fit can contribute to overfitting of the model to the data and reduced replicability (Collins, 2010). In addition, the cross-validation approach directly tests the model replicability. The sample is split into two random samples, and the models are independently run in each sample. Replicability is then considered during selection of the final model solution. If the model does not replicate, this means the solution is not stable and the findings cannot be generalized to the population.

The potential latent class compositions for the current study are outlined in Table 5. The first set of classes exhibit uniform levels of success across the latent indicators: low, average, or high. These classes are generally expected across all of the models. The next set of classes contain varying levels of the economic success indicators. They include classes that are high in economic success in a particular capacity and low in another. These classes capture the multi-faceted and holistic view of economic success. These classes are not expected across all of the models and are generally likely to include a smaller portion of the sample. Finally, the last set of classes includes combinations of latent indicators that are not generally expected in any of the models. If such a class is observed, it will be thoroughly critiqued to determine whether the class is plausible in the context or if it might be a result of model overfitting.

Table 5

Potential Latent Classes

Latent classes	Latent indicators		
	Income	Earnings potential	Occupational prestige
Uniform Classes:			
Low overall success	Low	Low	Low
Average overall success	Average	Average	Average
High overall success	High	High	High
Mixed Classes:			
High earnings, low prestige	High	High	Low
Prestigious, low income with little potential for more	Low	Low	High
Prestigious, low income with potential for more	Low	High	High
High income in low potential field	High	Low	Average
Unlikely Classes:			
Low income and prestige, high potential	Low	High	Low
High income in field with low potential and prestige	High	Low	Low

Summary

The relationship between postsecondary education and economic success is not well understood on an individual level. Previous research has focused on the average relationship but has not aimed to understand relationships among undiscovered subgroups. The current chapter outlines theory underlying and supporting the relationship of interest and reviews previous research on the topic. Both theory and previous research were used to help inform the current study design. The design was briefly reviewed above and is further outlined in the next chapter.

CHAPTER THREE

METHODS

Sample

A subsample from the 2014 American Community Survey (ACS) was used for the current study. The ACS is a yearly survey conducted by the United States Census Bureau that utilizes a multistage, cluster random sampling design. The Census Bureau's Master Address File was used to randomly select samples of houses within 3,143 counties and county equivalents in the US. Each county or county equivalent has five sub-frames that are rotated through so households can only be selected once in a five-year period. Samples were randomly assigned to one of the 12 months of the year, and questionnaires were mailed out at the beginning of each month. In addition to sampling households, a small sample of group quarters was also conducted using a similar process. Group quarters include college residence halls, residential treatment centers, military barracks, correctional facilities, and other places that house groups of people. Follow-ups were conducted to evaluate non-response bias (Treat, 2014). The current study includes 365,315 subjects between the ages of 25 and 35 who were employed during the time of the survey.

External Occupational Data

The sample was merged with occupational data from the O*NET database, the Occupational Outlook Handbook (OOH), and the National Opinion Research Center

(NORC) occupational data. The O*NET database (Version 21.1; 2016b) is a federally-funded database providing standardized and detailed occupational information on hundreds of jobs. It is updated regularly through systematic rating tasks completed by occupational experts and job incumbents. The OOH is produced by the Bureau of Labor Statistics (2016c) and provides occupation profiles that are updated every two years. Finally, the NORC occupational data includes several occupational measures (e.g., earnings threshold, occupational prestige) that were created using data from the 2010 ACS for use in the General Social Survey (Hout, Smith, & Marsden, 2015). The current study used the O*NET database for education, experience, training, skill, and ability information; the OOH as a secondary source for education, experience and training information; and the NORC data for occupational prestige and earnings threshold information.

Several steps were taken to aggregate and merge the occupational data to represent the census 2010 occupational codes captured in the ACS data. These steps are detailed in Appendix A. In general, the NORC and ACS data used the census 2010 classification system, but the O*NET and OOH data used another more comprehensive classification system known as the Standard Occupational Classification (SOC) system. A crosswalk provided by the US Bureau of Labor Statistics (2011) was used to map the 1110 detailed SOC codes to the 539 census 2010 occupation codes. The O*NET and OOH data were then aggregated to represent the census 2010 codes using the crosswalk and the NORC data were merged in using the census 2010 code. The final dataset included complete information on education, experience, training, earnings potential, and occupational prestige for all 539 occupations in the census 2010 classification system.

Complete information on the abilities and skills associated with the occupations was only available for 515 of the occupations. This final occupational dataset was merged into the ACS data by census 2010 occupation code.

Measures

From the ACS survey data

Race/Ethnicity. A revised race/ethnicity variable was constructed by the researcher based on two items on the questionnaire about race and Hispanic origin. Participants were asked to identify their race based on 15 predetermined categories. Open-response fields were provided to permit write-in responses identifying other racial categorizations, more specific classifications (e.g., other Asian – Hmong), and tribal classifications. Participants also were asked to identify any Hispanic, Latino, or Samish origin through four pre-defined categories (including the option not of Hispanic, Latino, or Spanish origin) and one open-ended response field. The Census Bureau used these questions to create a race variable with nine categories[2] and a Hispanic variable with 24 categories. For the purpose of this study, this information were combined and collapsed into the following seven categories: 1) White, 2) Black or African American, 3) Native American (combination of American Indian, Alaska Native, American Indian and Alaska Native), 4) Asian & Pacific Islander (combination of Asian and Native Hawaiian and Other Pacific Islander), 5) Other (did not identify as any of the previous categories), 6) Multiracial (identified as two or more of the previous categories), and 7) Hispanic (identified as of Hispanic origin and selected Other for the race question without identifying another race).

[2] Note, two other more detailed 68 and 100 category race variables were also created.

Gender. One item captured gender on the questionnaire. Participants were asked to choose between two categories: female and male.

Attained education. The highest level of education completed was collected through a multiple choice item. Participants were asked to choose between 14 categories that were collapsed into the following six categories: 1) Less than high school, 2) High school diploma or equivalent, 3) Some college no degree, 4) Associate's degree, 5) Bachelor's degree, 6) Graduate degree. These categories were treated as ordinal data such that comparisons do not assume a consistent increase in knowledge and skills across education levels. The survey did not collect information about different types of credentials or vocational training programs outside of an associate's degree or some college.

Bachelor field of study. Participants' Bachelor's field of study was determined from an open-ended response item asking participants to identify their major(s) for any bachelor's degree received. The survey did not collect information about fields for individual's with some college or an associate's degree, and it did not ask about fields for any higher degrees (e.g., master's, PhD). Because many graduate programs have content prerequisites, it can be assumed that most individuals that receive graduate degrees obtain them in similar or related fields to their undergraduate major. Thus, the field of study for bachelor's degree can serve as a proxy for field of study for graduate degrees. Responses to the open-ended question were coded into 192 areas. These areas were then classified by the Census Bureau into the following five overarching degree fields that were used in the current analysis: 1) science and engineering, 2) science and engineering related, 3) business, 4) education, and 5) arts, humanities, and other. See Appendix B for a summary of the areas coded into the overarching five categories.

Major occupational group. The occupation of each participant was captured through two open-ended response items about the kind of work and activities or duties for the work. The Census Bureau used this information to code participants into one of 539 specific occupation categories, using the census 2010 occupational codes. The 539 census occupations correspond to 23 minor occupational groups and 9 major occupational groups which are summarized in Appendix B. The major occupational group of each participant was assigned according to the taxonomy. The 9 major groups are as follows: 1) Computer, Engineering, and Science Occupations; 2) Education, Legal, Community Service, Arts, and Media Occupations; 3) Healthcare Practitioners and Technical Occupations; 4) Management, Business, and Financial Occupations; 5) Military Specific Occupations; 6) Natural Resources, Construction, and Maintenance Occupations; 7) Production, Transportation, and Material Moving Occupations; 8) Sales and Office Occupations; and 9) Service Occupations.

Income. Participant income over the past 12 months was collected by several items on the questionnaire. The Census Bureau created this reported composite variable as the sum of separately reported information on the following: wage or salary income; net self-employment income; interest, dividends, or net rental or royalty income or income from estates and trusts; Social Security or Railroad Retirement income; Supplemental Security Income (SSI); public assistance or welfare payments; retirement, survivor, or disability pensions; and all other income. Because the income distribution is known to be heavily skewed, the log transformation was applied to this variable before inclusion in any statistical models. Additionally, because negative values of income were permitted to account for a loss in earning or investment, the lowest observed income of -$11,800, plus 1, was added to the value before taking the log to permit estimation of all valid income values. The final transformation applied was: log(income+11801).

From the external occupational data

Earnings potential. This measure represents the proportion of individuals in each occupation that earn more than $45K a year. It is from the NORC occupational database and was constructed using the 2010 American Community Survey data. The proportions were computed from survey participants that indicated they were working full-time and had been working for the past year (Hout et al., 2015). Thresholds do not vary geographically; thus, they offer a useful type of measurement when working with large, nationally-representative datasets. In contrast to the previous measure of participant *income,* the current variable offers a reference for average returns to an occupation. Individuals within an occupation vary significantly in earnings, providing a benchmark by which to compare. Note, the NORC database calls this measure "occupational earnings threshold" in the NORC database, but I renamed it as earnings potential in the current study as this name was deemed more interpretable.

Occupational prestige. Occupational prestige is a measure of the social status or perceived prestige associated with a particular occupation. The current measure is from the NORC occupational database and was developed through a study that took place as part of the General Social Survey (Smith & Son, 2014). The study included 1,001 participants who were tasked with categorizing occupations into nine subsequent prestige categories based on their thoughts of where the occupation fell on the social ladder. Each participant rated 90 occupations and a total of 860 occupations were rated across all participants. Participant ratings were converted into threshold ratings to indicate whether they fell above the median of 5 and a logistic hierarchical linear model was fit to estimate occupational prestige scores for the 2010 census occupations controlling for rater effects. Final prestige scores fell on a 0-100 scale and represented the percentage of prestige ratings above the threshold for a particular occupation (Hout et al., 2015).

Required level of education. The required level of education for each occupation was obtained from the O*NET database and the OOH. The O*NET database uses a form of worker self-assessment with occupational experts and incumbents evaluating the required level of education for an occupation. The results are summarized as the proportion of subject matter experts that chose each education level (Peterson et al., 1997). These ratings were collapsed into a single required level of education for each occupation by identifying the category with the highest proportion of responses. Any occupations that did not have education information available in O*NET used the required level of education in the OOH. The Handbook uses a job analysis derived measure of required education (U.S. Bureau of Labor Statistics, 2016a). The following 7 categories for required level of education were used: 1) Less than high school, 2) High school diploma or equivalent, 3) post-secondary certificate, 4) Some college no degree, 5) Associate's degree, 6) Bachelor's degree, and 7) Graduate degree.

Required work experience. The required work experience measure was created for the O*NET database and the OOH in a similar manner as the above measure of required level of education; thus it was constructed in a similar way as required level of education. The O*NET database served as the primary source and the OOH served as a secondary source. The O*NET ratings were collapsed into a single category corresponding to each occupation, and the OOH were only used in instances where data were missing from O*NET. The following five categories for related work experience were used: 1) none, 2) up to 2 years, 3) over 2 years, up to 6 years, 4) over 6 years, up to 10 years, and 5) over 10 years.

Level of on-the-job-training. The level of on-the-job-training measure also was created in the O*NET database and OOH in a similar manner as required level of education and required work experience; thus, it was constructed in a similar way as those variables. The O*NET database served as the primary source and the OOH served as a secondary source. The O*NET ratings were collapsed into a single category corresponding to each occupation and the OOH were only used in instances where data is missing from O*NET. The following six categories for on-the-job-training were used: 1) none or short demonstration, 2) anything beyond short demonstration, up to 1 month, 3) over 1 month, up to 1 year, 4) over 1 year, up to 2 years, 5) over 2 years, up to 4 years, and 6) over 4 years.

Occupational skills. Occupational skills was obtained from the O*NET database. Trained occupational analysists provided ratings on the degree of importance of a particular skill to an occupation, from 1 (not important) to 5 (extremely important). Thirty-five different skills were rated and final scores for each skill is captured as the mean ratings provided across reviewers (Fleisher & Tsacoumis, 2012b). These ratings were collapsed into the six major O*NET skill groupings by taking the mean of the importance ratings for all skills within a major skill category. The final six categories are: 1) basic skills, 2) complex problem solving skills, 3) resource management skills, 4) social skills, 5) systems skills, and 6) technical skills. See Appendix A for a list of the skills inside each major skill category.

Occupational abilities. Occupational abilities were obtained from the O*NET database and were measured in a similar manner as skills. Trained occupational analysists provided ratings of the importance of an ability to an occupation on a scale from 1 (not important) to 5 (extremely important). In total, 52 abilities were rated and final scores capture mean importance ratings provided (Fleisher & Tsacoumis, 2012a). These categories were collapsed into the four major O*NET ability groupings by taking the mean of the ratings within each grouping. The final categories were: 1) cognitive abilities, 2) physical abilities, 3) psychomotor abilities, and 4) sensory abilities. See Appendix B for a list of the abilities inside each major ability category.

Researcher constructed

Education level match/mismatch. This variable was constructed using information about participant educational attainment and the required level of education for an occupation. Each participant's attained education level was compared to the required education level associated with their occupation, and I subsequently categorized each participant as: 1) *undereducated* if they had less education than is generally required for the occupation; 2) *adequately educated* if they had the same level of education as that generally required for the occupation; and 3) *overeducated* if they had more education than is generally required for the occupation. The attained education measure and required level of education measure each contain the same six education categories: 1) Less than high school, 2) High school diploma or equivalent, 3) Some college no degree, 4) Associate's degree, 5) Bachelor's degree, 6) Graduate degree. However, the required level of education measure also includes one additional education category not captured in the attained education measure: post-secondary certificate. This means that the current data categorizes some occupations as generally requiring a post-secondary certificate but individuals were not permitted to indicate whether they had a post-secondary certificate. Because the O*NET documentation (O*NET, 2016a) generally defines a post-secondary certificate as being “awarded for training completed after high school” and the ACS survey captures some college through two distinct categories referring explicitly to college (i.e., “Some college credit, but less than 1 year of college credit” and “1 or more years of college credit, no degree”), I considered a high school diploma or equivalent as an adequate education level for an occupation that requires a post-secondary certificate. In this way, because a post-secondary certificate could not be observed in attained level of education, the next lowest level of education was considered a proxy match. This reduced level of accuracy in education level match for occupations requiring a post-secondary certificate was taken into consideration during analysis and discussion.

Field match/mismatch. This variable was created for individuals with a bachelor’s degree or higher. Information about field of study was used in combination with the National Center for Education Statistics’ Classification of Instructional Program’s Crosswalk (National Center for Education Statistics, 2000). The NCES crosswalk includes the 2,846 specific fields of study in the Classification of Instructional Program (CIP) taxonomy along with any related occupations from the SOC system (also used by O*NET and the OOH). This crosswalk provided the link between fields of studies and occupations to inform whether or not they were related. The specific fields of study in the CIP taxonomy are associated with 53 broader CIP families that were I linked to the 192 degree fields collected in the ACS data. I then used the NCES crosswalk to identify the SOC occupations associated with each degree field. Because the NCES crosswalk identifies occupations using the SOC system as opposed to the census 2010 system, the Bureau of Labor Statistics (2011) crosswalk was used to identify the corresponding census 2010 occupations. These steps resulted in a list of related ACS fields of study for each census 2010 occupation. Participants were considered to have field match if their degree field is in the list of those related to their occupation. A more detailed description of this process and the steps that were taken is presented in Appendix C.

Data Analysis

Descriptive and correlational analysis were conducted in SAS 9.4 (SAS, 2013) to explore trends in the overall data. Mean, frequencies, and correlations were examined to identify overarching relationships within and between variables, to review for potential data issues (e.g., illogical values, skewed distribution), and to identify missing data trends. Missing data trends were further explored to identify the prevalence and type of missing data in the sample prior to analysis (i.e., missing completely at random, MCAR; missing at random, MAR; or not missing at random, NMAR). This information was subsequently used to inform modeling decisions about treatment of missing data before addressing the research questions. These analyses and all subsequent analyses were weighted using a person-weight (PWGTP) variable included in the ACS dataset to correct for oversampling/undersampling and to allow analyses to represent the population. When standard errors or confidence intervals were desired, the descriptive analyses also used replicate weights to account for the complex survey design. The use of replicate weights is an alternative method to the use of primary sampling units (PSU), cluster and/or stratification information for the estimation of standard error. The ACS data do not provide the latter.

The first research question—*How often do individuals' educational background misalign with the entry level requirements and field of their occupation*—was addressed through descriptive analysis. The rates of educational level match/mismatch and field match/mismatch were examined through weighted frequency tables. Confidence intervals were estimated with the complex survey design accounted for through replicate weights.

The second research question—*Within the groups outlined in Table 6, are there latent classes of individuals who succeed greater than or less than the group norm?*—was addressed through LCA. LCA is a form of mixture modeling that is used to identify mutually exclusive latent classes based on observed data (Collins, 2010). The model iteratively estimates class inclusion to minimize within-class differences and maximize between-class differences, estimating until the most homogenous class structure has been identified. This results in a set of latent classes that capture unique experiences and/or trends within the sample. It is important to note that the model does not assign participants into specific latent classes; instead it uses conditional probabilities and assigns participants a set of class membership probabilities (e.g., 80% chance of being in Class 1, 20% in Class 2). Some have likened LCA to a factor analysis of people, where the factor analysis items are characteristics about people and the latent factors are classes of people (Cattell, 1966). The current study uses a form of LCA known as latent profile analysis, where continuous variables are used as the latent class indicators. Income, earnings potential, and occupational prestige served as the observed variables used to identify the latent classes of economic success. The research question was addressed by identifying the optimal class solution and reviewing the class composition.

Table 6

Groups Identified for Analysis

Analytic groups	Required level of education for occupation	Educational attainment	Field match/ Mismatch
1. No required education	HS Diploma or Less	--	--
2. Education required, has less than Bachelor's	More than a HS Diploma	Less than Bachelor's	--
3. Education required, field mismatch	More than a HS Diploma	Bachelor's or more	Mismatch
4. Education required, field match	More than a HS Diploma	Bachelor's or more	Match

The LCA was conducted in Mplus 7.1 (Muthén & Muthén, 1998-2012). I categorized the sample into the four groups outlined in Table 6 based on information about required level of education for an occupation, attained education, and field match. A separate model was run for each of the groups in order to provide information on the latent classes that might be found within each group. A full model containing all of the data, with the groups entered as a grouping variable, also was run to provide information on the latent classes spanning the groups. As previously mentioned, income, earnings potential, and occupational prestige served as the observed variables used to identify the latent classes of economic success. A cross-validation approach was used to verify the model solutions. Thus, each sample initially was split into two random samples, each containing half of the data. One sample was used to build the model, and the other was used to verify the model solution. The final model then was run with the complete data for each group/sample, and the latent classes within the model were examined and explored.

The class size of each model was determined by incrementally increasing the number of classes estimated and successively evaluating both statistical and theoretical model fit. Five decision criteria were used to evaluate and compare the class solutions: 1) Bayesian Information Criterion (BIC); 2) Entropy; 3) adjusted Lo-Mendell-Rubin (LMR); 4) Classification accuracy; and 5) Theoretical Fit. The BIC is an absolute fit index that provides an indication of the overall fit of the model to the data. Lower values suggest better fit. Special attention was paid to changes in this statistic across models; with class solutions (*k*) that show large drops in this statistic from previous solution (*k-1*) and a flattening out in the latter solutions (*k+n*) indicating better fit (Nylund, Asparouhov, & Muthén, 2007). The entropy statistic is a measure of classification uncertainty. It captures the capacity of the model to separate cases into distinct latent classes. The statistic ranges from zero to one, and values closer to one indicate clearer delineation of classes (Celeux & Soromenho, 1996). The adjusted LMR is a test of incremental model fit. It assesses the difference in likelihood estimates between a class solution (*k*) and the previous solution (k-1) to test the hypothesis that there is no improvement in model fit. A significant difference in likelihood indicates improved fit (Lo, Mendell, & Rubin, 2001). Classification accuracy provides an indicator of the precision in class assignment after accounting for error. The numbers included in the current review are the diagonals in the classification accuracy table, representing the probability of being correctly assigned into a particular latent class. Values closer to 100% represent higher probabilities of correct assignment. Finally, the theoretical fit of the model was assessed by reviewing the mean latent indicator values for each class and evaluating whether they were theoretically plausible.

The third research question—*Do demographic, educational, and occupational characteristics predict class membership?*— also was addressed through the LCA model. Differences between latent classes were explored through the inclusion of a set of covariates within each model. The covariates included race, gender, attained education, bachelor field of study, major occupational group, required level of education, required work experience, level of on-the-job training, occupational abilities, occupational skills, education level match/mismatch, and field match/mismatch. The inclusion of covariates provides estimates of class membership for each specified covariate. In this way, the LCA model also provided information on the attributes that predict class membership. This information was used to understand class composition and begin to construct pathways to economic success.

The 3-step approach for LCA with predictors, outlined by Asparouhov and Muthén (2014), was used in the current study. Using this approach, the latent class model without any predictors was identified first. The latent class predictors were then added to the model as indirect predictors of latent classes. This modeling approach allowed for prediction of the latent classes without influencing the class solution. Demographic variables (race and gender), educational background (attained education, field of study), educational-occupational match (education level match/mismatch, field match/mismatch) and occupational measures (major occupational, required level of education, required work experience, on-the-job training, occupational skills, occupational abilities) were entered into each model as predictors.[3]

The complex survey design could not be accounted for in the LCA models. Mplus does not permit the use of replicate weights for LCA. A person-weight (PWGTP) variable was included in all of the models to account for the unequal probability of selection, but the models did not account for stratification or non-independence of observations. Although not desirable, this approach was deemed acceptable after consideration of the effect this would have on the model and the results. In general, this approach will likely lead to increased estimates of variance and subsequently reduce the statistical power (Davern & Strief, 2008). However, because the sample is extremely large and the goal of the study is to identify trends and examine magnitude of effect, it was decided that the loss in power was acceptable.

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[3] Note, field of study was not included in the models for Group 1 and Group 2. Although Group 1 had some variation in field of study (see Table 7), there was not much, and Group 2 did not include any individuals with Bachelor's degrees.

CHAPTER FOUR

RESULTS

Sample Characteristics

The distribution of variables and their correlations with the latent indicators were reviewed to understand the sample composition and examine trends. Frequencies and means were reviewed in both the full sample and the four pre-defined analytic groups for any indication of data issues and for understanding of overall rates or ranges within each variable. Next, correlations between the variables and the indicators of economic success were computed as a general measure of association amongst the variables. Lastly, rates of missing data were reviewed and examined to identify the prevalence of missing data and the type. This information was used to determine the best method of addressing any issues it might introduce.

Distributions

The frequencies of categorical variables are presented in Table 7. Approximately 71% of the sample identified as White, 13% identified as Black, 7% identified as Asian or Pacific Islander, 6% identified as Hispanic, and less than 5% identified as Native American, Hispanic, or other. The majority of the sample was male (52%), did not obtain a bachelor's degree (64%), and worked in occupations that generally require a high school degree or equivalent (50%), up to 2 years of work experience (51%), and over 1 month and up to 1 year of on-the-job training (68%). The most popular bachelor field of study was science and engineering (13%) and the most popular occupational group was sales and office (23%).

Table 7 also presents the distribution for each analytic group. These serve as a reference for understanding the composition of each group for later analyses. The sample in Group 1 (no required education) was the largest of the four groups and contained more than half of the sample. This group included a slightly larger proportion of Blacks (16%), males (55%), individuals without a Bachelor's degree (84%), individuals working in sales and office (34%) or service (30%) occupations, and lower levels of required work experience and on-the-job training than the full sample. In contrast, the remain groups each have successively smaller proportions of Blacks (12%-7%), males (51%-45%), and individuals working sales and office (12%-6%) and service (16%-1%) occupations; and larger proportions of individuals working in occupations that have higher work experience requirements and levels of on-the-job training.

Table 7

Sample and Analytic Group Distribution Within Categorical Variables

Variable	Category	Full sample (%)	Analytic group [a]			
			1 (%)	2 (%)	3 (%)	4 (%)
Race/ Ethnicity	White	71.12	68.53	73.64	74.49	75.57
	Black	12.87	15.54	12.27	8.34	6.83
	Asian & Pacific Islander	6.55	4.26	4.81	11.89	13.13
	Hispanic	5.58	7.51	5.29	1.81	1.61
	Native American	0.78	1.01	0.87	0.25	0.26
	Multiracial	2.87	2.95	2.9	2.95	2.37
	Other	0.23	0.21	0.23	0.28	0.24
Gender	Male	51.94	55.47	51.23	45.11	44.78
	Female	48.06	44.53	48.77	54.89	55.22

Variable	Category	Full sample (%)	Analytic group [a]			
			1 (%)	2 (%)	3 (%)	4 (%)
Attained education	Less than high school	9.05	14.38	5.51	0.00	0.00
	High school or equivalent	22.82	32.53	26.53	0.00	0.00
	Some college, no degree	23.25	28.46	42.78	0.00	0.00
	Associate's degree	9.33	9.04	25.18	0.00	0.00
	Bachelor's degree	24.39	13.24	0.00	61.23	65.29
	Graduate degree	11.16	2.35	0.00	38.77	34.71
Bachelor field of study	No Bachelor's Degree	64.45	84.41	100.00	0.00	0.00
	Arts, Humanities, and Other	9.41	5.27	0.00	33.47	14.31
	Business	7.08	3.58	0.00	9.60	28.55
	Education	2.86	0.79	0.00	2.74	15.49
	Science and Engineering	13.17	5.08	0.00	50.50	26.09
	Science and Engineering Related Fields	3.04	0.87	0.00	3.69	15.56
Major occupational group	Computer, Engineering, & Science	5.99	0.00	8.79	15.07	18.75
	Education, Legal, Community Service, Arts, & Media	11.37	0.83	14.28	31.04	32.61
	Healthcare Practitioners & Technical	6.00	1.25	12.01	12.00	12.52
	Management, Business, & Financial	12.56	1.45	23.83	28.61	29.38
	Military Specific	0.52	0.85	0.13	0.15	0.01
	Natural Resources, Construction, & Maintenance	9.65	13.36	11.52	1.25	0.06
	Production, Transportation, & Material Moving	11.48	19.50	2.05	0.68	0.21
	Sales and Office	22.84	33.69	11.81	8.11	5.57
	Service	19.58	29.08	15.58	3.10	0.91
	Less than high school	6.52	11.53	0.00	0.00	0.00

Variable	Category	Full sample (%)	Analytic group [a]			
			1 (%)	2 (%)	3 (%)	4 (%)
Required level of education	High school or equivalent	49.98	88.47	0.00	0.00	0.00
	Post-secondary certificate	5.08	0.00	27.71	2.81	0.44
	Some college, no degree	0.63	0.00	2.58	1.10	0.35
	Associate's degree	3.94	0.00	11.55	6.10	8.91
	Bachelor's degree	27.50	0.00	54.11	65.46	72.49
	Graduate degree	6.36	0.00	4.06	24.54	17.82
Required work experience	None	18.49	30.37	3.31	3.58	2.19
	Up to 2 years	51.37	59.34	48.16	35.89	37.21
	Over 2 years, up to 6 years	27.51	9.58	44.72	54.96	54.20
	Over 6 years, up to 10 years	1.97	0.00	3.63	5.16	5.02
	Over 10 years	0.67	0.71	0.18	0.41	1.37
Level of on-the-job training	None or short demonstration	4.05	2.69	2.92	6.19	9.12
	Beyond short demonstration, up to 1 month	25.13	40.78	7.53	3.72	2.51
	Over 1 month, up to 1 year	68.16	54.83	85.68	84.60	86.15
	Over 1 year, up to 2 years	0.99	0.38	0.12	4.77	0.86
	Over 2 years, up to 4 years	0.78	0.26	3.52	0.31	0.02
	Over 4 years	0.87	1.06	0.24	0.40	1.34
Education level match/ mismatch	Undereducated	19.32	11.40	66.84	7.12	5.84
	Adequately Educated	37.45	31.40	16.84	63.55	62.76
	Overeducated	43.23	57.20	16.71	29.33	31.40
Field match/ mismatch	No Bachelor's Degree	64.45	84.41	100.00	0.00	0.00
	Matched	14.62	2.60	0.00	0.00	100.00
	Not Matched	20.94	12.99	0.00	100.00	0.00
Unweighted Sample N		*365,315*	*199,265*	*60,550*	*53,862*	*51,638*

[a] Groups: 1=No required education; 2=Education required, has less than Bachelor's; 3=Education required, field mismatch; 4=Education required, field match.

The mean and range of the numeric variables are presented in Table 8. The mean age of subjects was 29.9 and ranged from 25 to 35 (as expected). The skill and ability variables were measured on a 5-point importance rating scale from not important (1) to extremely important (5) and then averaged to represent the skill and ability groups presented. The range on the measures suggests that no skill or ability groups were found to be not important or extremely important for an occupation, thus the range in the variables was slightly truncated. There were also some missing data on these measures, with 7,785 fewer cases used to estimate the distribution, which I will discuss in the next section. Across the sample, the yearly income ranged from -$11,800 to $1,027,000, and the average participant earned $35,448. The earnings potential, or the occupational potential for earning over $45,000, ranged from 3% to 97%, and the average was 41%. The prestige score, measured on a 0-100 scale, exhibited nearly the full range in the current sample. The average prestige score was approximately 46.

Table 8

Sample Distribution Within Numeric Variables

Variable	N	Mean	SD	Min	Max
Age	365315	29.93	3.17	25.00	35.00
Cognitive abilities	357530	2.90	0.29	1.79	3.59
Physical abilities	357530	1.80	0.60	1.00	3.61
Psychomotor abilities	357530	2.07	0.57	1.07	3.57
Sensory abilities	357530	2.28	0.25	1.45	3.53
Basic skills	357530	2.98	0.41	1.91	3.93
Complex problem solving skills	357530	3.02	0.42	1.88	4.38
Resource management skills	357530	2.37	0.45	1.25	4.06
Social skills	357530	2.97	0.42	1.50	3.96

Variable	N	Mean	SD	Min	Max
Systems skills	357530	2.70	0.51	1.63	4.25
Technical skills	357530	1.71	0.44	1.02	3.25
Income (in dollars)	365315	35448.01	37935.59	-11800.00	1027000.00
Earnings potential	365315	40.83	26.83	3.19	96.51
Occupational prestige	365315	46.49	25.82	5.24	97.24

Table 9 also presents the means and standard deviations of the numeric variables by analytic group . The average importance of cognitive abilities, basic skills, complex problem solving skills, resource management skills, and system skills successively increases across the groups, from 1 (No education required) to 4 (education required, field match); and the average importance of physical abilities and psychomotor abilities decreases across the groups. The remaining skills and abilities—sensory abilities, social skills, and technical skills—do not exhibit large or systematic differences between the groups. Finally, the three indicators of economic success—income, earnings potential, and occupational prestige—exhibit increases in average values with each successive group.

Table 9

Analytic Group Distribution Within Numeric Variables

Variable	Mean (SD) by analytic group [a]			
	1	2	3	4
Age	29.75 (3.3)	30.15 (3.2)	30.21 (3.0)	30.14 (3.0)
Cognitive abilities	2.72 (0.2)	3.07 (0.2)	3.17 (0.2)	3.19 (0.1)
Physical abilities	2.33 (0.5)	1.96 (0.6)	1.62 (0.4)	1.58 (0.4)
Psychomotor abilities	2.05 (0.5)	1.68 (0.5)	1.39 (0.4)	1.37 (0.4)
Sensory abilities	2.30 (0.3)	2.31 (0.2)	2.23 (0.2)	2.22 (0.1)
Basic skills	2.70 (0.3)	3.23 (0.3)	3.39 (0.2)	3.43 (0.2)

Complex problem solving skills	2.77 (0.4)	3.17 (0.4)	3.27 (0.3)	3.25 (0.3)
Resource management skills	2.72 (0.3)	3.27 (0.3)	3.48 (0.3)	3.49 (0.2)
Social skills	1.69 (0.4)	1.84 (0.5)	1.66 (0.3)	1.66 (0.3)
Systems skills	2.36 (0.3)	3.01 (0.4)	3.21 (0.3)	3.23 (0.3)
Technical skills	2.17 (0.4)	2.60 (0.4)	2.63 (0.4)	2.62 (0.3)
Income (in thousands)	25.22 (26.0)	35.45 (32.4)	56.63 (53.7)	57.49 (45.1)
Earnings potential	24.23 (16.9)	51.89 (23.8)	66.59 (18.5)	71.37 (14.8)
Occupational prestige	29.97 (16.7)	59.46 (18.6)	70.24 (17.6)	76.34 (15.8)
Unweighted Sample N [b]	*199,265*	*60,550*	*53,862*	*51,638*

[a] Groups: 1=No required education; 2=Education required, has less than Bachelor's; 3=Education required, field mismatch; 4=Education required, field match.
[b] The N for the ability and skill measures was lower due to missing data. They are instead 192,396, 60,324, 53,303, and 51,507 respectively for groups 1-4.

Correlations

Table 10 presents the correlations between the indicators of economic success. Each measure is moderately to strongly related to the other measures, but none of the correlations exceeded .80. This indicates that although the measures are related, they do not measure the same thing. Each targets a different aspect of economic success.

Table 10

Correlations Among Indicators of Economic Success

Variables	1	2
1. Log Income	--	--
2. Earnings potential	0.50	--
3. Occupational prestige	0.41	0.78

In order to get a sense of the relationship between each latent class predictor variable and the latent class indicators, correlations were computed. Categorical variables were dummy coded for inclusion in this analysis, with correlations computed for each category compared to all other categories within a variable (e.g., White vs all other race/ethnicity categories). The results are presented in Table 11 and correlations exceeding .30 are flagged with an asterisk (*). As expected, there is a lot of variance in the correlations at the sample level, and many are zero or small in magnitude. However, there were some larger patterns. The largest correlations were seen among the skill and ability variables. Cognitive abilities and most skills had moderate to large positive correlations with the indicators. In contrast, physical abilities and psychomotor abilities had moderate negative associations with the indicators. A number of other variables and/or variable categories also had moderate size correlations with the economic success indicators. A few of the conditions that resulted in moderate positive associations with at least one indicator are as follows: studying science and engineering; working in a field related to bachelor's field; working in an occupation requiring over 2 years and up to 6 years of work experience, and over 1 month and up to 1 year of on-the-job training.

Table 11

Correlations Between Class Predictors and Indicators of Economic Success

Main variable	Category/Related variables	Log income	Earnings potential	Occupational prestige
Race/ Ethnicity	White	0.08	0.08	0.07
	Black	-0.10	-0.11	-0.09
	Asian & Pacific Islander	0.06	0.12	0.10
	Hispanic	-0.06	-0.11	-0.11
	Native American	-0.03	-0.03	-0.03
	Multiracial	-0.02	-0.01	-0.01
	Other	0.00	0.00	0.00
Gender	Male	0.15	0.09	-0.07
Attained education	Less than high school	-0.17	-0.22	-0.22
	High school or equivalent	-0.16	-0.26	-0.28
	Some college, no degree	-0.10	-0.16	-0.14

Main variable	Category/Related variables	Log income	Earnings potential	Occupational prestige
	Associate's degree	0.00	-0.01	0.02
	Bachelor's degree	0.20	0.30*	0.28
	Graduate degree	0.24	0.35*	0.36*
Bachelor field of study	Arts, Humanities, and Other	0.09	0.14	0.14
	Business	0.17	0.18	0.13
	Education	0.03	0.08	0.17
	Science and Engineering	0.21	0.33*	0.30*
	Science and Engineering Related Fields	0.09	0.17	0.18
Major occupational group	Computer, Engineering, & Science	0.19	0.38*	0.30*
	Education, Legal, Community Service, Arts, & Media	0.04	0.17	0.36*
	Healthcare Practitioners & Technical	0.12	0.23	0.37*
	Management, Business, & Financial	0.23	0.42*	0.24
	Military Specific	0.03	0.01	0.08
	Natural Resources, Construction, & Maintenance	-0.01	-0.05	-0.11
	Production, Transportation, & Material Moving	-0.07	-0.13	-0.25
	Sales and Office	-0.11	-0.21	-0.31
	Service	-0.24	-0.48*	-0.30*
Required level of education	Less than high school	-0.14	-0.27	-0.24
	High school or equivalent	-0.28	-0.56*	-0.60*
	Post-secondary certificate	-0.02	-0.08	0.04
	Some college, no degree	-0.04	-0.09	0.01
	Associate's degree	0.08	0.20	0.24
	Bachelor's degree	0.30*	0.59*	0.49*
	Graduate degree	0.14	0.30*	0.36*

Main variable	Category/Related variables	Log income	Earnings potential	Occupational prestige
Required work experience	None	-0.18	-0.28	-0.34*
	Up to 2 years	-0.15	-0.32*	-0.14
	Over 2 years, up to 6 years	0.28	0.53*	0.38*
	Over 6 years, up to 10 years	0.12	0.21	0.15
	Over 10 years	0.05	0.10	0.09
Level of on-the-job training	None or short demonstration	0.00	0.07	0.15
	Beyond short demonstration, up to 1 month	-0.29	-0.48*	-0.48*
	Over 1 month, up to 1 year	0.23	0.36*	0.34*
	Over 1 year, up to 2 years	0.09	0.14	0.11
	Over 2 years, up to 4 years	0.02	0.04	0.01
	Over 4 years	0.04	0.07	0.06
Education level match/mismatch	Undereducated	-0.06	0.12	0.08
	Adequately Educated	0.09	0.15	0.12
	Overeducated	-0.04	-0.25	-0.18
Field match/mismatch	Matched	0.14	0.30*	0.32*
Age	--	0.16	0.09	0.07
Ability	Cognitive abilities	0.43*	0.79*	0.81*
	Physical abilities	-0.25	-0.47*	-0.41*
	Psychomotor abilities	-0.17	-0.36*	-0.36*
	Sensory abilities	0.09	0.12	0.07
Skill	Basic skills	0.40*	0.76*	0.83*
	Complex problem solving skills	0.44*	0.82*	0.79*
	Resource management skills	0.34*	0.59*	0.52*
	Social skills	0.25	0.47*	0.54*
	Systems skills	0.44*	0.81*	0.79*
	Technical skills	0.13	0.21	0.12

Main variable	Category/Related variables	Log income	Earnings potential	Occupational prestige
Analytic Group	No required education	-0.35*	-0.70*	-0.73*
	Education required, has less than Bachelor's	0.03	0.19	0.23
	Education required, field mismatch	0.22	0.38*	0.36*
	Education required, field match	0.26	0.44*	0.45*

* Correlation coefficients ≥ .30.

Missing Data

The sample included complete data for all variables except the occupational skill and ability measures. As described in Appendix A, 24 of the 539 census occupations did not have occupational skill and ability data available in the external source (O*NET). This resulted in a univariate pattern of missing data that encompassed 2.1% of the sample (7,785 cases). Because the data were missing for specific occupations, the missing pattern could be attributed the occupation. Additionally, with the exception of the military occupations, the O*NET database intends eventually to include ratings for all of the occupations with missing data. The database has expanded slowly to include more occupations each year as funds have become available. Thus, it can be expected that the occupations that do not currently have skill and ability data should not be systematically different from the other occupations, particularly on the latent indicators. In order to review this assumption, the occupations were examined and the cases containing missing data were compared to those without. The occupations containing missing data are presented in Table 12 and the comparisons on the latent indicators are presented in Table 13.

Table 12

Census Occupations with Missing Skill and Ability Data

Census 2010 occupational code and job title	*N* in ACS data	Median income (from ACS)	Earnings potential	Occupational prestige
0030 - Legislators	0	--	87.0	76.0
1660 - Life scientists, all other	0	--	81.7	65.0
2060 - Religious workers, all other	168	22,715	33.6	27.8
2760 - Entertainers and performers, sports and related workers, all other	129	29,876	42.2	8.6
2960 - Media and communication equipment workers, all other	0	--	57.4	44.4
3245 - Therapists, all other	575	34,590	50.7	82.5
3730 - First-line supervisors of protective service workers, all other	147	44,060	51.9	39.8
4160 - Food preparation and serving related workers, all other	0	--	3.8	23.0
4650 - Personal care and service workers, all other	344	16,543	12.8	5.6
4965 - Sales and related workers, all other	627	43,541	56.5	25.6
5030 - Communications equipment operators, all other	39	32,654	40.8	25.9
5165 - Financial clerks, all other	267	54,512	46.5	33.5
5420 - Information and record clerks, all other	241	30,690	28.8	38.6
5940 - Office and administrative support workers, all other	1605	32,340	34.1	5.6
7855 - Food processing workers, all other	331	26,241	19.0	24.6
8220 - Metal workers and plastic workers, all other	914	28,526	24.7	46.5
8460 - Textile, apparel, and furnishings workers, all other	52	22,278	27.0	26.5
8550 - Woodworkers, all other	49	28,688	22.6	35.5

Census 2010 occupational code and job title	*N* in ACS data	Median income (from ACS)	Earnings potential	Occupational prestige
9150 - Motor vehicle operators, all other	53	22,357	15.7	24.6
9750 - Material moving workers, all other	119	30,507	35.7	17.4
9800 - Military officer special and tactical operations leaders	173	51,748	70.5	95.5
9810 - First-line enlisted military supervisors	422	48,187	66.4	84.7
9820 - Military enlisted tactical operations and air/weapons specialists and crew members	435	36,652	19.0	52.5
9830 - Military, rank not specified	1095	41,275	42.8	76.2

As displayed in Table 12, the occupations with missing data capture a variety of occupations that generally represent a wide range in the observed latent indicators. The majority of the occupation titles include the words "all other," thereby representing a category of other jobs within a particular field. A review of the occupations with data revealed that a number of the occupations representing "other jobs" in a field did have ability and skill data, thus all such jobs did not have missing data. In addition, most occupations with missing skill and ability data do have the data for other jobs in the minor or major occupational category. It is assumed that the skill and ability data for jobs within the same occupational categories would be similar.

Table 13 summarizes the results from two comparisons between the cases with complete data and the cases with missing data on the skill and ability variables. The first comparison, the Z-statistic, provides a test of statistically significant differences between the two distributions. It finds significant differences between the samples for each latent indicator. However, these results may be questionable because tests of statistical significance are known to be inflated by sample size (Thompson, 1993). With a sample of nearly 358,000 in one group and 8,000 in the other, small differences may be flagged as statistically significant even if they are not practically significant. Thus, the purpose of the second comparison is to evaluate practical significance. Hedges' G is an effect size that provides an indication of the magnitude of the difference in sample means, after accounting for differences in sample size and variance. The effect size is measured on a scale from 0 to 1 and values close to 0 suggest no relative difference. The results from this second comparison propose that there are no practical differences between the two sets of data on the three latent indicators.

Table 13

Comparison of ACS Cases With and Without Missing Data

Variable	Contain complete data (n=357,530)			Contain missing data (n=7,785)			Comparisons	
	Mean	SD	SE [a]	Mean	SD	SE [a]	Z [a]	Hedges' G
Log income	10.55	6.94	0.01	10.60	6.11	0.02	-2.58*	-0.01
Earnings potential	40.89	292.76	0.42	37.64	155.49	0.81	3.57**	0.01
Occupational prestige	46.63	278.67	0.57	39.72	311.79	1.38	4.62**	0.02

[a] Corrected standard errors were computed according to the ACS documentation (U.S. Census Bureau, 2014) using the person weight in conjunction with replicate weights. The subsequent Z statistic was computed as $(M_1-M_2)/\text{sqrt}(SE_1^2+SE_2^2)$.
Note. *$p < .01$, ** $p < .001$.

As a whole, these results suggest that the skill and ability data are missing at random (MAR). Although it is not believed that the missing data have a systematic relationship with the latent indicators, it is known that the missingness is based on occupation and related to other occupational measures in the model (e.g., major occupational group, required level of education). Thus, even if there is a relationship between the missingness and latent indicators, it is believed that the other variables in the model can be used to understand the difference. Because the data are believed to be MAR, multiple imputation was used to estimate missing data. Multiple imputation is known to provide robust estimates in instances where missing data are MAR or missing completely at random (MCAR; Enders, 2010). Ten datasets were imputed from available information on income, earnings potential, occupational prestige, major occupational category, and occupational skill and ability data. This step was conducted for all of the data prior to model estimation as Mplus does not permit use of multiple imputation for indirect predictor variables during LCA estimation.

Research Question 1: Rate of Mismatch

The first research question was addressed through examination of educational level match and field match. Rates of match were examined by attained education level to provide context for the results. The correspondence between the two types of match also were examined to understand rates of field mismatch and education level mismatch. Confidence intervals were computed for all estimates through use of replicate weights.

Table 14 presents the rates of educational level match . Only 37.5% of the sample was found to be appropriately educated for their occupation. The majority (43.2%) were considered to be overeducated, and another 19.3% were considered to be undereducated. These rates were found to vary by level of attained education. As might be expected, rates of undereducation generally decreased as attained education level increased. However, rates of adequate education and overeducation varied by education level. Individuals with a high school diploma or equivalent or a bachelor’s degree experienced the highest rates of being employed in occupations for which they were considered adequately educated (77.4% and 53.1%, respectively). In contrast, individuals with some college but no degree, an associate's degree, or a graduate degree experienced the highest rates of being overeducated for their job (77.4%, 64.4%, and 64.7%, respectively).

Table 14

Educational Level Match by Attained Education

Attained education	Percent of education level match and 95% CI			% of sample
	Undereducated	Adequately educated	Overeducated	
Less than high school	81.38 (77.8, 84.9)	18.62 (15.1, 22.2)	0.00 (0.0, 0.0)	9.05
High school or equivalent	12.49 (11.5, 13.5)	77.35 (76.7, 78.0)	10.16 (9.5, 10.8)	22.82
Some college, no degree	21.90 (21.0, 22.8)	0.75 (0.6, 0.9)	77.35 (76.3, 78.4)	23.25
Associate's degree	24.36 (22.6, 26.1)	11.28 (8.3, 14.2)	64.36 (62.7, 66.0)	9.33
Bachelor's degree	7.12 (6.8, 7.5)	53.10 (52.4, 53.8)	39.78 (39.0, 40.6)	24.39
Graduate degree	0.00 (0.0, 0.0)	35.31 (33.4, 37.2)	64.69 (62.8, 66.6)	11.16
Full Sample	**19.31** **(18.4, 20.2)**	**37.45** **(35.9, 39.0)**	**43.23** **(42.5, 43.9)**	**100.00**

There was some error introduced into this evaluation for occupations that generally required a post-secondary certificate. As summarized in the methods section, completing a post-secondary certificate was not captured as a level of attained education in the ACS survey, but it was captured as a required level of education in the occupational data. Thus, the next lowest level, having a HS diploma or equivalent, was considered as an adequate match for occupations that require a post-secondary certificate. In order to evaluate the impact this may have had on the results, the match was examined for the 5.1% of the occupation in occupations that generally required a post-secondary certificate. Among these individuals, 6.4% had less than a high school diploma or equivalent, 31.4% had a high school diploma or equivalent, 47.5% had some college but no degree, 16.1% had an associate's degree, 7.6% had a bachelor's degree, and 1.1% had a graduate degree. As mentioned in the methods section, some college was not considered an appropriate match due to the definition of post-secondary certificate in the occupational data and the specific nature of the question about attained education on the ACS survey. However, it is possible that some post-secondary certificate programs may not require a HS diploma or equivalent to participate. Therefore, the overall rates of education level match also were reviewed for a comparison where having less than a high school diploma was considered an adequate match for an occupation an occupation that required a post-secondary certificate. This comparison yielded identical percentages to those reported for the full sample in Table 14. These results suggest that the reduced level of accuracy surrounding the assignment of education level match to occupations that required a post-secondary certificate did not influence the results reported.

Table 15 presents the rates of educational field match. Overall, only 41.1% of individuals with a bachelor's degree or higher were working in an occupation that was evaluated to be related to their bachelor's degree field; the other 58.9% worked in an unrelated field. These rates of field mismatch were similar across individuals with a bachelor's degree and those with a graduate degree. Approximately 59.5% of bachelor's degree holders and 57.5% of graduate degree holders demonstrated field mismatch. However, it is important to note that mismatch was evaluated based on bachelor's degree field, thus rates of mismatch among those with graduate degrees may be different if they were computed based on graduate degree field.

Table 15

Educational Field Match by Attained Education

Attained education	Percent of educational field match and 95% CI			% of sample
	No Bachelor's degree	Field mismatch	Field match	
Bachelor's degree	--	59.54 (58.2, 60.9)	40.46 (39.1, 41.8)	24.39
Graduate degree[a]	--	57.46 (53.5, 61.5)	42.54 (38.5, 46.5)	11.16
Bachelor's or higher	--	58.89 (56.7, 61.0)	41.11 (39.0, 43.3)	35.55
Full Sample	**64.45 (63.3, 65.6)**	**20.94 (20.7, 21.2)**	**14.62 (13.4, 15.8)**	**100.00**

[a] Field match was evaluated for individuals with graduate degrees based on their Bachelor's degree field.

Table 16 presents the correspondence between the two types of education and occupation match. These results only are presented for the subset of the sample with a Bachelor's degree or more because field match only could be examined for this group. As displayed in the table, 23.3% of individuals with Bachelor's degree or more were working in an occupation related to their field of study and in a position that required the level of education they had obtained. In contrast, 31.8% were working in an occupation unrelated to their field of study and for which they were overeducated. Only 2.7% were working in an unrelated field and in a position for which they were undereducated.

Table 16

Education Level and Field Match Among Bachelor and Graduate Degree Holders

	Percent of bachelor/graduate degree holders and 95% CI	
Education level match	Field match	Field mismatch
Undereducated	2.17 (2.0, 2.3)	2.72 (2.6, 2.9)
Adequately Educated	23.27 (22.8, 23.8)	24.26 (23.9, 24.6)
Overeducated	15.79 (15.2, 16.4)	31.79 (31.4, 32.2)

Research Question 2: Latent Classes

The second research question was addressed through LCA. Prior to analysis, several steps were taken to prepare the data for analysis. First, the latent indicators of economic success were transformed into z-scores, with a mean of 0 and a standard deviation of 1, to allow easier within and across model comparison and interpretation of results. Z-scores for the log income were computed across the sample of employed 25 to 35 year olds to represent the range of income across participants. Z-scores for earnings potential and occupational prestige were computed at the occupational level, across the 539 occupations captured in the current study, in order to represent the range across occupations as opposed to people.

Next, the full sample was randomly split into two samples to be used for the cross-validation of results. The sample was split into two samples using uniform random sampling, with the sample stratified by analytic group. This resulted in the samples outlined in Table 17. The LCA then was conducted on Sample 1 for each analytic group, and the results were confirmed in the corresponding Sample 2. The model solution that performed the best across both samples was replicated on the full sample. Although these were generally done as separate steps, the results for each are presented together for easier cross-sample comparison.

Table 17

Cross-Validation Samples

Analytic group	Sample 1	Sample 2	Total
1. No required education	99,633	99,632	199,265
2. Education required, has less than Bachelor's	30,275	30,275	60,550
3. Education required, field mismatch	26,931	26,931	53,862
4. Education required, field match	25,819	25,819	51,638

The results for each of the five models are presented below. Models 1 through 4 examined latent classes within the analytic groups, or subsets of the sample, outlined in Table 17. Model 5 examined the latent classes that span all of the analytic groups. For each model, the model-level fit statistics (i.e., BIC, Entropy, and adjusted LMR) are presented first followed by a summary of class-level results (average classification accuracy, composition of latent classes, posterior distribution of latent classes). The model-level results are presented for all of the samples (Sample 1, Sample 2, and the full sample), whereas the class-level results are primarily presented for Sample 1 with an indicator of solution replicability. The final solution is identified in bold within each table. The last table presented summarizes the class-level fit statistics for the final solution across all of the samples.

Throughout this section and the remainder of the dissertation, latent classes are identified and represented through a coding of the mean latent indicator values within each class. As mentioned above, the latent indicators were standardized to have a mean of 0 and a standard deviation of 1 prior to entry in the model. Thus, the mean results for a class reflect the relative level of a variable in the group compared to the entire sample. For the purpose of this study, standardized mean values equal to or below 0.50 standard deviations below the mean are categorized as **L**ow; standardized mean values between 0.50 standard deviations below the mean and 0.50 standard deviations above the means are categorized as **A**verage; and standardized mean values equal to or above 0.50 standard deviations above the mean are categorized as **H**igh. Using this classification scheme, the mean values of each latent indicator within a class was identified using a three-character code. The first character corresponds to the level of income, the second the second to the level earnings potential, and the last to the level of occupational prestige. For example, a code of LAH would represent a latent class with low levels of income, average levels of earnings potential, and high levels of occupational prestige. This coding system was used for easier identification of class composition and cross model comparison.

Model 1: No Required Education

Table 18 presents the fit statistics for the iterative estimations of Model 1. The models with three and five classes exhibited generally good model-level fit in Sample 1, with the five-class solution exhibiting slightly better fit. The model-level results were slightly different in Sample 2. The four- and five-class solutions exhibited better fit in this second sample.

Table 18

Model 1 Fit Statistics

Sample	Class size	BIC	Entropy	Adjusted LMR	p-value
1	2	596491.15	0.77	49102.61	<0.001
	3	570184.15	0.83	25792.77	<0.001
	4	570109.92	0.86	117.71	0.169
	5	**542123.22**	**0.92**	**4489.51**	**<0.001**
	6	538226.35	0.80	3859.09	<0.001
	7	532749.35	0.86	4810.12	<0.001
	8	537371.78	0.86	119.86	0.087
2	2	595795.86	0.77	49231.04	<0.001
	3	570331.52	0.82	24968.03	<0.001
	4	546783.16	0.90	23092.78	<0.001
	5	**542212.24**	**0.92**	**4518.80**	**<0.001**
	6	538188.26	0.80	5054.41	<0.001
	7	532610.62	0.87	4529.92	<0.001
	8	530779.08	0.87	5928.46	<0.001
Full	2	1192203.67	0.77	98449.23	0.333
	3	1140425.08	0.83	50786.89	<0.001
	4	1138697.44	0.86	1740.78	<0.001
	5	**1084144.48**	**0.92**	**9013.95**	**<0.001**
	6	1076190.17	0.80	7842.45	<0.001
	7	1065105.80	0.87	9359.23	<0.001
	8	1074052.91	0.86	0.00	0.500

Table 19 presents a summary of the class-level fit indicators. Based on the model-level fit statistics, I reviewed the three-, four-, and five-class solutions for class-level fit. The three-class solution captured the three uniform classes proposed a priori: C1) LLL; C2) AAA; and C3) HHH (see Table 5). The four-class solution was generally similar to the three-class solution, with the LLL class in the prior solution splitting into two distinct

LLL classes (one with lower income levels) in the latter. This solution did not replicate in Sample 2 (indicated by the asterisk presented in Column 1) and generally was not considered theoretically plausible because it contained a latent class representing less than 0.1% of the sample with an average income eight standard deviations below the mean.

Next, the five-class solution introduced two additional classes not in previous solutions: C3) ALH; and C4) ALA. These classes captured approximately 1.6% and 12.7% of the sample, respectively (based on the posterior distribution), and both contained combinations of economic success of theoretical interest. The third class, ALH, is conceptually similar to a class proposed a priori: individuals in prestigious occupations but low income and little potential (LLH). The fourth class was not proposed a priori, but represents individuals who generally experience average earnings and prestige but who are in occupations that are associated with lower than normal earnings. In this way, these individuals may be experiencing higher levels of economic success than is normal for their occupations. Finally, the average classification accuracy was relatively high for the five-class solution, indicating that about 93.1% of the sample would be correctly classified based on the solution.

Table 19

Model 1 Class-Level Results for Sample 1

Class size	Average classification accuracy	Latent class composition [a] (Income, earnings potential, & occupational prestige)						
		1	2	3	4	5	6	7
2	90.0%	LLL (76.5%)	AAA (23.5%)					
3	92.2%	LLL (64.5%)	AAA (31%)	HHH (4.6%)				

Class size	Average classification accuracy	Latent class composition [a] (Income, earnings potential, & occupational prestige)						
		1	2	3	4	5	6	7
4*	94.2%	LLL (<0.1%)	AAA (31.0%)	LLL (64.5%)	HHH (4.6%)			
5	**93.1%**	**LLL (61.7%)**	**AAA (19.9%)**	**ALH (1.6%)**	**ALA (12.7%)**	**HHH (4.2%)**		
6	88.8%	LLL (39.0%)	AAA (18.1%)	ALH (1.8%)	ALA (12.4%)	HHH (4.1%)	ALL (24.7%)	
7	92.7%	ALH (1.7%)	ALA (8.1%)	LLL (36.6%)	ALL (26.9%)	LLA (5.6%)	AAA (17.0%)	HHH (4.2%)

[a] Latent indicators codes are presented to represent income, earnings potential, and occupational prestige, respectively. L=Low (≤.50 SD); A=Average (>-.50 SD and <.50 SD); H=High (≥.50 SD). Proportions are based on the posterior distribution.
Note. Solutions with an asterisk (*) presented next to the class size did not replicate in Sample 2.

The five-class solution was identified as the best-fitting solution across the five fit indices. This solution had the best overall model fit, was theoretically justifiable, and had results that replicated. Table 20 displays the class-level fit statistics for this model, across the samples. In general, the results replicated with only small differences in the various point estimates. This suggests a high degree of precision in the estimates and generalizability of the solution to other similar samples.

Table 20

Final Model 1 Class Solution Across Samples

Model characteristics		Latent class composition [a]				
	Sample	1: LLL	2: AAA	3: ALH	4: ALA	5: HHH
Proportion [b]	1	61.7%	19.9%	1.6%	12.7%	4.2%
	2	61.8%	20.1%	1.5%	12.4%	4.1%
	Full	61.7%	20.0%	1.6%	12.6%	4.2%
Classification Accuracy	1	97.7%	90.9%	88.6%	90.2%	98.1%
	2	97.7%	91.4%	88.1%	89.9%	97.7%

Model characteristics	Sample	Latent class composition [a]				
		1: LLL	2: AAA	3: ALH	4: ALA	5: HHH
	Full	97.7%	91.2%	88.4%	90.0%	97.9%
Indicator Means:						
Income	1	-0.52	0.15	-0.01	-0.36	0.60
	2	-0.52	0.17	0.04	-0.38	0.60
	Full	-0.52	0.16	0.02	-0.37	0.60
Earnings potential	1	-1.18	-0.18	-0.82	-0.96	0.83
	2	-1.18	-0.18	-0.82	-0.99	0.81
	Full	-1.18	-0.18	-0.82	-0.98	0.82
Occupational prestige	1	-1.10	-0.45	0.99	0.06	0.88
	2	-1.10	-0.45	0.98	0.06	0.88
	Full	-1.10	-0.45	0.98	0.06	0.88

[a] Latent indicators codes are presented to represent income, earnings potential, and occupational prestige, respectively. L=Low (≤.50 SD); A=Average (>-.50 SD and <.50 SD); H=High (≥.50 SD).
[b] Proportions are based on the posterior distribution.

Model 2: Education Required, has less than Bachelor's

Table 21 presents the fit statistics for the iterative estimations of Model 2. The models with three and seven classes generally exhibited the best model-level fit within each sample. The five-class solution in Sample 1 also demonstrated good model fit, but it showed a lower degree of desired change in the BIC (i.e., a larger decrease in value from the previous solution and small change in comparison to the latter solutions) than the other two class solutions.

Table 21

Model 2 Fit Statistics

Sample	Class size	BIC	Entropy	Adjusted LMR	p-value
1	2	214092.78	0.81	12453.36	<0.001
	3	**208677.25**	**0.83**	**5327.71**	**<0.001**
	4	205659.07	0.79	2987.08	<0.001

Sample	Class size	BIC	Entropy	Adjusted LMR	p-value
	5	202013.59	0.89	3414.72	<0.001
	6	199035.83	0.86	4155.70	<0.001
	7	194767.46	0.89	6639.84	<0.001
	8	194143.16	0.86	6566.11	<0.001
2	2	214239.89	0.81	12382.75	<0.001
	3	**209139.00**	**0.83**	**5020.52**	**<0.001**
	4	206709.43	0.81	2412.39	<0.001
	5	206395.37	0.75	23.03	0.314
	6	201857.01	0.85	2128.70	<0.001
	7	194742.90	0.93	9248.97	<0.001
	8	193787.48	0.88	7738.84	<0.001
Full	2	428251.10	0.81	24874.61	<0.001
	3	**417705.06**	**0.83**	**10354.98**	**<0.001**
	4	412792.84	0.81	4846.23	<0.001
	5	411541.14	0.82	4480.00	0.001
	6	398790.64	0.86	5841.79	<0.001
	7	390137.46	0.89	12803.71	<0.001
	8	386729.42	0.88	15677.01	<0.001

Table 21 presents a summary of the class-level fit indicators. Based on the model-level fit statistics, the class-level results for the three- and seven-class solutions in particular were scrutinized. The three-class solution captured one class proposed a priori: C2) AAA. The other two classes consisted of: C1) ALA; and C3) AHH. The latter class, AHH, is conceptually similar to a class proposed a priori: prestigious, low income with potential for more (LHH). Additionally, although the former class, ALA, was not proposed a priori, it is similar to a class that emerged from Model 1. Although the classification accuracy of the three-class solution is slightly lower than the two-class solution, the three-class solution offers a further conceptualization of the AAA and AHH classes that the two-class solution generally collapsed into the AHH class.

In comparison, the seven-class solution was not found to capture theoretically meaningful representations of economic success. Five of the seven classes captured individuals who were average on at least two of the latent indicators. Categorization of average in itself is not indicative of bad theoretical fit, but numerous categorizations including average might suggest overfitting of the model. Thus, although the seven-class solution exhibited good statistical fit, it did not exhibit good theoretical fit.

Table 22

Model 2 Class-Level Results for Sample 1

Class size	Average classification accuracy	Latent class composition [a] (Income, earnings potential, & occupational prestige)						
		1	2	3	4	5	6	7
2	94.2%	ALA (27.4%)	AHH (72.6%)					
3	**93.6%**	**ALA (20.2%)**	**AAA (37.1%)**	**AHH (42.7%)**				
4*	88.7%	ALA (19.4%)	AHA (32.7%)	AAA (29.6%)	AHH (18.3%)			
5*	92.7%	ALL (9.7%)	AAA (37.2%)	AHA (10.6%)	ALA (14.8%)	AHH (27.7%)		
6*	91.9%	ALL (8.5%)	AAA (22.2%)	AHA (28.0%)	ALA (11.4%)	AAH (7.9%)	AHH (22.1%)	
7	93.2%	ALL (8.1%)	ALA (11.8%)	AAH (7.1%)	AAA (19.9%)	AAL (6.0%)	AHH (21.2%)	AHA (25.9%)

[a] Latent indicators codes are presented to represent income, earnings potential, and occupational prestige, respectively. L=Low (≤.50 SD); A=Average (>-.50 SD and <.50 SD); H=High (≥.50 SD). Proportions are based on the posterior distribution.
Note. Solutions with an asterisk (*) presented next to the class size did not replicate in sample 2.

The three-class solution was the best fitting solution across the five fit indices. The solution had good model fit and was the most parsimonious solution. Table 23 presents the class-level fit statistics for this model, across the samples. Similar to Model

1, the results replicated with only minor differences in the various point estimates, suggesting a high degree of precision in the estimates and generalizability of the solution to other similar samples.

Table 23

Final Model 2 Class Solution Across Samples

Model characteristics		Latent class composition [a]		
	Sample	C1: ALA	C2: AAA	C3: AHH
Proportion [b]	1	20.2%	37.1%	42.7%
	2	20.6%	37.1%	42.3%
	Full	20.4%	37.1%	42.5%
Classification Accuracy	1	98.3%	90.1%	92.3%
	2	98.3%	89.8%	92.3%
	Full	98.3%	89.9%	92.3%
Indicator Means:				
Income	1	-0.42	-0.01	0.38
	2	-0.43	0.01	0.36
	Full	-0.42	0.00	0.37
Earnings potential	1	-1.24	0.06	1.04
	2	-1.24	0.05	1.03
	Full	-1.24	0.05	1.04
Occupational prestige	1	-0.14	0.39	0.76
	2	-0.14	0.39	0.74
	Full	-0.14	0.39	0.75

[a] Latent indicators codes are presented to represent income, earnings potential, and occupational prestige, respectively. L=Low (≤.50 SD); A=Average (>-.50 SD and <.50 SD); H=High (≥.50 SD).
[b] Proportions are based on the posterior distribution.

Model 3: Education Required, Field Mismatch

Table 24 presents the fit statistics for the iterative estimations of Model 3. The three- and six-class solutions show the largest dips in BIC and also exhibited relatively large entropy and adjusted LMR statistics across both samples. The five- and seven-class solutions also demonstrated reasonable fit, but they had slightly inferior fit according to examination of the change in the BIC.

Table 24

Model 3 Fit Statistics

Sample	Class size	BIC	Entropy	Adjusted LMR	p-value
1	2	185832.48	0.79	12297.86	<0.001
	3	179890.73	0.89	5839.45	<0.001
	4	177160.31	0.78	2704.93	<0.001
	5	175036.64	0.82	2112.70	<0.001
	6	**170961.47**	**0.85**	**3467.74**	**<0.001**
	7	168275.37	0.87	2661.68	<0.001
	8	168155.50	0.87	156.83	0.008
2	2	185290.38	0.79	12046.88	<0.001
	3	180733.50	0.81	4487.70	<0.001
	4	176552.61	0.78	4120.71	<0.001
	5	174528.10	0.82	2015.92	<0.001
	6	**170702.68**	**0.84**	**3387.33**	**<0.001**
	7	168322.50	0.86	2341.27	<0.001
	8	169817.65	0.85	-1738.58	1.000
Full	2	371034.48	0.79	24379.30	<0.001
	3	359088.07	0.89	11721.01	<0.001
	4	353490.47	0.89	5514.63	<0.001
	5	349385.17	0.82	4129.90	<0.001
	6	**341457.88**	**0.84**	**6866.38**	**<0.001**
	7	336164.23	0.86	5332.19	<0.001
	8	332554.80	0.87	8373.87	<0.001

Table 25 displays a summary of the class-level fit indicators. Based on the model-level fit statistics, the class-level results for the three-, four-, five-, and six-class solutions were considered. Of these four solutions, the average classification accuracy was highest for the three- and six-class solutions, although the four- and five-class solutions were not far below.

A review of the composition revealed that the three-class solution captured a uniformly high class and two uniformly average classes, one with a higher level of occupational prestige than the other (M_{C1}=-0.43, M_{C2}=0.48). Conceptually, these classes did not appear to be distinct enough to warrant separate comparison. Furthermore, the three-class solution did not replicate in Sample 2.

The four-class solution introduced three new classes: C1) ALA; C2) AAH; and C4) HHA: high income, high earnings potential, and average occupational prestige. The first class, ALA, has been observed in the previous two models, and the fourth class, HHA, is similar to a class that was proposed a priori: high earnings, low prestige (HHL). The five-class solution introduced the uniformly average class (proposed a priori) back into the solution, and the six-class solution further split the classes and removed the uniformly average class to introduce: C1) AAL; and C2) AHH. Although neither class was proposed a priori, both represent groups of theoretical interest. The AAL class represents individuals who have at least a bachelor's degree but work in occupations with low occupational prestige, and the AHH class represents individuals in occupations with high earnings potential and prestige, who may earn slightly less than others in their occupation.

Table 25

Model 3 Class-Level Results for Sample 1

Class size	Average classification accuracy	Latent class composition [a] (Income, earnings potential, & occupational prestige)						
		1	2	3	4	5	6	7
2	94.1%	AAA (40.5%)	HHH (59.5%)					
3*	94.2%	AAA (13.4%)	AAA (33.9%)	HHH (52.8%)				
4	88.9%	ALA (5.9%)	AAH (28.8%)	HHH (40.7%)	HHA (24.6%)			
5	88.6%	ALA (5%)	AAH (29.5%)	HHA (19.4%)	AAA (6.4%)	HHH (39.7%)		
6	**89.3%**	**AAL (5.7%)**	**AHH (21.8%)**	**HHA (19.3%)**	**ALA (5.1%)**	**AAH (16.4%)**	**HHH (31.6%)**	
7*	91.2%	ALA (4.9%)	AAA (4.8%)	AAH (16.2%)	HHA (18.0%)	AHH (15.4%)	HHH (20%)	HHH (20.7%)

[a] Latent indicators codes are presented to represent income, earnings potential, and occupational prestige, respectively. L=Low (≤.50 SD); A=Average (>-.50 SD and <.50 SD); H=High (≥.50 SD). Proportions are based on the posterior distribution.
Note. Solutions with an asterisk (*) presented next to the class size did not replicate in sample 2.

The six-class model solution was the best fitting model solution across the five fit indices. This model was more complex than others, but it exhibited good model fit across the samples, was theoretically justifiable, and included significant structural changes in class composition from the previous model, which led to improved model fit. Thus, although it is not the most parsimonious model, the classes each represent a distinct group of theoretical importance. Table 26 presents the class-level fit statistics for this model, across the samples. Similar to the previous two models, the results replicated with only small differences in the various point estimates, suggesting a high degree of precision in the estimates and generalizability of the solution to other similar samples.

Table 26

Final Model 3 Class Solution Across Samples

Model characteristics	Sample	Latent class composition [a]					
		C1: AAL	C2: AHH	C3: HHA	C4: ALA	C5: AAH	C6: HHH
Proportion [b]	1	5.7%	21.8%	19.3%	5.1%	16.4%	31.6%
	2	5.7%	22.2%	18.8%	5.1%	17.4%	30.9%
	Full	5.7%	22.0%	19.1%	5.1%	16.9%	31.3%
Classification Accuracy	1	83.8%	83.7%	89.6%	98.2%	86.5%	93.8%
	2	84.0%	83.9%	88.5%	98.2%	86.8%	93.8%
	Full	83.7%	83.8%	89.0%	98.2%	86.6%	93.8%
Indicator Means:							
Income	1	-0.01	0.30	0.75	-0.33	0.20	1.05
	2	-0.01	0.34	0.78	-0.30	0.21	1.05
	Full	-0.01	0.32	0.77	-0.31	0.20	1.05
Earnings potential	1	0.12	0.74	0.88	-1.16	0.07	1.55
	2	0.15	0.76	0.88	-1.17	0.08	1.56
	Full	0.14	0.75	0.88	-1.16	0.07	1.55
Occupational prestige	1	-0.51	1.29	0.20	-0.13	0.67	1.45
	2	-0.52	1.27	0.20	-0.09	0.68	1.46
	Full	-0.52	1.28	0.20	-0.11	0.68	1.46

[a] Latent indicators codes are presented to represent income, earnings potential, and occupational prestige, respectively. L=Low (≤.50 SD); A=Average (>-.50 SD and <.50 SD); H=High (≥.50 SD).
[b] Proportions are based on the posterior distribution.

Model 4: Education Required, Field Match

Table 27 presents the fit statistics for the iterative estimations of Model 4. The four-, five-, and seven-class solutions exhibited the best model fit on BIC, entropy, and adjusted LMR in Sample 1, and the four- and eight-class solutions exhibited the best fit in

Sample 2. Although the two- and three-class solutions generally yielded high entropy statistics, an evaluation of the change in BIC across models suggested that the introduction of additional classes greatly improved model fit.

Table 27

Model 4 Fit Statistics

Sample	Class size	BIC	Entropy	Adjusted LMR	*p*-value
1	2	152961.12	0.91	13313.85	<0.001
	3	149256.46	0.91	3655.34	<0.001
	4	**145292.82**	**0.95**	**4023.66**	**<0.001**
	5	142796.10	0.96	1981.09	<0.001
	6	141751.11	0.82	1059.55	<0.001
	7	137766.24	0.87	2159.20	<0.001
	8	136525.33	0.85	2235.09	<0.001
2	2	153936.48	0.91	13423.45	<0.001
	3	150244.04	0.90	3643.41	0.001
	4	**146311.20**	**0.95**	**3922.57**	**<0.001**
	5	143833.79	0.81	2457.57	<0.001
	6	143341.18	0.84	3073.81	<0.001
	7	140524.64	0.82	1809.29	<0.001
	8	137527.36	0.85	2306.13	<0.001
Full	2	306815.70	0.91	26774.74	<0.001
	3	295975.00	0.94	10639.02	<0.001
	4	**291457.08**	**0.95**	**4458.62**	**<0.001**
	5	286526.22	0.96	4119.53	<0.001
	6	285855.00	0.86	5560.71	<0.001
	7	280012.38	0.82	3925.91	<0.001
	8	273779.43	0.85	4535.73	<0.001

Table 28 displays a summary of the class-level fit indicators. Although the model-level results suggested potentially larger class solutions, the smaller class solutions were reviewed first to determine whether a larger class solution was theoretically plausible. The two-class solution introduced one class proposed a priori (uniformly high: HHH) and one not: HHA. This latter class was observed in the final solution for the previous model and is similar to a class that was proposed a priori: high earnings, low prestige (HHL). The three-class solution introduced an additional class that was not proposed a priori: AAH. Next, based on the model-level fit results, I evaluated the class-level results for the four-, five-, and six-class solutions. The four-class solution further refined and decomposed the HHA class and removed the AAH class to introduce two new classes: C1) HAH; and C3) ALA. Neither of these classes were proposed a priori, but the ALA class has been observed in each of the previous model solutions and represents a theoretically valuable class of individuals with high levels of education who experience average to low economic success. The latter solutions further decomposed the classes examined above. The uniformly high class is split into two distinct classes, one with higher levels of the latent indicators than the other. The low to average classes also are further decomposed. None of these solutions replicated in Sample 2; thus, they were not considered as final solutions.

Table 28

Model 4 Class-Level Results for Sample 1

Class size	Average classification accuracy	Latent class composition [a] (Income, earnings potential, & occupational prestige)						
		1	2	3	4	5	6	7
2	96.3%	HHA (28.8%)	HHH (71.2%)					
3	90.9%	AAH (6.2%)	HHA (22.8%)	HHH (71.0%)				

Class size	Average classification accuracy	Latent class composition [a] (Income, earnings potential, & occupational prestige)						
		1	2	3	4	5	6	7
4	**94.3%**	**HAH (21.1%)**	**HHA (9.5%)**	**ALA (1.4%)**	**HHH (68%)**			
5*	95.6%	HHH (20.3%)	AAL (1.1%)	HHA (9.1%)	ALH (1.6%)	HHH (67.9%)		
6*	88.8%	ALA (2.1%)	HHA (15.5%)	LHH (5.4%)	HHH (32.5%)	HHH (32.5%)	AAA (11.9%)	
7*	91.9%	HHA (8.6%)	HHH (29.6%)	AAA (15.3%)	ALH (1.6%)	AHH (35.7%)	AAL (1.2%)	HHH (8.0%)

[a] Latent indicators codes are presented to represent income, earnings potential, and occupational prestige, respectively. L=Low (≤.50 SD); A=Average (>-.50 SD and <.50 SD); H=High (≥.50 SD). Proportions are based on the posterior distribution.
Note. Solutions with an asterisk (*) presented next to the class size did not replicate in sample 2.

The four-class model solution was the best fitting model across the fit indices. The model exhibited good fit across the indices, was theoretically justifiable, and the solution replicated. Table 29 presents the class-level fit statistics for this model, across the samples. Similar to the previous three models, the results replicated with only small differences in the various point estimates. Again, this suggests a high degree of precision in the estimates and generalizability of the solution to other similar samples.

Table 29

Final Model 4 Class Solution Across Samples

Model characteristics		Latent class composition [a]			
	Sample	C1: HAH	C2: HHA	C3: ALA	C4: HHH
Proportion [b]	1	21.1%	9.5%	1.4%	68.0%
	2	21.5%	9.1%	1.4%	68.0%
	Full	21.3%	9.3%	1.4%	68.0%
Classification Accuracy	1	94.2%	93.7%	90.7%	98.7%
	2	93.8%	95.0%	93.3%	98.8%
	Full	94.1%	94.2%	91.9%	98.7%

Model characteristics	Sample	Latent class composition [a]			
		C1: HAH	C2: HHA	C3: ALA	C4: HHH
Indicator Means:					
Income	1	0.59	0.83	-0.36	0.68
	2	0.59	0.86	-0.29	0.67
	Full	0.59	0.84	-0.32	0.68
Earnings potential	1	0.49	0.97	-0.90	1.15
	2	0.48	0.97	-0.94	1.15
	Full	0.48	0.97	-0.92	1.15
Occupational prestige	1	0.54	-0.20	-0.33	1.47
	2	0.53	-0.21	-0.34	1.48
	Full	0.53	-0.21	-0.34	1.47

[a] Latent indicators codes are presented to represent income, earnings potential, and occupational prestige, respectively. L=Low (≤.50 SD); A=Average (>-.50 SD and <.50 SD); H=High (≥.50 SD). Proportions are based on the posterior distribution.
[b] Proportions are based on the posterior distribution.

Model 5: All Groups

The final model aimed to identify latent classes that might exist across the four analytic groups that have been separately modeled to this point. For this model, the analytic groups were entered as a known class. The class membership probabilities were permitted to vary across the groups because there are known differences in the latent indicators across the groups (see Table 9) and class membership is expected to vary. In addition, class means and variances were fixed across the analytic groups in order to identify distinct latent classes that spanned the groups.

Table 30 displays the fit statistics for the iterative estimations of Model 5. The adjusted LMR statistic is not presented as it is not available for multi-group models. Overall, the BIC generally suggests the four- and five-class solutions offer the best fit across the samples. In contrast, the entropy statistic identifies the two-class solution as having the best fit but suggests the other solutions have good fit as well.

Table 30

Model 5 Fit Statistics

Class size	Sample 1		Sample 2		Full Sample	
	BIC	Entropy	BIC	Entropy	BIC	Entropy
2	1622092.28	0.98	1624593.48	0.98	3246527.00	0.98
3	1587031.96	0.93	1588850.63	0.93	3175652.11	0.93
4	1549759.51	0.94	1552900.04	0.94	3102360.71	0.94
5	**1519899.61**	**0.95**	**1522399.00**	**0.95**	**3041924.07**	**0.95**
6	1501987.34	0.94	1504462.91	0.94	3006013.17	0.94
7	1491978.65	0.95	1494122.69	0.95	2985592.75	0.95
8	1484031.52	0.94	1486020.29	0.94	2969733.08	0.94

Table 31 presents a summary of the class-level fit indicators. Because the probabilities of class membership were permitted to vary across groups, the proportion of the sample within each latent class (based on the posterior distribution) is presented separately by group. The classification accuracy results also are averaged for the overall model and by group. Based on the model-level fit results, the class-level results for the two-, three-, four-, and five-class solutions were reviewed.

The two-class solution includes an average to low class and a uniformly high class. The three-class solution introduces a uniformly average class. The four-class solution further decomposes and refines the two average and average to low classes to include: C1) ALA; C2) ALL; and C3) AHA. These three classes were not proposed a priori, but each has theoretical value and represent a sizeable portion of the sample. The ALA class is the only class that has been observed in each of the previous models presented in the previous sections; the ALL class has been refined to have a mean income value just above the cut (M_{Income}=-0.46) and is thus close to representing a class proposed a priori (i.e., LLL); and the AHA class represents individuals with average economic success and high earnings potential. The five-class solution further redefines the classes to include a uniformly average and a uniformly low class in addition to the uniformly high. It also retains the previous two classes of interest: C1) AHA; and C5) ALA. The six-class solution further introduces an AHH class which represents approximately 5% of the overall sample.

Table 31

Model 5 Class-Level Results for Sample 1

Class size	Group	Average classification accuracy	Latent class composition [a] (Income, earnings potential, & occupational prestige)						
			1	2	3	4	5	6	7
2	1-4	94.8%	ALL	HHH					
	1	96.2%	53.6%	3.0%					
	2	95.5%	4.8%	11.9%					
	3	94.1%	1.0%	12.6%					
	4	93.6%	0.2%	12.9%					
3	1-4	86.6%	AAA	ALL	HHH				
	1	83.9%	5.0%	50.6%	0.9%				
	2	88.6%	9.8%	3.2%	3.7%				
	3	88.9%	5.1%	0.6%	8.0%				
	4	85.2%	2.5%	0.1%	10.5%				
4	1-4	87.4%	ALA	ALL	AHA	HHH			
	1	89.2%	13.8%	39.6%	1.9%	1.3%			
	2	90.1%	3.6%	1.3%	7.1%	4.7%			
	3	87.1%	0.8%	0.3%	4.9%	7.7%			
	4	83.5%	0.3%	<0.1%	3.3%	9.5%			

Class size	Group	Average classification accuracy	Latent class composition [a] (Income, earnings potential, & occupational prestige)						
			1	2	3	4	5	6	7
5	**1-4**	**89.6%**	**AHA**	**HHH**	**LLL**	**AAA**	**ALA**		
	1	90.2%	1.8%	1.3%	35.2%	10.9%	7.5%		
	2	92.3%	7.1%	4.5%	1.2%	1.2%	2.7%		
	3	89.4%	4.7%	7.4%	0.1%	0.9%	0.5%		
	4	86.4%	3.5%	9.3%	<0.1%	0.2%	0.2%		
6	1-4	88.1%	LLL	HHH	ALA	AAA	AAH	AHA	
	1	92.1%	35.0%	1.1%	7.3%	11.1%	0.4%	1.6%	
	2	90.6%	1.2%	3.2%	2.7%	1.2%	2.0%	6.5%	
	3	86.3%	0.2%	6.5%	0.4%	0.8%	1.8%	3.8%	
	4	83.6%	<0.1%	8.8%	0.2%	0.1%	0.8%	3.1%	
7	1-4	87.4%	LLL	AAA	ALA	AAH	HHA	AHA	HHH
	1	86.7%	34.9%	11.2%	7.3%	0.3%	0.2%	1.6%	1.1%
	2	91.1%	1.2%	1.1%	2.6%	1.5%	1.2%	6.0%	3.1%
	3	87.0%	0.2%	0.7%	0.4%	1.0%	0.9%	3.9%	6.5%
	4	84.9%	<0.1%	0.1%	0.2%	0.5%	1.1%	2.4%	8.8%

[a] Latent indicators codes are presented to represent income, earnings potential, and occupational prestige, respectively. L=Low (≤.50 SD); A=Average (>-.50 SD and <.50 SD); H=High (≥.50 SD). Proportions are based on the posterior distribution.
Note. Solutions with an asterisk (*) presented next to the class size did not replicate in sample 2.

Based on the above results, the five-class model solution was the best-fitting model. The model generally exhibited good fit according to the BIC, entropy, and classification accuracy statistics and the best fit according to theory. Table 32 presents a summary of the five-class solution results, across the samples; and Table 33 displays the final distribution of the sample across the classes. Similar to the previous models, the results replicated with only small differences in the various point estimates. Again, this suggests a high degree of precision in the estimates and generalizability of the solution to other similar samples.

Table 32

Final Model 5 Class Solution Across Samples

Model characteristics	Sample	Latent class composition [a]				
		C1: AHA	C2: HHH	C3: LLL	C4: AAA	C5: ALA
Proportion [b]	1	17.0%	22.5%	36.5%	13.1%	10.9%
	2	17.1%	22.3%	36.6%	13.3%	10.8%
	Full	17.0%	22.4%	36.5%	13.2%	10.8%
Average Classification Accuracy	1	91.4%	96.8%	79.9%	86.5%	93.4%
	2	91.2%	97.1%	81.7%	86.5%	93.0%
	Full	91.3%	97.0%	83.6%	86.4%	93.2%
Indicator Means:						
Income	1	0.42	0.62	-0.52	0.11	-0.33
	2	0.42	0.62	-0.53	0.13	-0.34
	Full	0.42	0.62	-0.52	0.12	-0.33
Earnings potential	1	0.58	1.09	-1.18	-0.20	-0.98
	2	0.58	1.08	-1.18	-0.20	-1.00
	Full	0.58	1.08	-1.18	-0.20	-0.99
Occupational prestige	1	0.32	1.40	-1.08	-0.49	0.22
	2	0.32	1.41	-1.08	-0.49	0.21
	Full	0.32	1.41	-1.08	-0.49	0.22

[a] Latent indicators codes are presented to represent income, earnings potential, and occupational prestige, respectively. L=Low (≤.50 SD); A=Average (>-.50 SD and <.50 SD); H=High (≥.50 SD).
[b] Proportions are based on the posterior distribution.

Table 33

Final Model 5 Posterior Distribution Across Groups and Classes

Group	Posterior distribution of classes					Total
	C1: AHA	C2: HHH	C3: LLL	C4: AAA	C5: ALA	
1	1.8%	1.2%	35.2%	10.9%	7.4%	56.5%
2	7.1%	4.5%	1.2%	1.2%	2.7%	16.8%
3	4.7%	7.4%	0.1%	0.9%	0.5%	13.6%
4	3.5%	9.3%	<0.1%	0.2%	0.2%	13.1%
Total	17.0%	22.4%	36.5%	13.2%	10.8%	

Summary: Levels of Economic Success and Comparison to the Norm

The series of analyses above identified latent classes of economic success that exist within the four analytical groups and the overall sample. Table 34 presents a summary of the classes that were identified in each model. The posterior distribution of class membership is presented as an indicator of class size and classes related to a priori class expectations are indicated. As displayed in the table, only a few of the class appeared in multiple models and the majority were related to classes proposed a priori. The ALA, AAA, and HHH classes appeared in three or more models while the remaining classes only appeared in one or two models. The classes that were not related to a priori class expectations either encompassed a large percentage of the distribution or represented a group of interest.

Table 34 also summarizes another trend of interest. The latent classes are presented in order of relative economic success levels, from low levels to high. The majority of classes in the first model represent average to low levels of economic success, the majority in the second represent average to high, and the majority in the third and fourth represent high levels. Within each model, there is at least one class that offers a deeply contrasting experience of economic success, such as the HHH class in the first model or the ALA class in the other three models. In addition, if one were only to examine the model with all of these groups, a very different view of economic success would be provided. This view would primarily be driven by subjects in the first model who encompass half of the overall sample and would mask some of the classes unique to specific analytic groups. For example, the AHH and HHA classes represent classes of a priori interest and are each observed in two of the four models, but not observed in the overall model.

Table 34

Summary of Latent Class Models

Latent class[a]	Distribution[b] of class membership by model					Related class proposed a priori
	1. No required education	2. Education required, has less than BA	3. Education required, field mismatch	4. Education required, field match	5. All groups	
LLL	61.7%	--	--	--	36.5%	LLL
ALA	12.7%	20.4%	5.1%	1.4%	10.8%	--
AAL	--	--	5.7%	--	--	--
ALH	1.6%	--	--	--	--	LLH
AAA	19.9%	37.1%	--	--	13.2%	AAA
AAH	--	--	16.9%	--	--	--
AHA	--	--	--	--	17.0%	--
AHH	--	42.5%	22.0%	--	--	LHH
HHA	--	--	19.1%	9.7%	--	HHL
HAH	--	--	--	21.3%	--	--
HHH	4.2%	--	31.3%	68.0%	22.4%	HHH

[a] Latent indicators codes are presented to represent income, earnings potential, and occupational prestige, respectively. L=Low (≤.50 SD); A=Average (>-.50 SD and <.50 SD); H=High (≥.50 SD).
[b] Percentages are based on the posterior distribution.

An additional examination of the results was necessary to fully address the second research question. The second research question aimed to identify latent classes representing individuals who succeed greater than or less than the group norm. To specifically address this question, the norm group was identified in each of the above models as the latent class which represented the largest proportion of group participants. Latent classes that captured individuals who succeed less than or greater than the norm were then identified based on a comparison of the mean values on the latent indicators. Table 35 provides a summary of the comparison. The distributions based on both the posterior distribution used for model building and the observed distribution based on most-likely class membership are presented in order to demonstrate the similarity between the two and assist with interpretation. The norm group is presented in bold for each model.

Table 35

Latent Classes Above and/or Below the Group Norm

Model	Norm?	Class [a]	Distribution		Mean latent indicators		
			Posterior	Observed	Income	Earnings potential	Occup. prestige
1. No required education	**Norm**	**LLL**	**61.7%**	**62.0%**	**-0.52**	**-1.18**	**-1.10**
	Above	ALA	12.7%	12.7%	-0.37	-0.98	0.06
		AAA	19.9%	19.7%	0.16	-0.18	-0.45
		ALH	1.6%	1.6%	0.02	-0.82	0.98
		HHH	4.2%	4.0%	0.60	0.82	0.88
2. Education required, has less than Bachelor's	**Norm**	**AHH**	**42.5%**	**43.3%**	**0.37**	**1.04**	**0.75**
	Below	ALA	20.4%	19.5%	-0.42	-1.24	-0.14
		AAA	37.1%	37.2%	-0.00	0.05	0.39
	Norm	**HHH**	**31.3%**	**30.7%**	**1.05**	**1.55**	**1.46**

Model	Norm?	Class [a]	Distribution		Mean latent indicators		
			Posterior	Observed	Income	Earnings potential	Occup. prestige
3. Education required, field mismatch	Below	AAL	5.7%	6.1%	-0.01	0.14	-0.52
		ALA	5.1%	5.0%	-0.31	-1.16	-0.11
		AAH	16.9%	17.4%	0.20	0.07	0.68
		AHH	22.0%	21.8%	0.32	0.75	1.28
		HHA	19.1%	18.9%	0.77	0.88	0.20
4. Education required, field match	**Norm**	**HHH**	**68.0%**	**68.5%**	**0.68**	**1.15**	**1.47**
	Below	ALA	1.4%	1.4%	-0.32	-0.92	-0.34
		HAH	21.3%	21.3%	0.59	0.48	0.53
		HHA	9.7%	8.8%	0.84	0.97	-0.21
5. All Groups	**Norm**	**LLL**	**36.5%**	**36.9%**	**-0.52**	**-1.18**	**-1.08**
	Above	ALA	10.8%	10.9%	-0.33	-0.99	0.22
		AAA	13.2%	12.7%	0.12	-0.20	-0.49
		AHA	17.0%	17.2%	0.42	0.58	0.32
		HHH	22.4%	22.3%	0.62	1.08	1.41

[a] Latent indicators codes are presented to represent income, earnings potential, and occupational prestige, respectively. L=Low (≤.50 SD); A=Average (>-.50 SD and <.50 SD); H=High (≥.50 SD).
Note. Classes identified as the norm for the model sample are presented in bold.

The class representing the norm within each analytic group fell on either the high or the low end of the economic success spectrum, never in the middle. In the first model containing individuals in occupations that required a HS diploma or less, the majority fell into the LLL class. All other classes identified within the group captured relatively higher levels of economic success: ALA, AAA, ALH, and HHH. Thus, although the majority who work in occupations with little to no education requirements experienced low levels of economic success, approximately 38% experience higher levels of economic success in some capacity. The opposite trend was seen among the other three analytic groups. The class representing the norm generally captured the highest levels of observed economic success and the other latent classes comparatively represented lower levels of economic success. These trends suggest that although higher levels of economic success may be the norm within these groups, approximately 32-67% experience relatively lower levels of success. Finally, the last model containing the full sample provided results similar to the first model. This is not surprising as the analytic group used in the first model contained over half of the full sample. The LLL group was identified as the norm and approximately 63% of the sample experienced comparatively higher levels of economic success. Taken together, these results emphasize the existence and considerable size of groups who experience different levels of economic success than the norm.

Research Question 3: Predicting Latent Class Membership

The third research question was addressed through examination of predictors of latent class membership. The final classes identified to address Research Question 2 were regressed on several demographic, educational, and occupational variables to understand class composition better. The predictors were modeled to have an indirect relationship with the latent classes so as to predict class membership without influencing the solution. The norm class (identified in Table 34) generally was used as the reference group in the interpretation of the results. This focused the examination on understanding experiences outside of the norm and the ways they contrast from the norm.

Two data transformation steps were necessary before the models were run. First, the categorical predictors had to be dummy coded for inclusion in the LCA model. The reference category (coded to represent the intercept in the model) was chosen based on the distribution of the variable across the latent classes. Categories that captured the largest proportion of the sample and were observed in each latent class were sought as reference categories to further permit comparisons to the norm and for the model to yield reasonable estimates. During the dummy coding process, any categories that contained 3% of a sample or less were collapsed with other categories before inclusion in the model. Some additional collapsing of categorical variables was done during the modeling process if zero or near zero cell counts in latent classes were observed. The final dummy coding scheme by model is presented in Appendix D. Second, the skill and ability variables were transformed to z-scores with a mean of 0 and a standard deviation of 2.[4] This standardization of the skill and ability measures permitted interpretation of the results in standard deviation units as opposed to the 5-point importance scale on which these scales are measured. Because these variables were measured at the occupational level, they also were transformed at the occupational level to represent to range across occupations as opposed to people.

Separate models were run for each of the educational and occupational variable predictor sets. Many of the predictor sets were correlated with one another, both in expected ways (e.g., attained education and education level match) and unexpected ways (e.g., job training and occupational field), and this approach allowed the overarching relationships to be observed without introducing confounding variables. In addition, each of the skill and ability measures were estimated in separate models. Several of the measures were correlated with one another at the sample level (see Appendix D) and even more so at the class level within a group. This frequently led to complete or quasi-separation of data and unreliable point estimates when the variables were modeled together. Thus, I modeled these variables separately in order to gain an understanding of

[4] A larger unit was used to represent the standard deviation because initial models produced extremely large log odds. The rescaling helped to reduce the log odds.

each variable's relationship with the latent classes. All of the models that were run included the demographic variables (age, sex, race/ethnicity) as control variables. This further allowed the models to identify relationships that exist above and beyond participant demographics. Table 36 presents a summary of the successive models that were run for each of the five overall models.

Table 36

Summary of Successive Models Run

Model and predictors		Models run within each overall model				
		1. No required education	2. Education required, has less than BA	3. Education required, field mismatch	4. Education required, field match	5. All groups
1	Demographics (age, gender, race/ethnicity)	X	X	X	X	X
Models controlling for demographics…						
2	Attained education	X	X	X	X	X
3	Bachelor field of study	--	--	X	X	X
4	Major occupational group	X	X	X	X	X
5	Required level of education	X	X	X	X	X
6	Required work experience	X	X	X	X	X
7	On-the-job training	X	X	X	X	X
8	Educational level match	X	X	X	X	X
9	Field match	X	--	--	--	X
10	Cognitive abilities	X	X	X	X	X
11	Physical abilities	X	X	X	X	X
12	Psychomotor abilities	X	X	X	X	X
13	Sensory abilities	X	X	X	X	X
14	Basic skills	X	X	X	X	X

Model and predictors		Models run within each overall model				
		1. No required education	2. Education required, has less than BA	3. Education required, field mismatch	4. Education required, field match	5. All groups
15	Complex problem solving skills	X	X	X	X	X
16	Resource management skills	X	X	X	X	X
17	Social skills	X	X	X	X	X
18	Systems skills	X	X	X	X	X
19	Technical skills	X	X	X	X	X
	Total models run	*18*	*17*	*17*	*17*	*19*

The results for the models are presented and reviewed below. Odds ratios are used as the primary statistic to interpret the results. In the current study, the odds ratios represent the odds of membership in a class based on a predictor value, compared to the norm or most frequently observed experience. Because the reference class and reference categories were determined based on what represents the norm, this allows some more general comparisons to the group norm to be made. Additionally, the odds ratios are used as indicators of practical significance. Although each of the odds ratios presented could be interpreted and are meaningful in their own way, I focus on odds ratios equal to or below 0.33 and equal to or above 3.0 when identifying the most important predictors of class membership. These ratios are associated with a 75% chance of not belonging to the class and a 75% chance of belong to the class, respectively. Therefore, I used them as cuts to identify predictors that have a high likelihood of discriminating between class membership. Together, these results are used to begin to understand the pathways to different latent classes. The log odds and standard errors for each model shown below, along with the distribution of the variables across the latent classes, are presented in Appendix D for reference.

Model 1: No Required Education

Table 37 presents the regression results to predict class membership among individuals in the first analytic group—individuals in occupations that do not require more than a HS diploma or equivalent. The LLL class, representing individuals with uniformly low levels of economic success, was the norm class and, thus, was used as the reference class for these comparisons. This means all results reflect odds of class membership in comparison to odds of membership in the LLL class. Within the table, reference categories for the categorical predictors are identified by an [R] next to the category name along with the percentage within the category. The percentage is provided as an indicator of the relative size and subsequent normativity of the reference group.

A number of overall trends can be observed about class membership in classes outside of the norm. In general, higher levels of attained education, required education, and on-the-job training were associated with non-LLL class membership. Some level of work experience also was associated with membership in three of the four non-LLL classes. However, individuals in occupations with no work experience requirements had slightly higher odds of belonging to the HHH class than the LLL class (*OR*=1.8). This contradicts expectation but a review of the distributions (see Appendix D) confirmed this trend. Finally, having a Bachelor's degree and working in the same field (compared to having a Bachelor's degree and working in an unrelated field), being overeducated, and working in an occupation with a higher importance of the skill and ability measures were all associated with higher odds of non-LLL membership.

Table 37

Odds Ratios to Predict Class Membership for Model 1

Model and variable(s)	Class comparisons: AAA vs. LLL	ALH vs. LLL	ALA vs. LLL	HHH vs. LLL
1. Demographics:				
Age	1.05*	0.98*	1.04*	1.11*
Male [R: 55.5%]	-----	-----	-----	-----
Female	0.35*	1.49*	**3.12***	**0.17***
White [R: 68.5%]	-----	-----	-----	-----
Black	0.65*	0.8*	1.12*	0.49*
Asian	0.81*	1.53*	1.01	0.56*
Hispanic	0.55*	0.36*	0.66*	0.34*
Other [a]	0.76*	0.89	1.02	0.73*
2. Attained education:				
Less than HS	0.57*	**0.08***	0.69*	0.43*
HS diploma or equiv. [R: 32.5%]	-----	-----	-----	-----
Some college, no degree	1.17*	2.87*	1.36*	2.11*
Associate’s degree	1.29*	**5.41***	1.60*	2.86*
Bachelor’s degree or more	1.48*	**4.41***	1.51*	**4.16***
3. Occupational group:				
Sales and Office [R: 33.7%]	-----	-----	-----	-----
Natural Resources, Construction, and Maintenance	2.06*	----[c]	2.82*	**7.76***
Production, Transportation, and Material Moving	2.54*	----[c]	0.55*	**8.31***
Service	**0.05***	----[c]	1.25*	**9.46***
Other [b]	----[c]	----[c]	----[c]	----[c]
4. Required level of education:				
Less than HS	0.54*	**0.21***	**0.00***	**0.16***
HS or equivalent [R: 88.5%]	-----	-----	-----	-----
5. Required work experience:				
None	**0.13***	0.66*	**0.28***	1.78*

Model and variable(s)	Class comparisons			
	AAA vs. LLL	ALH vs. LLL	ALA vs. LLL	HHH vs. LLL
More than none [R: 69.6%]	-----	-----	-----	-----
6. On-the-job training:				
None, up to 1 month	0.34*	**0.00***	0.46*	**0.05***
Over 1 month [R: 56.5%]	-----	-----	-----	-----
7. Education level match:				
Undereducation	0.58*	**0.01***	0.71*	**0.22***
Adequate education	0.82*	**0.31***	0.80*	0.40*
Overeducation [R: 57.2%]	-----	-----	-----	-----
8. Field match:				
No Bachelor's degree[d]	0.84*	0.49*	0.91*	0.44*
Mismatch [R: 13.0%]	-----	-----	-----	-----
Match	**4.01***	2.41*	**3.33***	**5.57***
9-12. Occupational abilities:				
Cognitive	**5.12***	2.47*	**3.08***	3.14
Physical	**4.60***	2.06*	2.87*	2.10*
Psychomotor	**4.85***	2.10*	2.83*	2.20*
Sensory	**4.87***	2.13*	2.91*	2.33*
13-18. Occupational skills:				
Basic	**5.09***	2.67	**3.20***	2.91
Complex problem solving	**5.34***	2.54*	**3.08***	3.61
Resource management	**5.08***	2.25*	**3.02***	2.35*
Social	**4.69***	2.16*	2.95*	2.30*
Systems	**5.44***	2.55*	**3.10***	2.92*
Technical	**4.95***	2.23*	2.89*	2.21*

[a] Other includes: Native American; Asian & Pacific Islander; and Other.
[b] Other includes: Education, Legal, Community Service, Arts, and Media; Healthcare Practitioners and Technical; Management, Business, and Financial; and Military Specific occupations.
[c] Cell counts for one or more categories were relatively small or zero and a reliable estimate could not be produced.
[d] Included as a control variable to estimate the relationship of interest.
Note. $*p<.05$. Statistically significant odds ratios ≥ 3.0 or ≤ .33 are presented in bold. Reference groups are identified with an [R] next to the variable name, along with the percentage in the sample. Demographic variables presented at the top of the table were included in all subsequent models as control variables.

Table 38 summarizes the largest predictors of membership within each non-LLL class. The summary includes statistically significant predictors with an odds ratio equal to or below 0.33 or equal to or above 3.00 (representing 75% likelihood of not belonging or belonging to a class, respectively). Furthermore, only statistically significant results are included because the non-significant results generally had larger estimates of associated error, thereby reducing confidence in the reliability of the results. Characteristics that were associated with only one class are identified with an asterisk (*). Finally, it is important to note that the relationships summarized reflect individual relationships between the predictors and classes. Many of the predictors are related to one another and when considered together, the results could be different. Thus, caution should be taken to interpret these results as the overarching relationship between each predictor and the classes, accounting for differences in demographics, but not accounting for the other predictor variables.

Table 38

Characteristics Associated with Model 1 Class Membership

Latent class (% of sample)	Characteristics associated with increased likelihood of membership: (Compared to membership in the LLL class - 61.7%)
ALA (12.7%)	– Female* – Occupation requires a HS diploma or equivalent – Occupation requires some level of work experience – Has a Bachelor's degree and is working in a related field – Occupation is associated with higher importance of cognitive abilities – Occupation is associated with higher importance of basic, complex problem solving, resource management, or systems skills

Latent class (% of sample)	Characteristics associated with increased likelihood of membership: (Compared to membership in the LLL class - 61.7%)
AAA (19.9%)	– Does not work in a service occupation – Occupation requires some level of work experience – Working in a related field as Bachelor's degree – Occupation is associated with higher importance of cognitive, physical, psychomotor, or sensory abilities* – Occupation is associated with higher importance of basic, complex problem solving, resource management, social, systems, or technical skills*
ALH (1.6%)	– Has an Associate's degree or more* – Does not have less than a high school diploma* – Works in a military specific or healthcare practitioners and technical occupation [a]* – Occupation requires a HS diploma or equivalent – Occupation requires more than 1 month of on-the-job training – Is overeducated for their occupation* – Working in a related field as Bachelor's degree
HHH (4.2%)	– Male* – Has a Bachelor's degree or more* – Works in a natural resources, construction, and maintenance; production, transportation, and material moving; or service occupation; but not in sales and office occupation* – Occupation requires a HS diploma or equivalent – Occupation requires more than 1 month of on-the-job training – Is not undereducated for their occupation* – Working in a related field as Bachelor's degree

[a] This characteristic was not flagged due to the odds ratio presented in Table 37, but was instead noticed during a confirmation of unreliable estimates due to low cell counts. A review of the distributions identified that 86.9% and 52.4% of cases in these respective occupations comprised 1.5% of the 1.6% of cases in this class.
Note. Only statistically significant odds ratios ≥ 3.0 or ≤ .33 are summarized in the above table. Characteristics flagged with an asterisk (*) were only associated with one class.

As displayed in Table 38, each of the classes have some distinguishing characteristics compared to the LLL class. The AAA class was the second largest class (19.9%) and individuals were more likely to belong to the class than the LLL class if they: did not work in a service occupation, worked in an occupation that has some experience requirements, or worked in an occupation that requires higher levels of a skill or ability. The ALA class was the third largest class (12.7%) and was generally similar to the AAA class, with the exception that females were more likely to belong to this class. Next, the ALH class was the smallest class (1.6%) and individuals were more likely to belong to the class if they: had at least an Associate's degree, worked in a military specific or healthcare practitioners and technical occupation, or were overeducated. Finally, the HHH class was the second smallest class (4.2%) and individuals who are male, have a Bachelor's degree or more, or work in a natural resource, construction, maintenance, production, transportation, material moving, or service occupation were more likely to be members.

Model 2: Education Required, has less than Bachelor's

Table 39 presents the regression results to predict class membership among individuals in the second analytic group—individuals with less than a Bachelor's degree who are in occupations that require more than a HS diploma or equivalent. The AHH class, representing individuals with respectively high levels of economic success, was the norm class and, thus, was used as the reference class for these comparisons. This means all results reflect odds of class membership in comparison to odds of membership in the AHH class. Similar to the presentation of model 1 results, the reference categories for the categorical predictors are identified by an [R] next to the category name along with the percentage within the category.

Overall, the two non-AHH classes shared some characteristics of class membership. Both classes were more likely to include individuals working in a service occupation and less likely to include individuals working in the following: computer, engineering, and science; healthcare practitioners and technical; management, business, and financial; natural resources, construction, and maintenance; and other occupational groups. Although odds ratios are not presented for several of these occupational groups for the ALA comparison, this conclusion can be made based on the observance of zero or near-zero rates of category membership within the ALA class (see Appendix D). In addition, the non-AHH classes had higher odds of including individuals who were overeducated or with lower levels of attained education; and individuals who were in occupations requiring a post-secondary certificate, some college, up to 2 years of work experience, or over 1 month of on-the-job training. They also were more likely to include individuals in occupations associated with lower importance of most occupational skills and cognitive ability, and higher importance of physical and psychomotor abilities.

Table 39

Odds Ratios to Predict Class Membership for Model 2

Model and variable(s)	Class comparisons	
	ALA vs. AHH	AAA vs. AHH
1. Demographics:		
Age	0.94*	0.96*
Male [R: 51.2%]	-----	-----
Female	**5.27***	0.86*
White [R: 73.6%]	-----	-----
Black	1.55*	1.16*
Asian	2.12*	0.80*
Hispanic	1.73*	1.28*
Other [a]	1.08	0.99
2. Attained education:		
Less than HS	2.45*	1.93*

Model and variable(s)	Class comparisons	
	ALA vs. AHH	AAA vs. AHH
HS diploma or equiv.	1.90*	1.49*
Some college, no degree [R: 42.8%]	-----	-----
Associate's degree	0.54*	0.63*
3. Occupational group:		
Education, Legal, Community Service, Arts, and Media [R: 14.3%] [b]	-----	-----
Computer, Engineering, and Science	----[c]	**0.01***
Healthcare Practitioners and Technical	----[c]	**0.14***
Management, Business, and Financial	----[c]	**0.02***
Natural Resources, Construction, and Maintenance	----[c]	**3.34***
Service	**>50.00***	**4.21***
Other [d]	----[c]	**0.19***
4. Required level of education:		
Post-secondary certificate or some college	**>50.00***	**>50.00***
Associate's degree	2.59*	0.92
Bachelor's degree [R: 54.1%]	-----	-----
Graduate degree	1.49*	1.78*
5. Required work experience:		
None	**0.00***	1.16
Up to 2 years [R: 48.2%]	-----	-----
Over 2 years	**0.04***	**0.32***
6. On-the-job training:		
None, up to 1 month	**4.69***	**5.72***
Over 1 month [R: 89.6%]	-----	-----
7. Education level match:		
Undereducation [R: 66.5%]	-----	-----
Adequate education	**5.70***	1.94*
Overeducation	**>50.00***	**39.85***
8-11. Occupational abilities:		
Cognitive	**0.09***	**0.33***

Model and variable(s)	Class comparisons	
	ALA vs. AHH	AAA vs. AHH
Physical	2.43*	2.20*
Psychomotor	1.81*	1.93*
Sensory	0.83*	2.23*
12-17. Occupational skills:		
Basic	**0.18***	0.38*
Complex problem solving	**0.05***	**0.24***
Resource management	**0.29***	0.80*
Social	0.61*	0.77*
Systems	**0.10***	**0.32***
Technical	0.88*	1.41*

[a] Other includes: Native American; Asian & Pacific Islander; and Other.
[b] The Management, Business, and Financial group contained the largest portion (23.8%) of the sample but was not observed in the ALA class thus the reference category was changed.
[c] Cell counts for one or more categories were relatively small or zero and a reliable estimate could not be produced.
[d] Other includes: Military Specific; Production, Transportation, and Material Moving; and Sales and Office occupations..
Note. *p<.05. Statistically significant odds ratios ≥ 3.0 or ≤ .33 are presented in bold. Reference groups are identified with an [R] next to the variable name, along with the percentage in the sample. Demographic variables presented at the top of the table were included in all subsequent models as control variables.

Table 40 summarizes the largest predictors of membership within the two non-AHH classes. Similar to the Model 1 presentation of results, this summary only includes statistically significant predictors with an odds ratio equal to or below 0.33 or equal to or above 3.00. Characteristics that were associated with only one class are identified with an asterisk (*). The ALA class was the smallest class (20.4%) and was distinct from the other non-AHH class because it had higher odds of containing the following: females, individuals with an adequate education for their occupation or higher and it was associated with a lower importance of basic and resource management skills. The AAA class was the second largest class (37.1%) and was very similar to the ALA class except it was more likely to contain individuals from the following two occupational groups:

education, legal, community service, arts, and media; and natural resources, construction, and maintenance.

Table 40

Characteristics Associated with Model 2 Class Membership

Latent class (% of sample)	Characteristics associated with increased likelihood of membership: (Compared to membership in the AHH class - 42.7%)
ALA (20.4%)	– Female* – Works in a service occupation – Occupation requires a post-secondary certificate or some college – Occupation requires up to 2 years of work experience* – Occupation requires up to 1 month of on-the-job training – Has an adequate or higher level of education than required for their occupation* – Occupation is associated with lower importance of cognitive abilities – Occupation is associated with lower importance of basic, complex problem solving, resource management, or systems skills*
AAA (37.1%)	– Works in an education, legal, community service, arts, and media; natural resources, construction, and maintenance; or service occupation* – Occupation requires a post-secondary certificate or some college – Occupation does not require over 2 years of work experience* – Occupation requires up to 1 month of on-the-job training – Has a higher level of education than required for their occupation – Occupation is associated with lower importance of cognitive abilities – Occupation is associated with lower importance of complex problem solving or systems skills

Note. Only statistically significant odds ratios ≥ 3.0 or ≤ .33 are summarized in the above table. Characteristics flagged with an asterisk (*) were only associated with one class.

Model 3: Education Required, Field Mismatch

Table 41 displays the regression results to predict class membership among individuals in the third analytic group—individuals with a Bachelor’s degree or more who are in occupations that do not match their Bachelor field of study. The HHH class, representing individuals with uniformly high levels of economic success, was the norm class and, thus, was used as the reference class for these comparisons. This means all results reflect odds of class membership in comparison to odds of membership in the HHH class. Similar to the presentation of the previous model results, the reference categories for the categorical predictors are identified in the table by an [R] next to the category name along with the percentage within the category.

Several general trends were associated with non-HHH class membership. The non-HHH classes were generally more likely to contain individuals with a Bachelor's degree (as opposed to a graduate degree) and also were more likely to contain individuals who worked in occupations that required a Bachelor's degree, required none to 2 years of work experience, and were associated with a lower importance of cognitive abilities, basic skills, complex problem solving skills, and systems skills. In addition, the classes were less likely to contain individuals working in a computer, engineering, and science occupation or a healthcare practitioners and technical occupation (although the latter only applies to four of the classes). The odds ratios are not presented for several of these comparisons for occupational groups, but the previous conclusions are supported by the observance of zero or near-zero rates of class membership within the two categories which prevented reliable estimates from being produced (see Appendix D).

Table 41

Odds Ratios to Predict Class Membership for Model 3

Model and variable(s)	Class comparisons				
	AAL vs. HHH	AHH vs. HHH	HHA vs. HHH	ALA vs. HHH	AAH vs. HHH
1. Demographics:					
Age	0.90*	0.95*	0.98*	0.92*	0.93*
Male [R: 45.1%]	-----	-----	-----	-----	-----
Female	1.53*	2.01*	0.89*	2.93*	1.67*
White [R: 74.5%]	-----	-----	-----	-----	-----
Black	1.33*	1.38*	1.26*	2.18*	1.78*
Asian	0.62*	0.34*	0.63*	0.50*	**0.32***
Other [a]	1.42*	1.12	1.07	2.09*	1.52*
2. Attained education:					
Bachelor's degree [R: 50.5%]	-----	-----	-----	-----	-----
Graduate degree	**0.27***	0.47*	**0.28***	**0.15***	0.35*
3. Field of Study:					
Science and Engineering Group [R: 61.3%]	-----	-----	-----	-----	-----
Science and Engineering Related Fields	2.46*	2.41*	2.21*	1.55*	0.69*
Business	1.53*	1.21*	0.49*	2.49*	1.23*
Education	1.54*	0.90	1.92*	0.95	2.11*
Arts, Humanities, and Other	2.03*	2.32*	1.39*	1.82*	1.44*
4. Occupational group:					
Management, Business, and Financial [R: 28.6%] [c]	-----	-----	-----	-----	-----
Computer, Engineering, and Science	0.41*	**0.11***	**0.30***	---- [c]	---- [c]
Education, Legal, Community Service, Arts, and Media	**3.14***	**3.10***	---- [c]	---- [c]	**>50.00***
Healthcare Practitioners and Technical	---- [c]	**0.10***	---- [c]	---- [c]	**3.34***
Sales and Office	**25.13***	---- [c]	**27.69***	---- [c]	**>50.00***

Model and variable(s)	Class comparisons				
	AAL vs. HHH	AHH vs. HHH	HHA vs. HHH	ALA vs. HHH	AAH vs. HHH
Other [b]	**5.23***	0.98	0.40*	----[c]	**>50.00***
5. Required level of education:					
Associate's degree or less	**0.29***	**0.09***	**0.03***	**4.63***	0.55*
Bachelor's degree [R: 65.5%]	-----	-----	-----	-----	-----
Graduate degree	----[c]	**0.13***	**0.04***	**0.20***	0.54*
6. Required work experience:					
None to 2 years	1.63*	**5.96***	0.93	**>50.00***	**5.08***
Over 2 years [R: 60.5%]	-----	-----	-----	-----	-----
7. On-the-job training:					
None, up to 1 month	**0.14***	**0.06***	----[c]	1.44*	0.39*
Over 1 month [R: 90.1%]	-----	-----	-----	-----	-----
8. Education level match:					
Undereducation	----[c]	1.16	**0.19***	2.47*	**3.26***
Adequate education [R: 63.6%]	-----	-----	-----	-----	-----
Overeducation	1.46*	1.58*	0.87*	**5.89***	1.04
9-12. Occupational abilities:					
Cognitive	**0.04***	**0.32***	**0.04***	0.69	**0.10***
Physical	2.08*	1.22*	1.85*	0.79*	1.13*
Psychomotor	1.04	0.66*	1.01	0.52*	0.74*
Sensory	0.90*	1.08*	0.60*	1.09*	0.91*
13-18. Occupational skills:					
Basic	**0.01***	**0.05***	**0.01***	**0.04***	**0.02***
Complex problem solving	**0.05***	**0.31***	**0.07***	0.43*	**0.21***
Resource management	**0.30***	1.02	0.36*	1.19*	0.93*
Social	0.87*	----[d]	0.87*	1.00	1.04
Systems	**0.07***	0.51*	**0.08***	0.75*	**0.24***
Technical	0.72*	0.68*	**0.32***	0.84*	0.68*

[a] Other includes: Native American; Asian & Pacific Islander; Hispanic; and Other.
[b] Other includes: Natural Resources, Construction, and Maintenance; Production, Transportation, and Material Moving; Military Specific; and Service occupations.
[c] Cell counts for one or more categories were relatively small or zero and a reliable estimate could not be produced.
[d] Estimate suffered from quasi-separation of data and was thus repressed.

[e] The education group contained the largest proportion of the sample (31%) but it contained a small number of observations for the third largest class, the HHA class, which did not permit reliable estimates for the class. Thus, the next largest group was used instead.
Note. *p<.05. Statistically significant odds ratios ≥ 3.0 or ≤ .33 are presented in bold. Reference groups are identified with an [R] next to the variable name, along with the percentage in the sample. Demographic variables presented at the top of the table were included in all subsequent models as control variables.

Table 42 summarizes the largest predictors of membership within each of the non-HHH classes. Similar to the presentation of previous model summaries, this table only includes statistically significant predictors with an odds ratio equal to or below 0.33 or equal to or above 3.00. Characteristics that were associated with only one class are identified with an asterisk (*).

Table 42

Characteristics Associated with Model 3 Class Membership

Latent class (% of sample)	Characteristics associated with increased likelihood of membership: (Compared to membership in the HHH class - 31.6%)
AAL (5.7%)	– Has a Bachelor's degree – Works in a sales and office; education, legal, community service, arts, and media; or other occupation – Occupation requires a Bachelor's degree – Occupation requires more than 1 month of on-the-job training – Occupation is associated with lower importance of cognitive abilities – Occupation is associated with lower importance of basic, complex problem solving, resource management, or systems skills
ALA (5.1%)	– Has a Bachelor's degree – Occupation requires an Associate's degree or less* – Occupation requires 2 years or less of work experience – Is overeducated for their occupation* – Occupation is associated with lower importance of basic skills

Latent class (% of sample)	Characteristics associated with increased likelihood of membership: (Compared to membership in the HHH class - 31.6%)
AAH (16.4%)	– Not Asian* – Works in a sales and office; education, legal, community service, arts, and media; healthcare practitioners or technical; or other occupation* – Occupation requires 2 years or less of work experience – Is undereducated for their occupation* – Occupation is associated with lower importance of cognitive abilities – Occupation is associated with lower importance of basic, complex problem solving, or systems skills
AHH (21.8%)	– Works in an education, legal, community service, arts, and media occupation – Does not work in a computer, engineering, and science or healthcare practitioners and technical occupation* – Occupation requires a Bachelor’s degree – Occupation requires 2 years or less of work experience – Occupation requires more than 1 month of on-the-job training – Occupation is associated with lower importance of cognitive abilities – Occupation is associated with lower importance of basic or complex problem solving skills
HHA (19.3%)	– Has a Bachelor’s degree – Works in sales and office – Does not work in a computer, engineering, and science occupation – Occupation requires a Bachelor’s degree – Has an adequate education level for their occupation* – Occupation is associated with lower importance of cognitive abilities – Occupation is associated with lower importance of basic, complex problem solving, resource management, systems, or technical skills

Note. Only statistically significant odds ratios ≥ 3.0 or ≤ .33 are summarized in the above table. Characteristics flagged with an asterisk (*) were only associated with one class.

Most of the classes contained distinguishing characteristics or combinations of characteristics that set them apart from one another. The ALA class is the smallest class

(5.1%) and has higher odds of containing individuals who have a Bachelor's degree (as opposed to a graduate degree), work in an occupation requiring an Associate's degree or less, and are overeducated for their occupation. In contrast, the HHA class (19.3%) is more likely to include individuals who have a Bachelor's degree, work in an occupation that requires a Bachelor's degree, and have an adequate level of education for their occupation. Although there some other differences between the two, they may generally be viewed as overeducated and adequately educated classes, respectively. The AAH class (16.4%) had higher odds of including individuals who are undereducated, not Asian, and who work in a healthcare practitioners or technical; sales and office; education, legal, community service, arts and media; or other occupation (the latter three of which were observed in other classes). Because this class did not contain additional large predictors related to attained education and required level of education, it could not be classified more generally as an undereducated class. The last two classes, AAL (5.7%) and AHH (21.8%), were generally very similar. They both include occupations that have higher odds of being within the education, legal, community service, arts and media group, requiring a Bachelor's degree, requiring 1 month of on-the job training and have low importance of specific skills and abilities. The few differences that exist were a higher chance of having a Bachelor's degree and working in a sales and office or other occupation within the AAL class and a higher chance of working in an occupation that requires less than 2 years of experience and does not fit within the computer, engineering, and science or healthcare practitioners and technical occupational groups in the AHH class.

Model 4: Education Required, Field Match

Table 43 presents the regression results to predict class membership among individuals in the fourth analytic group—individuals with a Bachelor's degree or more who are in occupations that match their Bachelor field of study. The HHH class, representing individuals with uniformly high levels of economic success, was the norm class and, thus, was used as the reference class for these comparisons. This means all results reflect odds of class membership in comparison to odds of membership in the HHH class. Similar to the presentation of the previous model results, the reference categories for the categorical predictors are identified in the table by an [R] next to the category name along with the percentage within the category.

Only a couple of overall trends can be observed about class membership in the three classes with levels of economic success below the norm. The classes were generally more likely not to include individuals working in science and engineering, science and engineering related, and education occupations. Although the odds ratios are not presented for the comparisons with the ALA class, this conclusion can be made based on the observance of zero or near-zero rates of category membership (see Appendix D) within the ALA class which caused unreliable estimates (with standard errors of zero) and led to the repression of the results. In addition, the classes contained similar levels of occupational abilities as the HHH class.

Table 43

Odds Ratios to Predict Class Membership for Model 4

Model and variable(s)	Class comparisons		
	HAH vs. HHH	HHA vs. HHH	ALA vs. HHH
1. Demographics:			
Age	1.00	1.04*	0.92*
Male [R: 44.8%]	-----	-----	-----
Female	0.90*	0.64*	2.48*
White [R: 75.6%]	-----	-----	-----
Black	1.33*	1.17	1.18
Asian	0.51*	0.67*	0.37*
Other [a]	1.25*	1.24*	1.59
2. Attained education:			
Bachelor's degree [R: 65.3%]	-----	-----	-----
Graduate degree	0.42*	0.56*	0.38*
3. Field of Study:			
Business [R: 28.6%]	-----	-----	-----
Science and Engineering Group	**0.14***	0.40*	----[c]
Science and Engineering Related Fields	**0.12***	**0.06***	----[c]
Education	**0.10***	**0.05***	----[c]
Arts, Humanities, and Other	1.50*	1.03	----[c]
4. Occupational group:			
Education, Legal, Community Service, Arts, and Media [R: 32.6%]	-----	-----	-----
Computer, Engineering, and Science	**0.31***	**>50.00***	**0.01***
Healthcare Practitioners and Technical	**0.09***	----[c]	**0.11***
Management, Business, and Financial	1.25*	**>50.00***	----[c]
Other [b]	**24.31***	----[c]	**>50.00***
5. Required level of education:			
Associate's degree or less	**0.08***	**0.01***	**5.71***

Model and variable(s)	Class comparisons		
	HAH vs. HHH	HHA vs. HHH	ALA vs. HHH
Bachelor's degree [R: 65.3%]	-----	-----	-----
Graduate degree	0.35*	0.47*	0.70*
6. Required work experience:			
None, up to 2 years	0.53*	**0.15***	**18.39***
Over 2 years [R: 60.6%]	-----	-----	-----
7. On-the-job training:			
None, up to 1 month	**0.16***	**0.00***	**3.61***
Over 1 month [R: 88.4%]	-----	-----	-----
8. Education level match:			
Undereducation	0.69*	**0.06***	0.84
Adequate education [R: 62.8%]	-----	-----	-----
Overeducation	0.35*	0.57*	2.42*
9-12. Occupational abilities:			
Cognitive	0.53*	2.69*	1.07
Physical	1.78*	1.08*	1.03
Psychomotor	1.18*	1.20*	1.00
Sensory	1.01	1.05	1.04
13-18. Occupational skills:			
Basic	0.56*	2.92*	1.04
Complex problem solving	**0.28***	1.77*	1.07
Resource management	**0.22***	0.73*	1.02
Social	1.06	0.86*	1.02
Systems	**0.16***	0.53*	1.06
Technical	**0.18***	0.65*	0.97

[a] Other includes: Native American; Asian & Pacific Islander; Hispanic; and Other.
[b] Other includes: Natural Resources, Construction, and Maintenance; Production, Transportation, and Material Moving; and Military Specific occupations.
[c] Cell counts for one or more categories were relatively small or zero and a reliable estimate could not be produced.
Note. *p<.05. Statistically significant odds ratios ≥ 3.0 or ≤ .33 are presented in bold. Reference groups are identified with an [R] next to the variable name, along with the percentage in the sample. Demographic variables presented at the top of the table were included in all subsequent models as control variables.

Table 44 summarizes the largest predictors of membership within each of the three non-HHH classes. Similar to the previous class summaries, this summary only includes statistically significant predictors with an odds ratio equal to or below 0.33 or equal to or above 3.00. Characteristics that were associated with only one class are identified with an asterisk (*). In general, the HHA (9.5%) and HAH (21.1%) classes were very similar. The both had higher odds of including individuals who studied business during their Bachelor's program, who work in an occupation requiring a bachelor's degree and more than 1 month of on-the-job training. Their biggest differences are in occupational group and associated skills. The HHA class is more likely to include individuals who work in a computer, engineering and science, or a management, business, and finance occupation with no differences from the HHH class in importance of occupational skills; whereas the HAH class is more likely to include individuals who work in service occupations, not in computer, engineering, and science or healthcare practitioners and technical occupations, and in occupations with lower importance of several skills. The ALA class was the smallest class (1.4%) and was more likely to contain individuals who work in an education, legal, community service, arts, and media or service occupation and an occupation that requires an Associate's degree or less, 2 years or less of work experience, and 1 month or less of on-the-job training.

Table 44

Characteristics Associated with Model 4 Class Membership

Latent class (% of sample)	Characteristics associated with increased likelihood of membership: (Compared to membership in the HHH class - 68.0%)
ALA (1.4%)	– Works in an education, legal, community service, arts, and media or service[a] occupation* – Occupation requires an Associate's degree or less* – Occupation requires 2 years or less of work experience* – Occupation requires 1 month or less of on-the-job training*
HHA (9.5%)	– Studied Business – Works in a computer, engineering, and science or management, business, and finance occupation* – Occupation requires a Bachelor's degree – Occupation requires more than 2 years of work experience* – Occupation requires more than 1 month of on-the-job training – Has an adequate level of education for their occupation*
HAH (21.1%)	– Studied Business – Does not work in a computer, engineering, and science, and healthcare practitioners and technical occupation* – Works in a service[a] occupation – Occupation requires a Bachelor's degree – Occupation requires more than 1 month of on-the-job training – Occupation is associated with lower importance of complex problem solving, resource management, systems or technical skills*

[a] Of the cases in the other occupational category within the ALA class, 94.5% were in service occupations; thus the results of the other category are being interpreted for service occupations.
Note. Only statistically significant odds ratios ≥ 3.0 or ≤ .33 are summarized in the above table. Characteristics flagged with an asterisk (*) were only associated with one class.

Model 5: All Groups

Table 45 presents the regression results to predict class membership among the full sample. The LLL class, representing individuals with uniformly low levels of economic success, was identified as the norm class and was thus used as the reference class for these comparisons. This means all results reflect odds of class membership in comparison to odds of membership in the LLL class. Similar to the presentation of the previous model results, the reference categories for the categorical predictors are identified in the table by an [R] next to the category name along with the percentage within the category. Note that although the adequate education category was not the education level match category exhibited by the largest proportion of the sample (see distributions in Table 7), it was modeled as the reference category in order to more easily evaluate the effects of education level match. Additionally, the Hispanic, Asian, and Other categories were collapsed for the estimation of the skill and ability models due to near zero variance on the measures within the Hispanic portion of the sample in the AHA class.

Based on these results, a number of overall trends can be observed about non-LLL class membership. The non-LLL classes were more likely to include individuals with a Bachelor's degree or more and individuals who worked in occupations that required a post-secondary certificate or higher, over 2 years of work experience, or over 1 month of on-the-job training. In addition, if individuals had a Bachelor's degree, they had higher odds of non-LLL membership if they worked in a field related to their degree. Across the classes, several occupational groups were also associated with non-LLL membership: computer, engineering, and science; education, legal, community service, arts and media; healthcare practitioners and technical; management, business, and financial; and military specific occupations. Finally, higher importance of cognitive abilities and importance of most occupational skills were associated with non-LLL membership.

Table 45

Odds Ratios to Predict Class Membership for Model 5

Model and variable(s)	Class comparisons ALA vs. LLL	AAA vs. LLL	AHA vs. LLL	HHH vs. LLL
1. Demographics:				
Age	1.02*	1.05*	1.07*	1.07*
Male [R: 51.9%]	-----	-----	-----	-----
Female	2.52*	0.36*	0.80*	1.22*
White [R: 68.5%]	-----	-----	-----	-----
Black	1.00	0.62*	0.52*	0.43*
Asian	1.03	0.75*	1.23*	2.23*
Hispanic	0.71*	0.51*	0.38*	**0.20***
Other [a]	0.98	0.75*	0.76*	0.66*
2. Attained education:				
Less than HS	0.43*	**0.26***	**0.04***	**0.01***
HS diploma or equiv.	0.65*	0.48*	**0.11***	**0.03***
Some college, no degree	0.93*	0.57*	**0.22***	**0.10***
Associate's degree	1.26*	0.71*	**0.33***	**0.28***
Bachelor's degree [R: 24.4%]	-----	-----	-----	-----
Graduate degree	1.10	1.33*	1.98*	**4.36***
3. Field of Study:				
No Bachelor's degree[b]	0.69*	0.51*	**0.12***	**0.04***
Science and Engineering Group [R: 13.2%]	-----	-----	-----	-----
Science and Engineering Related Fields	1.47*	1.14	0.84*	2.03*
Business	0.68*	1.05	1.02	0.56*
Education	1.55*	1.20*	0.37*	1.69*
Arts, Humanities, and Other	0.76*	1.03	0.79*	0.48*
4. Occupational group:				
Sales and Office [R: 22.8%]	-----	-----	-----	-----

Model and variable(s)	Class comparisons			
	ALA vs. LLL	AAA vs. LLL	AHA vs. LLL	HHH vs. LLL
Computer, Engineering, and Science; Education, Legal, Community Service, Arts, and Media; Healthcare Practitioners and Technical; Management, Business, and Financial; and Military Specific[e]	**50.00***	**>50.00***	**>50.00***	**>50.00***
Natural Resources, Construction, and Maintenance	**4.78***	1.96*	0.96	2.90*
Production, Transportation, and Material Moving	0.61*	2.41*	**0.28***	**4.20***
Service	1.89*	**0.05***	**0.02***	**13.44***
5. Required level of education:				
Less than HS	**0.02***	**0.53***	**0.17***	**0.00***
HS or equivalent [R: 50.0%]	-----	-----	-----	-----
Post-secondary certificate or some college	**6.99***	1.14*	**27.28***	**20.27***
Associate's degree or less	**>50.00***	**>50.00***	**>50.00***	**>50.00***
Bachelor's degree	**12.72***	**48.81***	**>50.00***	**>50.00***
Graduate degree	**>50.00***	**>50.00***	**>50.00***	**>50.00***
6. Required work experience:				
None	**0.27***	**0.13***	0.43*	**0.29***
Up to 2 years [R: 51.4%]	-----	-----	-----	-----
Over 2 years	**>50.00***	**>50.00***	**>50.00***	**>50.00***
7. On-the-job training:				
None or short demonstration	**3.12***	0.76*	**0.00***	**3.24***
Up to 1 month	**0.20***	**0.28***	**0.01***	**0.05***
Over 1 month [R: 70.8%]	-----	-----	-----	-----
8. Education level match:				
Undereducation	1.51*	0.95	2.77*	0.93*
Adequate education [R: 37.5%]	-----	-----	-----	-----
Overeducation	1.31*	1.01	**0.24***	0.38*

Model and variable(s)	Class comparisons ALA vs. LLL	AAA vs. LLL	AHA vs. LLL	HHH vs. LLL
9. Field match:				
No Bachelor's degree [b]	0.96	0.56*	**0.21***	**0.10***
Mismatch [R: 20.9%]	-----	-----	-----	-----
Match	**4.31***	**2.81***	**8.14***	**13.45***
10-13. Occupational abilities: [d]				
Cognitive	2.62*	2.98*	**14.54***	**>50.00***
Physical	0.93*	0.94	0.51*	0.55*
Psychomotor	0.92*	1.38*	0.48*	0.55*
Sensory	1.21*	1.70*	1.17*	1.24*
14-19. Occupational skills: [d]				
Basic	**3.65***	**3.17***	**17.10***	**46.48***
Complex problem solving	2.37*	**5.39***	**38.47***	**>50.00***
Resource management	1.94*	**5.37***	**6.75***	**5.84***
Social	1.36*	1.40*	2.59*	2.71*
Systems	**3.19***	**5.09***	**15.94***	**29.25***
Technical	1.32*	1.82*	1.31*	1.42*

[a] Other includes: Native American; Asian & Pacific Islander; and Other.
[b] Included as a control variable to estimate the relationship of interest.
[c] Cell counts for one or more categories were relatively small or zero and a reliable estimate could not be produced.
[d] The Hispanic, Asian, and Other categories were collapsed in the estimation of this model due to near zero variance for some of the class and race/ethnic combinations.
[e] These categories were collapsed due to low counts in the reference class.
Note. *p<.05. Statistically significant odds ratios ≥ 3.0 or ≤ .33 are presented in bold. Reference groups are identified with an [R] next to the variable name, along with the percentage in the sample. Demographic variables presented at the top of the table were included in all subsequent models as control variables.

Table 46 summarizes the largest predictors of membership within each of the non-LLL classes. Similar to the previous class summaries, this summary only includes statistically significant predictors with an odds ratio equal to or below 0.33 or equal to or above 3.00. Characteristics that were associated with only one class are identified with an asterisk (*). The HHH class was the second largest class (22.4%) and was uniquely associated with higher odds of membership if individuals were not Hispanic, had a Bachelor's degree or graduate degree, or did not work in a sales and office occupation. The AHA class was the third largest class (17.0%) and had higher odds of including individuals who were not overeducated, did not have less than a Bachelor's degree, and did not work in a service or production, transportation, and material moving occupation. The AAA class (13.2%) had higher odds of containing individuals who did not have less than a HS diploma and worked in an occupation requiring an Associate's or more. Finally, the ALA class (10.8%) was more likely to contain individuals who worked in a natural resources, construction and maintenance occupation.

Table 46

Characteristics Associated with Model 5 Class Membership

Latent class (% of sample)	Characteristics associated with increased likelihood of membership: (Compared to membership in the LLL class - 36.5%)
ALA (10.8%)	– Works in a computer, engineering, and science; education, legal, community service, arts and media; healthcare practitioners and technical; management, business, and financial; military specific; or natural resources, construction, and maintenance occupation* – Occupation requires more than a HS diploma or equivalent – Occupation requires over 2 years of work experience – Occupation requires no on-the-job training or over 1 month of training – Working in a field related to a Bachelor's field of study – Occupation is associated with higher importance of basic or systems skills
AAA (13.2%)	– Does not have less than a HS diploma or equivalent* – Works in a computer, engineering, and science; education, legal, community service, arts and media; healthcare practitioners and technical; management, business, and financial; or military specific occupation – Does not work in a service occupation – Occupation requires an Associate's degree or more* – Occupation requires over 2 years of work experience

Latent class (% of sample)	Characteristics associated with increased likelihood of membership: (Compared to membership in the LLL class - 36.5%)
	– Occupation requires over 1 month of on-the-job training – Working in a field related to a Bachelor's field of study – Occupation is associated with higher importance of basic, complex problem solving, resource management, or systems skills
AHA (17.0%)	– Does not have less than a Bachelor's degree* – Works in a computer, engineering, and science; education, legal, community service, arts and media; healthcare practitioners and technical; management, business, and financial; or military specific occupation – Does not work in a service or production, transportation, and material moving occupation* – Occupation requires more than a HS diploma or equivalent – Occupation requires over 2 years of work experience – Occupation requires over 1 month of on-the-job training – Not overeducated* – Working in a field related to a Bachelor's field of study – Occupation is associated with higher importance of cognitive abilities – Occupation is associated with higher importance of basic, complex problem solving, resource management, or systems skills
HHH (22.4%)	– Not Hispanic* – Has a Bachelor's degree or graduate degree* – Does not work in a sales and office occupation* – Occupation requires more than a HS diploma or equivalent – Occupation requires over 2 years of work experience – Occupation requires no on-the-job training or over 1 month of training – Working in a field related to a Bachelor's field of study – Occupation is associated with higher importance of cognitive abilities – Occupation is associated with higher importance of basic, complex problem solving, resource management, or systems skills

Note. Only statistically significant odds ratios ≥ 3.0 or ≤ .33 are summarized in the above table. Characteristics flagged with an asterisk (*) were only associated with one class.

Summary: Latent Class Predictors

The series of analyses above identified the major predictors of latent class membership. Major predictors were defined as predictors that were statistically significant and had odds ratios equal to or greater than 3.0 and less than or equal to 0.33; ratios associated with a 75% chance of belonging or not belonging to a class, respectively. Table 47 provides a summary of the major predictors that were identified. The reference class for each model is presented in bold with an [R] beside the class name and the reference categories for the categorical predictors are also presented on the same line in bold. The reference categories were determined as the categories containing the largest proportion of individuals within each analytic group (unless otherwise noted) and thus provide an indicator of the base rates of group membership. The major predictors are then indicated with abbreviations on the lines that follow. Note, the table only summarizes results for seven of the thirteen predictor variables included in the modeling. Six predictors (age, gender, race/ethnicity, field of study, required level of experience, and field match) were excluded because they were not identified frequently, were not present in all models, or did not contribute substantially to class meaning. In instances where the predictors were considered a major predictor of membership and contributed to class meaning, the relevant categories are indicated in the other column.

Table 47

Summary of Major Predictors of Class Membership

Model	Class	Attained educ.	Occupation					Ed. level match	Other
			Req. educ.	OTJ train.	Major group	Abilities	Skills		
1	**LLL**[R]	**HS**	**HS**	**>1M**	**SAL**	**--**	**--**	**Over**	
	ALA	--	HS	--	--	H	H	--	Fem.
	AAA	--	--	--	~~SER~~	H	H	--	
	ALH	≥AS	HS	>1M	MIL, HEA	--	--	Over	
	HHH	≥BA	HS	>1M	NaR, PRO, SER, ~~SAL~~	--	--	~~Under~~	Mal.
2	**AHH**[R]	**SC**	**BA**	**>1M**	**ED**[a]	**--**	**--**	**Under**	
	ALA	--	PS/SC	≤1M	SER	L	L	Adaq+	Fem.
	AAA	--	PS/SC	≤1M	ED, NaR, SER	L	L	Over	
3	**HHH**[R]	**BA**	**BA**	**>1M**	**MNG**[a]	**--**	**--**	**Adaq**	
	AAL	BA	BA	>1M	SAL, ED, OTR	L	L	--	
	ALA	BA	≤AS	--	--	--	L	Over	
	AAH	--	--	--	SAL, ED, HEA, OTR	L	L	Under	~~Asian~~
	AHH	--	BA	>1M	ED, ~~CMP~~, ~~HEA~~	L	L	--	
	HHA	BA	BA	--	SAL, ~~CMP~~	L	L	Adaq	
4	**HHH**[R]	**BA**	**BA**	**>1M**	**ED**	**--**	**--**	**Adaq**	
	ALA	--	≤AS	≤1M	ED	--	--	--	
	HHA	--	BA	>1M	CMP, MNG	--	--	Adaq	BUS
	HAH	--	BA	>1M	SER, ~~CMP~~, ~~HEA~~	--	L	--	BUS
5	**LLL**[R]	**BA**	**HS**	**>1M**	**SAL**	**--**	**--**	**Adaq**[a]	
	ALA	--	HS	≤1M	CMP, ED, HEA, MNG, MIL, NAT	--	H	--	FiMa

Model	Class	Attained educ.	Occupation					Ed. level match	Other
			Req. educ.	OTJ train.	Major group	Abilities	Skills		
	AAA	~~<HS~~	≥AS	>1M	CMP, ED, HEA, MNG, MIL, ~~SER~~	--	H	--	FiMa
	AHA	~~BA~~	>HS	>1M	CMP, ED, HEA, MNG, MIL, ~~SER~~, ~~PRO~~	H	H	~~Over~~	FiMa
	HHH	≥BA	>HS	None, >1M	~~SAL~~	H	H	--	~~Hisp~~, FiMa

[a] This was not the most commonly observed occupational group within the analytic group. See Table 7.
Note. Strikethrough words indicate a low odds ratio was observed and the category is less frequently observed in the class. The attained and required education level abbreviations are: HS=high school; PS=postsecondary credential; SC=some college; AS=Associate's and BA=Bachelor's. The occupational group abbreviations are: SAL=sales and office; SER=service; MIL=military specific; HEA=healthcare practitioners and technical; NaR=natural resources, construction, and maintenance; PRO=production, transportation, and material moving; ED= education, legal, community service, arts, and media; and MNG=management, business, and financial. The abbreviations for skills and abilities are: H=high and L=low.

The information presented in Table 47 was used to create profiles of class membership. These profiles offered further understanding of the demographic, educational, and occupational characteristics associated with each latent class of economic success. For example, the latent class experiencing uniformly high levels of economic success (HHH) in Model 1 (containing individuals in occupations that required a High School diploma or less) was more likely than the reference class (LLL) to include: males; individual's with a Bachelor's degree or more; individuals who work in an occupation that requires a High School diploma, or equivalent (as compared to less) and/or a month or more of work experience; individuals who work in a natural resource, construction, maintenance, production, transportation, material moving, or service occupation; and/or individuals who are not undereducated for their occupation. In this case, these predictors tell the story of a latent class representing individuals who experience higher levels of economic success than the rest in the analytic group and tend to be overeducated for their occupation, male, and/or work in specific industries. Overall, the information from these analyses was used to compile profiles for 18 classes that were not considered to be the "norm". In this way, the results provide information to further understand the composition of each latent class of economic success.

The results from the current analyses can also be aggregated to provide insight into the relative importance of each predictor in the understanding of economic success. Table 48 presents a summary of odds ratios and major predictors by model. The odds ratios represent the mean odds ratios for the predictors in a model, with odds ratios below 1 converted to an equivalent representation above 1. The conversion of odds ratios below 1 removed the direction of the effect and allowed both aggregation of the results within a model and examination of the relative magnitude of a predictor in understanding economic success. The rate of major predictor status in each model represents the number of times the predictor was classified as a major predictor out of the number of opportunities to be classified as such. This is presented as a percentage because the number of opportunities varied by model based on the number of classes predicted and the number of categories within a predictor. Mean odds ratios equal to or greater than 3.0 and rates of major predictor status greater than or equal to 50% are presented in bold to assist with interpretation.

Table 48

Mean Odds Ratios and Rates of Major Predictor Status by Model

Predictor	Mean odds ratio[a] by model						Rate (%) of major predictor status by model					
	M1	M2	M3	M4	M5	*All*	M1	M2	M3	M4	M5	*All*
Demographic characteristics:												
Age	1.1	1.1	1.1	1.0	1.0	*1.1*	0	0	0	0	0	*0*
Gender	**3.3**	**3.2**	1.9	1.7	2.2	*2.4*	**50**	**50**	0	0	0	*18*
Race/ethnicity	1.6	1.4	1.8	1.5	1.5	*1.6*	0	0	7	0	0	*2*
Educational characteristics:												
Attained education	**3.0**	1.9	**3.8**	2.3	**4.1**	***3.3***	25	0	**60**	0	33	*27*
Field of study	--	--	1.8	**8.4**	1.9	***3.0***	--	--	0	**63**	7	*14*
Occupational characteristics:												
Occupational group	**6.2**	**24.3**	**16.4**	**27.7**	**19.8**	***18.4***	44	**100**	**80**	**89**	**58**	***73***
Req. level of ed.	**15.7**	**17.8**	**10.4**	**12.4**	**33.6**	***21.1***	**75**	33	**78**	**50**	**87**	***70***
Req. work exp.	**3.6**	**19.8**	**12.8**	**9.0**	**27.3**	***15.8***	**50**	**75**	**60**	**67**	**83**	***68***
Req. on-the-job training	**18.8**	**5.2**	**7.0**	**20.0**	**18.8**	***15.1***	**50**	**100**	**50**	**100**	**83**	***74***
Cognitive abilities	**3.5**	**7.1**	**12.9**	1.9	**6.7**	***7.0***	**50**	**100**	**80**	0	33	***53***
Physical abilities	2.9	2.3	1.5	1.3	1.4	*1.9*	25	0	0	0	0	*6*
Psychomotor abilities	**3.0**	1.9	1.4	1.1	1.5	*1.8*	25	0	0	0	0	*6*
Sensory abilities	**3.1**	1.7	1.2	1.0	1.4	*1.7*	25	0	0	0	0	*6*
Basic skills	**3.5**	**4.1**	**39.0**	1.9	**8.0**	***14.5***	**50**	**50**	**100**	0	**100**	***65***
Complex problem solving skills	**3.6**	**12.1**	**8.9**	2.1	**15.4**	***8.0***	**50**	**100**	**80**	33	**67**	***65***
Resource management skills	**3.2**	2.4	1.9	2.3	4.7	*2.8*	**50**	**50**	20	33	**67**	*41*
Social skills	**3.0**	1.5	1.1	1.1	1.8	*1.7*	25	0	0	0	0	*6*
Systems skills	**3.5**	**6.6**	**6.9**	**3.1**	**8.1**	***5.6***	**50**	**100**	**60**	33	**100**	***65***
Technical skills	**3.1**	1.3	1.7	2.7	1.5	*2.1*	25	0	20	33	0	*18*
Educational & occupational match:												

Predictor	Mean odds ratio[a] by model						Rate (%) of major predictor status by model					
	M1	M2	M3	M4	M5	*All*	M1	M2	M3	M4	M5	*All*
Education level match	**8.2**	**24.4**	2.6	**4.4**	2.0	***6.8***	38	**75**	33	17	17	*33*
Field match	2.7	--	--	--	**3.8**	***3.2***	38	--	--	--	**50**	*43*

[a] The mean odds ratios are computed from all reported odds ratios, with ratios below 1 converted to equivalent representations above 1 and ratios truncated to a maximum value of 50.
Note. Mean odds ratios greater than or equal to 3.0 and rates of major predictor status greater than or equal to 50% are presented in bold.

According to Table 48, occupational characteristics and education level match contributed more to the understanding of economic success than demographic characteristics, educational characteristics, or field match. Across the models, occupational characteristics and education level match were associated with larger odds ratios and rates of major predictor status than the other predictors. The only exception to this finding was among a few of the occupational ability (physical, psychomotor, and sensory) and skill (resource management, social, and technical) measures, which were not associated with larger odds ratios or rates of major predictor status. Furthermore, the general agreement in this trend between the two statistics suggests that the results are representative of the overall relationship between the predictors and economic success and the large mean odds ratios are not driven by only a few instances of large odds ratios.

CHAPTER FIVE

SUMMARY OF FINDINGS

Three primary research questions were examined and addressed in the preceding chapter. The current chapter provides a brief review of the questions, the methods used to address them, and the major findings. This information is summarized by research question. Chapter 4 should be consulted for more detailed descriptions or summaries of the results.

RQ1: Rates of Education-Occupation Match/Mismatch

The first research question aimed to identify rates of misalignment between educational background and occupation. Two specific types of match or mismatch were examined: 1) match in educational level attained and the level generally required for an occupation; and 2) match in the field of study and field of work. Table 49 summarizes the results from this analysis. Overall, the majority (43.2%) of the sample was found to be overeducated for their occupation and about a fifth (19.3%) were undereducated. Only 37.5% were adequately educated for their occupation. Among those who had Bachelor's degrees or higher, 58.9% worked in occupations unrelated to their field of study and 31.8% were also overeducated for their occupation, illustrating that nearly a third of the individuals who obtained Bachelor's degrees experienced both field mismatch and overeducation.

Table 49

Summary of Education Level and Field Match

		Education level match			
Target audience	Field match	Undereducated	Adequately educated	Overeducated	% of aud.
Bachelor's/Graduate degree holders	Match	2.2%	23.3%	15.8%	41.1%
	Mismatch	2.7%	24.3%	31.8%	58.9%
	-------	4.9%	47.5%	47.6%	100.0%
Full Sample	-------	19.3%	37.5%	43.2%	100.0%

RQ2: Levels of Economic Success

The second research question aimed to identify and explore experiences of economic success that differ from the norm. Economic success was conceptualized as income, earnings potential, and occupational prestige. LCA was used to identify unique and naturally existing latent classes of economic success. To examine these trends at a finer level, the sample was separated into four different analytic groups: 1) Individuals in occupations that require a High School diploma or less; 2) Individuals with less than a Bachelor's degree and in occupations that require more than a High School diploma, or equivalent; 3) Individuals with a Bachelor's degree (or more) and experience field mismatch; and 4) Individuals with a Bachelor's degree (or more) and experience field match. Latent classes were identified separately within each analytic group as well as within the full sample. The research question was then addressed by identifying the class in each model that captured the largest portion of the sample. This class was identified as the "norm," and all others were identified as experiences of economic success that were less common.

Table 50 provides a summary of these analyses. The names assigned to the latent classes is based on a coding of their mean latent indicator values. Each latent indicator was transformed to have a mean of 0 and a standard deviation of 1 before entry into the model. Standardized mean values equal to or below 0.5 standard deviations below the mean are categorized as **L**ow; values between 0.5 standard deviations below the mean and 0.5 standard deviations above the means are categorized as **A**verage; and values equal to or above 0.5 standard deviations above the mean are categorized as **H**igh.

Table 50

Latent Classes Above and/or Below the Group Norm

				Mean latent indicators		
Model and analytic group	Comparison	Class [a]	Percent	Income	Earnings potential	Occupational prestige
1. No required education	**Norm**	**LLL**	**61.7%**	**-0.52**	**-1.18**	**-1.10**
	Above	ALA	12.7%	-0.37	-0.98	0.06
		AAA	19.9%	0.16	-0.18	-0.45
		ALH	1.6%	0.02	-0.82	0.98
		HHH	4.2%	0.60	0.82	0.88
2. Education required, has less than Bachelor's	**Norm**	**AHH**	**42.7%**	**0.37**	**1.04**	**0.75**
	Below	ALA	20.2%	-0.42	-1.24	-0.14
		AAA	37.1%	-0.00	0.05	0.39
3. Education required, field mismatch	**Norm**	**HHH**	**31.6%**	**1.05**	**1.55**	**1.46**
	Below	AAL	5.7%	-0.01	0.14	-0.52
		ALA	5.1%	-0.31	-1.16	-0.11
		AAH	16.4%	0.20	0.07	0.68
		AHH	21.8%	0.32	0.75	1.28
		HHA	19.3%	0.77	0.88	0.20
4. Education required, field match	**Norm**	**HHH**	**68.0%**	**0.68**	**1.15**	**1.47**
	Below	ALA	1.4%	-0.32	-0.92	-0.34
		HAH	21.1%	0.59	0.48	0.53

Model and analytic group	Comparison	Class [a]	Percent	Mean latent indicators: Income	Earnings potential	Occupational prestige
		HHA	9.5%	0.84	0.97	-0.21
5. All Groups	**Norm**	**LLL**	**36.5%**	**-0.52**	**-1.18**	**-1.08**
	Above	ALA	10.8%	-0.33	-0.99	0.22
		AAA	13.2%	0.12	-0.20	-0.49
		AHA	17.0%	0.42	0.58	0.32
		HHH	22.4%	0.62	1.08	1.41

[a] Latent indicators codes are presented to represent income, earnings potential, and occupational prestige, respectively. L=Low (≤.50 SD); A=Average (>-.50 SD and <.50 SD); H=High (≥.50 SD).
Note. Classes identified as the norm for the model sample are presented in bold.

The class representing the norm within each analytic group fell on either the high or the low end of the economic success spectrum, never in the middle. In the first model containing individuals in occupations that required a HS diploma or less, the majority fell into the uniformly low levels of economic success class (i.e., LLL). All other classes identified within the group captured relatively higher levels of economic success: ALA, AAA, ALH, and HHH. Thus, although the majority who work in occupations with little to no education requirements experienced low levels of economic success, approximately 38% experience higher levels of economic success in some capacity. The opposite trend was seen among the other three analytic groups. The class representing the norm generally captured the highest levels of observed economic success and the other latent classes comparatively represented lower levels of economic success. These trends suggest that although higher levels of economic success may be the norm within these groups, approximately 32-67% experience relatively lower levels of success. Finally, the last model containing the full sample provided results similar to the first model. This is not surprising as the analytic group used in the first model contained over half of the full sample. The LLL group was identified as the norm and approximately 63% of the sample experienced comparatively higher levels of economic success. Taken together, these results emphasize the existence and considerable size of groups who experience different levels of economic success than the norm.

RQ3: Predictors of Class Membership

The last research question aimed to identify predictors of class membership. A series of demographic, educational, and occupational measures were used to explore class membership. Because the focus of the study was on understanding experiences outside of the norm, the norm classes were modeled as the reference classes. Thus, all comparisons aimed to predict membership in comparison to the norm. Separate models were run for each of the predictor variables in order to understand the overall relationship and reduce introduction of confounding variables.

The results from this analysis were used to create profiles of class membership for the 18 classes outside of the norm. Table 51 presents a summary of these profiles. Variables were only included in the profiles and considered to be a major predictor if they were statistically significant and had an odds ratio ≤ .33, or ≥ 3.0; a ratio associated with a 75% chance of membership or non-membership. Furthermore, the current table only includes characteristics or combinations of characteristics from the profile that were uniquely associated with class membership and helped to distinguish between the latent classes. Overall, these profiles provide information to further understand the demographic, educational, and occupational composition of each latent class of economic success.

Table 51

Summary of Distinct Latent Class Predictors

Model & Class [a]	Distinct characteristics associated with increased likelihood of membership (Compared to membership in the reference [R] class)
1. LLL [R]	
ALA	similar to AAA class (occup. requires > no work experience; works in a field related to studies; or occup. is associated with > importance of cognitive abilities or basic, complex problem solving, resource management, or systems skills), except: female
AAA	similar to ALA class (see ALA characteristics in parentheses), except: does not work in a service occup.; works in an occup. that has some experience requirements; or works in an occup. that requires > importance of physical, psychomotor, or sensory abilities or social or technical skills
ALH	has at least an Associate's degree; works in a military specific or healthcare practitioners and technical occup.; or is overeducated
HHH	male; has a Bachelor's degree or more; or works in a natural resource, construction, maintenance, production, transportation, material moving, or service occup.
2. AHH [R]	
ALA	similar to AAA class (occup. requires a post-secondary certificate or some college or ≤ 1 month of on-the-job training; occup. is associated with < importance of cognitive abilities, complex problem solving skills, or systems skills), except: female; has an adequate education for their occup. or >; works in a service occup.; works in an occup. requiring ≤ 2 years of work experience; or works in an occup. with a < importance of basic and resource management skills
AAA	similar to ALA class (see ALA characteristics in parentheses), except: works in an education, legal, community service, arts, and media, or natural resources, construction, and maintenance, or service occup.; or works in an occup. that does not require > 2 years of work experience
3. HHH [R]	
AAL	similar to AHH class (work in an education, legal, community service, arts and media occup.; works in an occup. that requires a Bachelor's degree or 1 month of on-the job training), except: has a Bachelor's degree (as opposed to a graduate degree); works in a sales and office occup.
ALA	has a Bachelor's degree; works in an occup. requiring an Associate's degree or less; or is overeducated for their occup.
AAH	is not Asian; is undereducated for their occup.; or works in a healthcare practitioners or technical, sales and office, education, legal, community service, arts and media, or other occup.

Model & Class [a]	Distinct characteristics associated with increased likelihood of membership (Compared to membership in the reference [R] class)
AHH	similar to AAL class (see AAL characteristics in parentheses), except: does not work in a computer, engineering, and science or healthcare practitioners and technical occup.; works in an occup. that requires less than 2 years of experience
HHA	has a Bachelor's degree; works in an occup. that requires a Bachelor's degree; or has an adequate level of education for their occup.
4. HHH [R]	
ALA	works in an education, legal, community service, arts, and media or service occup.; or works in an occup. that requires an Associate's degree or less, 2 years or less of work experience, or 1 month or less of on-the-job training
HHA	similar to the HAH class (studied business during their Bachelor's program; works in an occup. requiring a bachelor's degree or > 1 month of on-the-job training), except: work in a computer, engineering and science, or a management, business, and finance occup.
HAH	similar to HHA class (see HHA characteristics in parentheses), except: work in service occupations, not in computer, engineering, and science or healthcare practitioners and technical occupations; or works in occupations with < importance of complex problem solving, resource management, systems or technical skills
5. LLL[R]	
ALA	similar to other non-LLL classes (occup. requires > 2 years of work experience, or > 1 month of training; occup. is associated with > importance of basic or systems skills; or works in a field related to studies), except: works in a natural resources, construction and maintenance occup.; or works in an occup. requiring > a HS diploma or equivalent
AAA	similar to other non-LLL classes (see ALA characteristics in parentheses), except: does not have less than a HS diploma or equivalent; does not work in a service occup.; or works in an occup. requiring an Associate's degree or more
AHA	similar to other non-LLL classes (see ALA characteristics in parentheses), except: is not overeducated; does not have less than a Bachelor's degree; does not work in a service or production, transportation, and material moving occup.; or works in an occup. requiring > a HS diploma or equivalent
HHH	similar to other non-LLL classes (see ALA characteristics in parentheses), except: is not Hispanic; has a Bachelor's degree or graduate degree; does not work in a sales and office occup.; or works in an occup. requiring > a HS diploma or equivalent

[a] Latent indicators codes are presented to represent income, earnings potential, and occupational prestige, respectively. L=Low (≤.50 SD); A=Average (>-.50 SD and <.50 SD); H=High (≥.50 SD).

Note. The current table includes predictors that were classified as major predictors (statistically significant with odds ratios ≤ .33 or ≥ 3.0) and distinctly contributed to class membership. Additional predictors were considered major predictors but are not included because they were major predictors for multiple categories and did not contribute to understanding of membership.

The results from this analysis also can be aggregated to the model level to provide insight into the relative importance of each predictor in the understanding of economic success. Table 52 summarizes the relative magnitude of each predictor variable by model and across all models. The relative magnitude is captured through both the mean odds ratio and the rate of major predictor status. The mean odds ratios represent the mean odds ratios for a predictor, across classes and categories (if the predictor is categorical), with odds ratios below 1 converted to an equivalent representation above 1. The conversion of odds ratios removed the direction of the effect and permitted the aggregation the magnitude across model results. The rates of major predictor status represent the instances in which each predictor was classified as a major predictor of class membership (with odds ratios ≤ .33, or ≥ 3.0). Since the opportunities to be classified as a major predictor varied by model, this is presented as a percentage. The mean odds ratios equal to or greater than 3.0 and the rates of major predictor status equal to or greater than 50% are presented in bold to assist with interpretation.

Table 52

Summary of the Relative Magnitude of each Predictor by Model

Predictor	Mean odds ratio [a] by model						Rate (%) of major predictor status by model					
	M1	M2	M3	M4	M5	*All*	M1	M2	M3	M4	M5	*All*
Demographic characteristics:												
Age	1.1	1.1	1.1	1.0	1.0	*1.1*	0	0	0	0	0	*0*
Gender	**3.3**	**3.2**	1.9	1.7	2.2	*2.4*	**50**	**50**	0	0	0	*18*
Race/ethnicity	1.6	1.4	1.8	1.5	1.5	*1.6*	0	0	7	0	0	*2*
Educational characteristics:												
Attained education	**3.0**	1.9	**3.8**	2.3	**4.1**	***3.3***	25	0	**60**	0	33	*27*
Field of study	--	--	1.8	**8.4**	1.9	***3.0***	--	--	0	**63**	7	*14*

Predictor	Mean odds ratio [a] by model						Rate (%) of major predictor status by model					
	M1	M2	M3	M4	M5	*All*	M1	M2	M3	M4	M5	*All*
Occupational characteristics:												
Occupational group	**6.2**	**24.3**	**16.4**	**27.7**	**19.8**	***18.4***	44	**100**	**80**	**89**	**58**	***73***
Req. level of ed.	**15.7**	**17.8**	**10.4**	**12.4**	**33.6**	***21.1***	**75**	33	**78**	**50**	**87**	***70***
Req. work exp.	**3.6**	**19.8**	**12.8**	**9.0**	**27.3**	***15.8***	**50**	**75**	**60**	**67**	**83**	***68***
Req. on-the-job training	**18.8**	**5.2**	**7.0**	**20.0**	**18.8**	***15.1***	**50**	**100**	**50**	**100**	**83**	***74***
Cognitive abilities	**3.5**	**7.1**	**12.9**	1.9	**6.7**	***7.0***	**50**	**100**	**80**	0	33	***53***
Physical abilities	2.9	2.3	1.5	1.3	1.4	*1.9*	25	0	0	0	0	*6*
Psychomotor abilities	**3.0**	1.9	1.4	1.1	1.5	*1.8*	25	0	0	0	0	*6*
Sensory abilities	**3.1**	1.7	1.2	1.0	1.4	*1.7*	25	0	0	0	0	*6*
Basic skills	**3.5**	**4.1**	**39.0**	1.9	**8.0**	***14.5***	**50**	**50**	**100**	0	**100**	***65***
Complex problem solving skills	**3.6**	**12.1**	**8.9**	2.1	**15.4**	***8.0***	**50**	**100**	**80**	33	**67**	***65***
Resource management skills	**3.2**	2.4	1.9	2.3	4.7	*2.8*	**50**	**50**	20	33	**67**	*41*
Social skills	**3.0**	1.5	1.1	1.1	1.8	*1.7*	25	0	0	0	0	*6*
Systems skills	**3.5**	**6.6**	**6.9**	**3.1**	**8.1**	***5.6***	**50**	**100**	**60**	33	**100**	***65***
Technical skills	**3.1**	1.3	1.7	2.7	1.5	*2.1*	25	0	20	33	0	*18*
Educational & occupational match:												
Education level match	**8.2**	**24.4**	2.6	**4.4**	2.0	***6.8***	38	**75**	33	17	17	*33*
Field match	2.7	--	--	--	**3.8**	***3.2***	38	--	--	--	**50**	*43*

[a] The mean odds ratios are computed from all reported odds ratios, with ratios below 1 converted to equivalent representations above 1 and ratios truncated to a maximum value of 50.
Note. Mean odds ratios greater than or equal to 3.0 and rates of major predictor status greater than or equal to 50% are presented in bold.

Table 52 displays the differences in relative magnitude between the predictor sets. Across the models, occupational characteristics and education level match contributed the most to the understanding of latent class membership. Most of the occupational characteristics and the education level match measure were associated with larger odds ratios than the demographic characteristics, educational characteristics, and field match measure. They also were associated with higher rates of identification as major predictors, a finding that indicates the higher odds ratios were generally experienced in a uniform manner and not as a result of a one or two high ratios. Overall, this means that occupational characteristics and education level match were the most helpful in differentiating between different experiences of economic success.

CHAPTER SIX

DISCUSSION AND CONCLUSIONS

The current study contributes to the literature by examining the relationship between postsecondary education and economic success through a person-centered lens. The study sought to understand individual experiences of education and success and the additional role that occupational characteristics might play. A method known as LCA was used to identify naturally occurring subgroups, or latent classes, that experience unique levels of economic success (i.e., income, occupational earnings potential, and occupational prestige). The role of educational and occupational characteristics then was analyzed through a series of regressions to predict membership in the latent classes identified. In this way, the current study identified multiple patterns of economic success and focused on understanding experiences outside of the norm.

Three primary research questions were addressed as part of this study. First, how often do individuals' educational backgrounds misalign with the entry level requirements and field of their occupation? Second, are there latent classes of individuals who succeed greater than or less than the group norm? And third, do demographic, educational, and occupational characteristics predict class membership? The first research question specifically addressed two gaps in the literature: general lack of research on match between field of study and field of work and lack of current research on rates of overeducation and undereducation. In addition, the second and third questions targeted another gap in the literature base concerning lack of person-centered research exploring this topic. As a whole, these questions also aimed to identify and elucidate patterns outside of the norm; patterns that could and sometimes did contradict the college-for-all direction of the current US education system.

This chapter offers a discussion of the study findings. The chapter begins with an examination of the current study's contributions to the literature. This is followed by a discussion of how the results relate back to the theoretical framework introduced in Chapter 2. Next, the results are summarized and aggregated for a discussion of pathways to economic success. A discussion of study limitations and recommendations for further research are then presented. Finally, the chapter concludes with a discussion of implications for policy and practice.

Contributions to the Literature

Rates of Education-Occupation Match/Mismatch

The rates of education level mismatch found in the current study are on the high end of those previously observed. Rates of overeducation had been estimated to be as low as 10% and as high as 50% (McGuinness, 2006); and rates of undereducation have ranged from 12% to 20% (Hartog, 2000). The current study finds 43.2% of the sample to be overeducated and 19.3% to be undereducated. These estimates are on the higher end of those previously observed in the literature. Furthermore, only 37.5% of the sample was considered adequately educated for their occupation. Taken together, this means that the majority of people are not adequately educated for their occupation.

The current rates of field mismatch are larger than those previously observed. The few studies that have examined field mismatch have found rates to range between 17.0-

39.0% (Lemieux, 2014; Yakusheva, 2010). Furthermore, very few studies have examined the correspondence between education level mismatch and field mismatch. Robst (2008) found that 10.5% of women and 9.6% of men experience field mismatch and overeducation and less than 1% of both women and men experience field mismatch and undereducation. The current study finds 58.9% of individuals with a Bachelor's degree or more (for whom a Bachelor's field of study was available) experienced field mismatch, 31.8% experienced both field mismatch and overeducation, and 2.7% experienced field mismatch and undereducation. All of these rates are higher than those previously observed, but it is the first two that are of the most practical interest. These rates suggest the majority of individuals with Bachelor's degrees or more work fields unrelated to their degree and a third are also overeducated for those jobs. Moreover, the rate of field mismatch is 1.5 to 3.5 times the size of those previously observed and the rate of overeducation and field mismatch is 3 times the size of previous estimates.

The relatively large rates of mismatch found in the current study could be attributed to actual changes in rates over time, to differences in measurement of mismatch, or to both. As discussed in Chapter 2, the majority of the research on this topic has used datasets from decades past, even studies that were published more recently. It is possible that overeducation and field mismatch are occurrences that are becoming increasingly more common. As K-12 schools are implementing practices to make more students college ready and more students are actually attending postsecondary institutes (Brown & Schwartz, 2014; Snyder et al., 2016), the value of a college degree may be decreasing. In addition, the studies that have examined mismatch have used several different types of measurement, including job analysis, self-reports, or trends within the data itself (i.e., education levels and fields associated with the majority in an occupation). The current study evaluated both types of match based on person level and occupation level data, with match generally evaluated based on expert ratings. Although this approach did allow examination of the issue in a large, nationally representative sample, it may have been less inclusive than other measures of peripherally related fields or variance in required levels of education.

Latent Classes of Economic Success

The current study is the first known study to identify naturally occurring groups with different experiences of economic success. Instead, most of the studies reviewed (e.g., Fan et al., 2016; Jepsen et al., 2014; Robst, 2007a) have examined income as an indicator of economic success and aimed to understand differences in income based on various predictor sets. As mentioned previously, this approach only identifies the average relationship and ignores relationships among sub-populations that may exist. The current study adds to the literature through identification of the latent classes of economic success that exist within the full sample and four specific subgroups: 1) Individuals in occupations that require a High School diploma or less; 2) Individuals with less than a Bachelor's degree and in occupations that require more than a High School diploma, or equivalent; 3) Individuals with a Bachelor's degree or more and experience field mismatch; and 4) Individuals with a Bachelor's degree or more and experience field match.

The latent classes identified within the four subgroups generally followed expectations based on prior research regarding postsecondary education and income. The four groups were created using information about attained education, required education for an occupation, and field mismatch. Prior research has repeatedly found higher levels of education to be associated with higher income (Baum, Ma, et al., 2013; Carnevale et al., 2011; Hout, 2012). Thus, it would be expected that groups containing individuals with higher levels of education (attained or required) would primarily contain classes representing higher levels of economic success than those identified in groups containing individuals with lower levels of education. In general, these expectations were met in the first group, containing individuals in occupations that require a High School diploma or less, and the third and fourth groups, containing individuals with Bachelor's degrees or more. However, these expectations were not met in the second group and there was considerable variance in the levels of economic success observed within each group.

The second group contained latent classes that contradicted expectation. The group was composed of individuals with less than a Bachelor's degree who worked in occupations that require more than a High School diploma. It represents non-traditional students that do not attend a 4-year institute directly after high school and only a quarter of whom have even received an Associate's degree. Previous research suggests that these individuals tend to make less than those with Bachelor's degrees (e.g., Baum, Ma, et al., 2013; Carnevale et al., 2011; Hout, 2012). However, the current study found this non-traditional group experienced similar levels of economic success as the two groups containing individuals with Bachelor's degrees (or more). The Bachelor's degree (or more) groups did include larger proportions experiencing higher levels of economic success than the non-traditional group, but all three groups contained relatively similar classes representing average to high levels of economic success. Furthermore, almost half (42.7%) of the non-traditional group was assigned to a class representing average income and high earnings potential and occupational prestige. If the average income of this class was 0.13 standard deviations higher, it would have been considered a uniformly high economic success class. Taken together, these results suggest that nearly half of the non-traditional students experienced levels of economic success that were not far below the highest levels observed in the Bachelor's degree (or more) groups. This trend defies expectation and exemplifies a subgroup for whom a 4-year college degree may provide little benefit.

There was considerable variance in the levels of economic success observed within the groups, even among the groups that followed expectations based on prior research. Three to six distinct classes of economic success were identified across the groups. The class containing the largest proportion of the group was considered the norm class or norm experience of economic success for the group. Across the groups, approximately 32-58% of the samples belonged to non-normative classes. Some of these non-normative classes captured subgroups that experienced much higher or lower levels of economic success than the norm. For example, the first group (capturing the lowest education requirements) included a class representing uniformly high levels of economic success (i.e., high income, earnings potential, and occupational prestige); and the third and fourth group (capturing the highest levels of education) both included a class representing low earnings potential and average income and occupational prestige. Together, these results shed light on the existence of several subgroups that do not uniformly benefit from a certain level of education.

Predictors of Latent Classes of Economic Success

Across the predictive models, educational background contributed less frequently to the understanding of class membership than occupational characteristics. As displayed in Table 52 (presented in Chapter 5), occupational characteristics more often were identified as a major predictor than educational characteristics, and they also were associated with larger odds ratios. This finding contradicts expectation based on previous research (e.g., Carnevale et al., 2012; Dadgar & Weiss, 2014; Hout, 2012). Most research reviewed for the current study focused on attained education level as a predictor of income and no studies investigated the role of occupational group or industry.

In addition, a few of the predictors did not contribute greatly to the understanding of economic success. Demographic variables (i.e., age, gender, race/ethnicity) were only identified as a major predictor of class membership for five of the 18 classes; and these five classes were not particularly different from the other classes (see Table 47 in Chapter 4). Field of study was only identified in two of the 12 classes in which it was included (Models 3-5). Both instances occurred in Model 4 (containing individuals who had obtained at least a Bachelor's degree and who worked in an occupation related to their degree) and did not offer much assistance in understanding class membership. Furthermore, these variables were associated with lower odds ratios compared to many of the other variables, with average odds ratios for the demographic variables ranging from 1.1-2.4 and the average ratio for the field of study estimated to be 3.0 (see Table 52 in Chapter 5). Finally, of the four types of abilities examined—cognitive, physical, psychomotor, and sensory—only cognitive ability was generally identified as a major predictor. Taken together, these findings offer both agreement and disagreement with previous research. Cognitive abilities have frequently been associated with higher levels of economic success (e.g., Barone & van de Werfhorst, 2011; Heckman et al., 2006), so these findings are not surprising. However, considerable differences in earnings have been found in the literature based on gender, race/ethnicity, and field of study (e.g., Black et al., 2006; Finnie & Frenette, 2003; Sites & Parks, 2011; Stanley & Jarrell, 1998). Thus, it is surprising that these trends were not identified in the current study.

The predictive importance of the variables may be influenced by the modeling approach used in the current study. Most studies in the literature (e.g., Carnevale et al., 2012; Dadgar & Weiss, 2014; Hout, 2012) have identified variables as important predictors based on average relationships. Because the current study decomposes the average to identify and predict membership in classes, there is an overall reduction in the variance that can be decomposed. Instead of using all the data, this study dissects the data to examine trends in variables within groups within classes. This addresses a different question than regressions to predict a continuous indicator of economic success (e.g., income) and thus can yield different results. Additionally, this approach may be more prone to issues with separation of data and near zero variance due to the partitioning of the data (Asparouhov & Muthén, 2014). There were a few instances during the modeling where combinations of predictors and classes perfectly separated the data or led to near zero variance in a predictor. Categories had to be collapsed to address this issue, but these trends could be indicative of existing relationships that could not be captured by the current results.

Theoretical Connections and Implications

The current study utilized theory from two literature bases to explore and explain the potential relationship between postsecondary education and economic success. The economic theories included job competition theory (Thurow, 1975), human capital theory (Becker, 1962), and assignment theory (Sattinger, 1993); and the developmental theories included bioecological theory (Bronfenbrenner & Ceci, 1994) and the person-centered theoretical approach (Bergman & Magnusson, 1997). The findings from the current study can be tied back to each of these theories.

Job competition theory (Thurow, 1975) highlights the role of the market in obtaining an occupation and a corresponding level of economic success. The theory is supported by the current estimates of educational and occupational mismatch, which are generally larger than estimates from past decades (e.g., Lemieux, 2014; McGuinness, 2006; Robst, 2008). Research suggests an increasing number of students are attending postsecondary institutes (Snyder et al., 2016), thus the increases in mismatch may be attributable to an increase in the educational supply. Job competition theory proposes that the market determines the number and types of jobs, and there is competition among the most qualified to get those jobs. If there is more supply than there is demand, not all will obtain their desired occupation. The theory also is supported by the finding that occupational characteristics contribute more to the understanding of economic success than educational characteristics. If the demand for an occupation remains constant, the value (i.e., economic success) associated with the occupation also will remain fairly constant. However, if the supply of educated individuals able to perform the occupation increases, the supply may outstrip the demand, mismatch will increase, and the value associated with the education may vary greatly. Thus, the value of an occupation may remain relatively constant while the value of an education may vary based on experiences of mismatch.

Human capital theory (Becker, 1962) emphasizes the role of education and training in experiences of economic success. The theory is supported by the general latent class distributions across the four models based on analytic subgroups of the overall sample. The four subgroups generally represented individuals with varying attained education or required education levels. Across the models, as education levels increased, the overall distribution of the observed latent classes of economic success increased and the mode class of membership also increased. These findings are in line with the expectations of human capital theory, that higher levels of education are associated with increasingly marketable knowledge and skills that will in turn yield higher levels of economic success. Furthermore, the theory suggests that the capital associated with the non-traditional postsecondary group (in Model 2) may not be well understood yet. Prior research (e.g., Baum, Ma, et al., 2013; Carnevale et al., 2011; Hout, 2012) suggests lower levels of economic success would be observed in this group, yet the current study identified experiences of economic success that were sometimes on par with traditional 4-year college graduates. Finally, the theory is also supported by the relative importance of cognitive abilities (e.g., deductive reasoning, mathematical reasoning, originality) and basic skills (e.g., critical thinking, learning strategies, writing) in the understanding of economic success. Although other skills and abilities were identified as major predictors, these two are commonly developed and refined through education. The relative importance of these variables provides direct evidence of the value of education-driven capital in the understanding of economic success.

Assignment theory (Sattinger, 1993) focuses on the role of worker-job match in the understanding of economic success. This theory is supported by the relative magnitude of the occupational and educational match measures in the prediction of economic success. Education level match was generally associated with larger odds ratios than attained education level or field of study, and field match was associated with similar odds ratios as the two educational characteristics (see Table 52 in Chapter 5). These results suggest that the match between the education and occupation are at least as important in determining economic success as the education level itself. In this way, assignment theory and human capital theory can be viewed as working together to offer insight into levels of economic success. Further support of this theory is provided through examination of the differences in latent class membership between the third and fourth analytic groups. These groups captured traditional 4-year (or more) graduates who only differed on whether they entered a field unrelated to their degree (group 3) or related to their degree (group 4). The full model (Model 5) found that the group experiencing field match generally experienced higher levels of economic success than the group experiencing field mismatch (see Table 33 in Chapter 4). These results suggest that individuals who work in occupations that match their skills are more likely to experience higher levels of economic success.

Bioecological theory (Bronfenbrenner & Ceci, 1994) focuses on the role of the environment, individual biology, and the interactions between and amongst these components. The theory is not specific to the relationship between postsecondary education and economic success but instead provides a broad framework in which to understand the relationships. The theory is supported through the observation of variance in the latent classes observed among individuals with similar attained or required education levels (Models 1-4) and the existence of classes that are diametrically opposed to the norm (e.g., the existence of the HHH class in the first model containing individuals in occupations requiring a High School diploma or less, where the majority fell within the LLL class). These findings generally support the notion that development is complex and involves many varied components that can interact to further influence outcomes and contribute to non-normative experiences. Additionally, although demographic characteristics were not identified as major predictors across the models, they did contribute to the understanding of a few of the latent classes observed. Race/ethnicity and gender are biological components that interact with and influence experiences across the lifespan and the current findings suggest they can play a role in the relationship between postsecondary education and economic success. Finally, the theory also is supported through the relative importance of cognitive abilities, basic skills, complex problem solving skills, and systems skills in the understanding of latent class membership. These abilities and skills incorporate both biological predispositions and experiences with the environment that interact to develop these competencies across the lifespan. The relative importance of these abilities and skills highlights another way in which the biology and the environment interact to influence experiences of economic success.

Finally, the person-centered theoretical approach (Bergman & Magnusson, 1997) synthesizes the previous theories to offer an understanding of the individual and the combination of factors that contribute to an outcome. This theory is not tied to any particular variables but instead aggregates the findings and connects them to understand unique pathways to success. Different pathways to similar levels of economic success and similar pathways to different levels of economic success were observed in the current study. These pathways are further explained and explored in the next section on pathways to success.

Together, these five theories offer a comprehensive view of the relationship between postsecondary education and economic success. The theories build off one another to offer insight into different types of trends and provide support of the underlying relationships observed. The findings from the current study were generally supported by at least one of these theories, and none offered contradiction of any theoretical assumptions. In this way, the theoretical framework used in the current study offered guidance for interpretation and was further strengthened through its relevance to the findings. Furthermore, the current study demonstrates that these theories can work together to inform the relationship under study and do not need to be used as mutually exclusive theories.

Pathways to Success

The results from the current study offer insights into different pathways to economic success. Although the study did not examine pathways in a longitudinal sense, it did capture information about educational and occupational decisions that individuals made previously, such as the decisions about whether or not to pursue postsecondary education, the field to study, and the occupation to enter. These decisions can be examined in aggregate to understand the different pathways to economic success.

Several different pathways to similar levels of economic success were identified in the current study. Pathways to uniformly high levels of economic success were observed among individuals who worked in occupations not requiring any education as well as among individuals with Bachelor's degrees who worked in fields related to their degree. Similarly, pathways to an average to low level of economic success (ALA) were identified among individuals with no postsecondary education, those with more than a high school degree but less than a Bachelor's, and those with a Bachelor's degree or more. This pattern of multiple paths to the same end is known as equifinality within the person-centered approach (Roeser & Peck, 2003). It emphasizes the existence of many pathways leading to the same end goal.

The results also demonstrate the existence of similar pathways to different experiences of economic success. For example, individuals with a Bachelor's degree who entered a field related to their studies could end up experiencing an average to low (ALA), average to high (HAH, HHA), or uniformly high level of economic success. Additionally, an individual with more than a high school education and less than a Bachelor's degree could achieve an average to low (ALA), uniformly average (AAA), or average to high (AHH) level of economic success. This pattern of similar paths to different endings is known as multifinality within the person-centered approach (Roeser & Peck, 2003). It emphasizes that similar experiences can interact with the individual in different manners and contribute to different endings.

Together, the current results suggest there is no single pathway to success that is applicable to all. Various levels of postsecondary education can be associated with experiences of high levels of economic success; and high levels of education can be associated with low levels of economic success. Decisions an individual makes, such as what occupation to enter, can serve to further differentiate their levels of economic success. These trends serve as evidence to contradict the college-for-all push of the US education system. The current study demonstrates that college does not uniformly benefit all and some experience similar levels of success without a traditional 4-year college education.

Limitations

There are a couple of limitations to the present study. First, the occupational coding system used within the American Community Survey dataset was the census 2010 occupational classification system. This classification system included 539 unique occupations. Another classification system known as the Standard Occupational Classification (SOC) system is more comprehensive and includes codes for 1110 distinct occupations. In fact, some of the occupational data used in the current study was measured at the SOC code level and then aggregated to represent the reduced set of census 2010 occupations. This less-detailed measurement of occupation decreased the variance in the occupational data that could be examined. In turn, variance issues were sometimes observed within the analyses.

Second, the study did not account for the complex survey design within the latent class analyses. This was done because the statistical software used could not account for the specification of replicate weights (the complex design variables offered in the data) and the data did not include information at the level to be able to identify PSU and clusters. It was determined this would have minimal impact on the current study as the study is exploratory in nature and not meant to test theory (via examination of statistical significance). However, this may have resulted in some larger estimates of standard error resulting in the flagging and review of fewer predictors.

Implications for Research and Practice

The current study offers evidence of overeducation, field mismatch, major predictors of economic success, and multiple pathways to economic success. Approximately 68.9% of individuals who had obtained Bachelor's degrees were working in unrelated fields to their degree, 43.2% were overeducated for their occupation, and 31.8% were both overeducated and working in unrelated fields. Additionally, occupational characteristics were found to be more important in the understanding of economic success than educational (i.e., attained education and field of study) and demographic characteristics (i.e., age, race/ethnicity, and gender); and interesting patterns were identified that captured high levels of success among non-traditional students with more than a high school diploma but less than a Bachelor's degree, and low to average levels of success among individuals with Bachelor's degrees or higher. As a whole, these findings offer several contributions to both policy and practice.

The US education system is generally pushing college for all students. As mentioned in Chapter 2, schools have been slowly reducing the number of vocational programs, increasing the rigor of academic tracks, and even changing graduation requirements to mirror college admission requirements (Brown & Schwartz, 2014; Schwartz, 2014). In the current study, I found that a traditional 4-year college degree is not necessary for all and that a large portion of those who obtain such a degree may not utilize it. Additionally, the type of education and the field studied mattered less than occupational characteristics (e.g., occupational group, required level of education, occupational skills) in understanding economic success. Based on these findings, K-12 schools may consider further exploration and understanding of career readiness as opposed to college readiness. Schools may consider re-introduction of vocational programs and incorporation of training or internship programs. Students may be better served by being prepared for college *OR* careers by the end of their studies.

Research exploring the relationship between postsecondary education and economic success has primarily aimed to understand the *average* relationship. The current study demonstrates there are substantial subgroups that experience this relationship differently. Examination of the average masks these subgroups and obscures the real relationships that may lie underneath. More studies examining and accounting for these underlying trends are needed. This person-centered approach to research offers insight into issues that may otherwise be hidden.

Recommendations for Future Research

Based on this study, there are several recommendations for future study. First, the rates of field mismatch observed in the current study were much larger than those observed previously. Additional research should work to replicate the rates and evaluate whether rates of overeducation and field match are rising. In addition, the field match rates produced by the process utilized in the current study should be compared to those produced by a self-report measure of field match. This comparison would offer additional understanding about the ways in which the two measurements compare and the types of error that might be introduced in each.

Second, the current study was purely exploratory in nature. The study identified latent classes of economic success and demographic, educational, and occupational characteristics associated with each. Future research should work to further explore patterns of interest, particularly the class of non-traditional students who experienced average to high levels of economic success. Future research should also work to explore how the different predictors interact with one another, which ones predict class membership above and beyond the others, and how the classes are changed when considering educational and occupational decisions in the identification of the latent classes. These analyses can offer further understanding of the latent classes identified in the current study.

Finally, the current study heavily relied on external occupational measures to explore the relationship between postsecondary education and economic success. As mentioned in the discussion of the limitations, this led to reduced variance in some instances. Additional studies should examine the role of occupational characteristics using the richer classification of occupations offered by the SOC coding system. Such research would offer more detailed examination of the role of occupational characteristics as the measurements would be more precise and more fully aligned to the individuals they represent.

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APPENDICES

Appendix A: Compilation of Occupational Data

The current study uses data from the American Community Survey (ACS) as well as three external sources of occupational information: 1) O*NET; 2) the Occupational Outlook Handbook (OOH); and 3) the National Opinion Research Center (NORC) occupational data. The first two sources of occupational data use a different, more comprehensive occupational classification system than that use by the ACS and the latter source of occupational data. The first two data sources use the Standard Occupational Classification (SOC) system, which includes 1110 occupations, whereas the latter uses the 2010 occupation classification system, which includes 540 occupations. This appendix outlines the process used to aggregate the occupational data and merge it to create a final dataset of occupational information for the current study.

Identifying Corresponding Occupational Codes

A crosswalk created by the US Bureau of Labor Statistics Crosswalk (2011) was used to identify the SOC codes that correspond to each 2010 census code. The crosswalk contains each 2010 census code along with the corresponding SOC code for 538 of the 540 occupations census 2010 occupations. Being unemployed (code 9920) or military with no rank specified (code 9830) in the census 2010 classification was not specified with any occupations in the SOC classification system. In general, however, the SOC classification may be considered to be more comprehensive than the 2010 census classification system. It includes information on 1,110 specific occupations that can be aggregated into 840 detailed occupations, 461 broad occupations, 97 minor occupation groups, and 23 major occupation groups. The crosswalk generally identified matches in occupations at the detailed occupational level of the SOC classification system, but it occasionally identified occupations at the broad or minor occupational level. In this way, there was not always a one-to-one correspondence between the occupations in the two classification systems.

Higher-level alignment in the SOC codes. Two specific types of higher-level alignment were possible in the crosswalk: 1) an alignment at the broad or minor occupation level in the SOC classification system; and 2) an alignment of an "other" or "miscellaneous" occupation category for a particular job category in the 2010 classification system to all occupations in a SOC broad or minor occupation category that were not already merged with occupations in the crosswalk. Such types of alignment were indicated in the crosswalk by inclusion of a '0' or 'X', respectively, in the lower levels of the hierarchical SOC classification code. An example of each of these scenarios is presented in Table A1 and A2 below.

Table A1

Example of alignment at broad occupation level

From crosswalk		Related occupations in SOC classification system	
SOC code	Census code & job title	SOC job title	SOC code
11-2020	0050 - Marketing and sales managers	Marketing Managers	11-2021
		Sales Managers	11-2022

Table A1 above demonstrates the first type of higher-level alignment, an alignment at the broad occupation level. The SOC code from the crosswalk specifies a '0' in the last digit and corresponds with a broad SOC occupational category of '11-202 Marketing and Sales Managers'. Notice that this category matches the census job title is for this occupation. This is not surprising as the 2010 census codes were originally derived from the SOC codes. Within the SOC classification system, this broad occupational category includes the two specific occupations listed in the left of the table: 'Marketing Managers' and 'Sales Managers.' Thus, the 2010 census code in the table corresponds with the two SOC codes.

Table A2

Example of alignment to 'other' census category

From crosswalk			Related occupations in SOC classification system	
Exact match	Census code & job title	SOC code	SOC code	SOC job title
Yes	2015 - Probation officers & correctional treatment specialist	21-1092	21-1092	Probation Officers & Correctional Treatment Specialists
Yes	2016 - Social and human service assistant	21-1093	21-1093	Social and Human Service Assistant
No	2025 - Miscellaneous community and social service specialists, including health educators and community health workers	21-109X	21-1091	Health Educators
			21-1094	Community Health Workers
			21-1099	Community and Social Service Specialists, All Other

Table A2 above demonstrates the second type of higher-level alignment, an alignment of "other" or "miscellaneous" occupations within an occupation category. The table includes all of the detailed occupations associated with the broad SOC occupation category of '21-1090 Miscellaneous Community and Social Service Specialists.' Notice that the occupations presented in rows 1 and 2 merge with specific 2010 census occupation codes based on the corresponding SOC code in the crosswalk; thus these occupations have an exact match among the census 2010 occupational codes. The SOC occupations in the bottom three rows do not merge with specific census 2010 occupations. The crosswalk does however contain a census 2010 occupation that is matched with an SOC code of ’21-109X.’ The first six digits match the broad SOC occupation category and the last digit of ‘X’ indicates that the occupation should match with all SOC occupations within the broad category that have not already been merged with census 2010 occupations. Thus the census 2010 code ’2025’ corresponds with three specific SOC codes: ’21-1091’, ’21-1094’, and ’21-2099’.

Census codes with no SOC code. As mentioned previously, two census codes did not correspond to any codes in the SOC system. These two codes represented: 1) unemployed individuals; and 2) individuals that are in the military with no rank specified. The first code capturing unemployed individuals is not of use in the current study as only employed individuals are included in the final sample. The second code captures a generic military occupation. Examples of this occupation include a sailor in the navy or a soldier (Smith & Son, 2014). In order to include a base level of occupational information for this occupation, it was decided to use occupational information associated with another census 2010 code—enlisted military tactical operations, air/weapons specialists and crew members (code 9820)—for this code as well. Of the three census military occupations matched to SOC occupations, the enlisted military occupation referenced above has the lowest levels of required education, experience and training; thus it offers a base level of evaluating the generic census occupation category. Table A3 below summarizes the SOC codes with occupational data that was subsequently associated with the military with no rank specified census category.

Table A3

SOC Occupations Linked to the Census Occupation for Military, No Rank Specified

SOC code	SOC job title
55-3011	Air Crew Members
55-3012	Aircraft Launch and Recovery Specialists
55-3013	Armored Assault Vehicle Crew Members
55-3014	Artillery and Missile Crew Members
55-3015	Command and Control Center Specialists
55-3016	Infantry
55-3017	Radar and Sonar Technicians
55-3018	Special Forces
55-3019	Military Enlisted Tactical Operations and Air/Weapons Specialists and Crew Members, All Other

Summary of results. All of the 1,110 specific SOC occupation codes were matched with one of the 2010 census occupation codes. The specific codes were matched using the corresponding detailed occupation code associated with each. Of the 540 census codes, 406 matched a specific SOC code, 116 matched a broad occupational category (e.g., 99-999**0)**, 8 corresponded with an "other" or "miscellaneous" subcategory of a broad occupational category (e.g., 99-999**X)**, 4 matched a minor occupational group (e.g., 99-99**00**), and 5 corresponded with an "other" or "miscellaneous" subcategory of a minor occupational group (e.g., 99-99**XX**).

Aggregating O*NET and OOH Data

The O*NET data had to be aggregated to represent the reduced number of occupational codes in the census 2010 classification system. This was necessary for two different types of data: 1) ratings capturing the average importance of particular skills and abilities to an occupation, and 2) percentages capturing the education, experience, and training level associated with an occupation by subject matter experts. The first two steps were similar for both types of data. First, if no occupational information was available at the detailed occupational level and at least half of the specific occupations within the detailed occupation had data for the particular variable being aggregated, then data was averaged across specific occupations to represent the detailed occupation. Next, if data for the variable was available for half of the SOC occupations that corresponded to a census occupation, then the data was aggregated to represent the census category. After this step, the importance ratings for 52 specific abilities were averaged to represent four general abilities for each occupation; and the ratings for 35 specific skills were averaged to represent six general skills. In addition, the education, experience and training level associated with each census occupation code was then identified as the level selected by the largest proportion of subject matter experts across occupations.

Twenty-six of the census occupations did not have education, training, and experience data available in O*NET. Data for these occupations was filled in using information from the OOH. The majority of data database is available for download in an XML format at https://www.bls.gov/ooh/xml-compilation.xml. In addition, the following OOH webpages were also used to gather information for a few occupations without complete occupational profiles in the database: http://www.bls.gov/ooh/About/Data-for-Occupations-Not-Covered-in-Detail.htm and https://www.bls.gov/ooh/military/military-careers.htm. These sources provided education, experience and training information for each of the occupations that were missing data in the O*NET database. The categories used to summarize education, experience and training data in the two databases are summarized in Table A4. Although there was not a perfect one-to-one correspondence among the categories, they were generally very close.

Table A4

*Education, Experience and Training Categories Correspondence in O*NET and OOH*

Variable	O*NET category	OOH category
Required education level	Less than high school*	No formal educational credential*
	High school or equivalent*	High school diploma or equivalent*
	Post-secondary certificate	Postsecondary nondegree award
	Some college no degree	Some college no degree
	Associate's degree	Associate's degree
	Bachelor's degree*	Bachelor's degree*
	Graduate degree	Graduate degree (mult. categories)
Required level of experience	None*	None*
	Up to 2 years	
	Over 2 years, up to 6 years*	Less than 5 years*
	Over 6 years, up to 10 years	5 years or more
	Over 10 years	
On-the-job training	None or short demonstration*	None*
	Anything beyond short demonstration, up to 1 month*	1 month or less*
	Over 1 month, up to 1 year*	More than 1 month up to 12 months*
	Over 1 year, up to 2 years	More than 12 months
	Over 2 years, up to 4 years	
	Over 4 years	

*At least one occupation with missing O*NET data was assigned this category through OOH data.

Twenty-four of the census occupations did not have skills and abilities data available in O*NET. A review of the occupations showed that these occupations did not have skills and ability information for *any* of the corresponding SOC occupations; thus relaxing the criteria for aggregating lower level information from 50% would not improve the results. Unfortunately, these ratings could not be filled in from another source as they are unique numeric ratings only captured by O*NET.

Final Merging

The final occupational dataset included data from three different sources. As described above, the data from O*NET was aggregated to represent the census 2010 occupations using the occupational crosswalk and the OOH was used to fill-in missing education, experience and training information not captured in the O*NET database. Finally, the occupational earnings threshold and occupational prestige measure was merged in from the NORC dataset by the census 2010 code. The final dataset included complete information on education, experience, training, occupational earnings threshold, and occupational prestige for all 539 occupations in the census 2010 list. Complete information on the abilities and skills associated with the occupations was only available for 515 of the occupations. This data was merged into the ACS data by census 2010 occupation code.

Appendix B: Code Lists

Table B1

Census 2010 Occupation Classification

Major group	Minor group	Example job titles
Management, Business, and Financial	Management	Medical and health services managers; Industrial production managers; Emergency management directors; Chief executives
	Business and Financial Operations	Credit analysts; Financial analysts; Fundraisers; Accountants and auditors
Computer, Engineering, and Science	Computer and mathematical	Computer programmers; Database administrators; Computer and information research scientists; Computer network architects
	Architecture and Engineering	Mining and geological engineers, including mining safety engineers; Architects, except naval; Nuclear engineers; Surveyors, cartographers, and photogrammetrists
	Life, Physical, and Social Science	Agricultural and food scientists; Geological and petroleum technicians; Economists; Medical scientists
Education, Legal, Community Service, Arts, and Media	Community and Social Service	Social workers; Counselors; Directors, religious activities and education; Clergy
	Legal	Judges, magistrates, and other judicial workers; Lawyers; Paralegals and legal assistants; Judicial law clerks
	Education, Training, and Library	Teacher assistants; Secondary school teachers; Preschool and kindergarten teachers; Special education teachers
	Arts, Design, Entertainment, Sports, and Media	Television, video, and motion picture camera operators and editors; Media and communication equipment workers, all other; Broadcast and sound engineering technicians and radio operators; Producers and directors

Healthcare Practitioners and Technical	Healthcare Practitioners and Technical	Podiatrists; Health practitioner support technologists and technicians; Other healthcare practitioners and technical occupations; Physicians and surgeons
Service	Healthcare Support	Dental assistants; Veterinary assistants and laboratory animal caretakers; Nursing, psychiatric, and home health aides; Occupational therapy assistants and aides
	Protective Service	Transit and railroad police; Lifeguards and other recreational, and all other protective service workers; Fire inspectors; First-line supervisors of fire fighting and prevention workers
	Food Preparation and Serving Related	Combined food preparation and serving workers, including fast food; Food servers, nonrestaurant; Chefs and head cooks; First-line supervisors of food preparation and serving workers
	Building and Grounds Cleaning and Maintenance	Pest control workers; First-line supervisors of housekeeping and janitorial workers; Maids and housekeeping cleaners; First-line supervisors of landscaping, lawn service, and groundskeeping workers
	Personal Care and Service	Personal care and service workers, all other; Embalmers and funeral attendants; Recreation and fitness workers; Miscellaneous entertainment attendants and related workers
Sales and Office	Sales and Related	First-line supervisors of non-retail sales workers; Retail salespersons; Insurance sales agents; Counter and rental clerks
	Office and Administrative Support	Postal service mail sorters, processors, and processing machine operators; Credit authorizers, checkers, and clerks; Postal service clerks; Procurement clerks
Natural Resources, Construction, and Maintenance	Farming, Fishing, and Forestry	Animal breeders; Forest and conservation workers; Fishers and related fishing workers; First-line supervisors of farming, fishing, and forestry workers
	Construction and Extraction	Miscellaneous construction and related workers; Painters, construction and maintenance; Roofers; Construction laborers

	Installation, Maintenance, and Repair	Signal and track switch repairers; Computer, automated teller, and office machine repairers; Electrical and electronics repairers, industrial and utility; Aircraft mechanics and service technicians
Production, Transportation, and Material Moving	Production	Model makers and patternmakers, metal and plastic; Welding, soldering, and brazing workers; Model makers and patternmakers, wood; Semiconductor processors
	Transportation and Material Moving	Taxi drivers and chauffeurs; Dredge, excavating, and loading machine operators; Ship and boat captains and operators; Driver/sales workers and truck drivers
Military Specific	Military Specific	Military, rank not specified; First-line enlisted military supervisors; Military officer special and tactical operations leaders; Military enlisted tactical operations and air/weapons specialists and crew members

Note. The above table was taken from the ACS 2014 documentation of Subject Definitions (ACS, 2014).

Table B2

Field of Degree Classification

Five-group classification	Fifteen-group classification	Example fields
Science and Engineering	Computers, Mathematics and Statistics	Computer Science, Mathematics, General Statistics
	Biological, Agricultural, and Environmental Sciences	Cellular and Molecular Biology, Soil Sciences, Natural Resource Management
	Physical and Related Sciences	Physics, Organic Chemistry, Astronomy
	Psychology	Psychology, Counseling, Child Psychology
	Social Sciences	Criminology, Sociology, Political Science
	Engineering	Chemical Engineering, Thermal Engineering, Electrical Engineering
	Multidisciplinary Studies	Nutritional Science, Cognitive Science, Behavioral Science
Science and Engineering Related	Science and Engineering Related	Pre-Med, Physical Therapy, Mechanical Engineering Technology
Business	Business	Business Administration, Accounting, Human Resources Development
Education	Education	Early Childhood Education, Higher Education Administration, Special Education
Arts, Humanities, and Other	Literature and Languages	English, Foreign Language and Literature, Spanish
	Liberal Arts and History	Philosophy, Theology, American History
	Visual and Performing Arts	Interior Design, Dance, Voice
	Communications	Mass Communications, Journalism, Public Relations

Note. The above table was taken from the ACS 2014 documentation of Subject Definitions (ACS, 2014).

Table B3

Major Skill Categorization

Major category	Skill
Basic Skills	Active Learning, Active Listening, Critical Thinking, Learning Strategies, Mathematics, Monitoring, Reading Comprehension, Science, Speaking, Writing
Complex Problem Solving Skills	Complex Problem Solving
Resource Management Skills	Management of Financial Resources, Management of Material Resources, Management of Personnel Resources, Time Management
Social Skills	Coordination, Instructing, Negotiation, Persuasion, Service Orientation, Social Perceptiveness
Systems Skills	Judgement and Decision Making, Systems Analysis, Systems Evaluation
Technical Skills	Equipment Maintenance, Equipment Selection, Installation, Operation and Control, Operation Monitoring, Operations Analysis, Programming, Quality Control Analysis, Repairing, Technology Design, Troubleshooting

Note. The above table reflects the O*NET major skill categorization.

Table B4

Major Ability Categorization

Major category	Ability
Cognitive Abilities	Category Flexibility, Deductive Reasoning, Flexibility of Closure, Fluency of Ideas, Inductive Reasoning, Information Ordering, Mathematical Reasoning, Memorization, Number Facility, Oral Comprehension, Oral Expression, Originality, Perceptual Speed, Problem Sensitivity, Selective Attention, Spatial Orientation, Speed of Closure, Time Sharing, Visualization, Written Comprehension, Written Expression
Physical Abilities	Arm-Hand Steadiness, Control Precision, Finger Dexterity, Manual Dexterity, Multilimb Coordination, Rate Control, Reaction Time, Response Orientation, Speed of Limb Movement
Psychomotor Abilities	Dynamic Flexibility, Dynamic Strength, Explosive Strength, Extent Flexibility, Gross Body Coordination, Gross Body Equilibrium, Stamina, Static Strength, Trunk Strength
Sensory Abilities	Auditory Attention, Depth Perception, Far Vision, Glare Sensitivity, Hearing Sensitivity, Near Vision, Night Vision, Peripheral Vision, Sound Localization, Speech Clarity Speech Recognition, Visual Color Discrimination

Note. The above table reflects the O*NET major ability categorization.

Appendix C: Systematic Evaluation of Field Match

The systematic evaluation of field match was possible after a series of steps were taken to build a crosswalk between the census 2010 occupations and ACS fields of study. First, the researcher linked the 192 degree fields in the ACS data to the CIPs degree fields. Next, the NCES crosswalk (2000) and the Bureau of Labor Statistics crosswalk (2011) were used to identify the related degree fields for each occupation. Finally, the final researcher created crosswalk was merged in with the ACS data to evaluate field match. Each of these steps is discussed in further detail below.

Identifying Linkage Between ACS and CIPs Degree Fields

In order to use the NCES crosswalk, the 192 degree fields in the ACS data had to be linked to the 53 CIP families present in the CIP taxonomy. This task was done in two steps. First, a fuzzy merge of degree field titles and the CIP titles (including titles from all levels in the hierarchy) was conducted. The fuzzy merge utilized the probabilistic approach presented in Wright (2011). It initially merged all ACS degree field with all of the CIP titles and calculated scores for each possible combination. Non-zero scores were assigned if any of the following conditions were met: 1) the ACS degree field title could be found within the CIPS title; 2) the ratio of the Levenshtein edit distance (a measure of the number of operations needed to make one string match the other) to the max number of characters in either title is less than or equal to .25; and 3) the ratio of the Levenshtein edit distance to the max number of characters in either title is less than or equal to .35. The first condition is the strictest and matches on this generally yield the highest quality of match. The second and third condition are each a little more lenient in match criterion and result in slightly less certain matches. As such, meeting the first criterion generally results in the highest merge score and meeting the second or third results in a successively lower merge scores. All non-zero merges were output and reviewed by the researcher to evaluate whether the results with the highest merge score represented the best match between the two degree classification systems. The SAS code for this step is presented below.

```
proc sql;
  create table matched as
  select a.*, b.*,
  case
    when find(b.ciptitle,a.FOD,'it')>0 then 12*length(a.FOD)/length(b.ciptitle)
    when complev(a.FOD,b.ciptitle)/max(length(a.FOD),length(b.ciptitle))<=.25
then 7
    when complev(a.FOD,b.ciptitle)/max(length(a.FOD),length(b.ciptitle))<.35
then 5
    else 0 end as merge_score
  from fod as a, cip2010 as b
  where calculated merge_score >0 ;
quit;
```

The above step resulted in 991 possible merges for 134 ACS degree fields. A review of the merge results found 105 degree fields where the highest merge score was determined by the researcher to be the best match, 18 where a lower merge score was determined to be the best match, and 13 where none of the merged CIP titles were determined to be a good match. This step resulted in links assigned to 121 of the 191 ACS degree fields.

Next, the remaining 70 ACS degree fields were manually linked with a CIP degree field. Linked fields were identified by either searching for key words or reviewing all occupations within the CIP family that was most logically related to the ACS field of study. It was possible to link an ACS field with multiple CIP fields. Although the ACS fields only needed to be linked to the CIP families, the linking process attempted to identify the lowest level match in the taxonomy that aligned in order to increase the precision in the alignment process. However, a match at the lowest level could not always be found. Some degree fields more fully aligned with a higher level of the taxonomy and others did not align with a specific title, but more generally fit within a CIP family. In such cases, the most appropriate level of the taxonomy was used. In total, 15 ACS degree fields were aligned by the researcher with CIP families. Table C1, presented at the end of this appendix, summarizes the CIP field assigned to each ACS field. The CIPS family is identified using the first two digits in the CIP code.

Identifying and Aggregating Related Occupations

The linkage between the ACS and CIP degree fields presented above was used in combination with the NCES crosswalk (2000) and the Bureau of Labor Statistics crosswalk (2011) to identify the occupations that are related to each ACS degree field. The NCES crosswalk containing the CIP code and corresponding SOC code was merged with the Bureau of Labor Statistics crosswalk containing the SOC code and corresponding census 2010 code. These two crosswalks were merged by SOC code and resulted in a crosswalk containing the corresponding SOC code and census 2010 code for each CIP degree field. Next, the CIP family was obtained as the first two characters of the CIP degree field code and all unique combinations of the census 2010 code and CIP family were output. This resulted in a list of the census 2010 occupations that correspond to each CIP family. This list was then merged by CIP family with the ACS to CIP degree field linkage information presented in Table C1. This merge resulted in a dataset containing the 191 ACS degree fields and all of the census 2010 occupations that are related to them. Finally, the data was reshaped and aggregated to include a row for each

2010 census occupation and a cell containing the codes for all of the related ACS degree fields, with different degree codes separated by commas. Table C2, presented at the end of this appendix, provides a summary of this final dataset containing the census 2010 occupations and the related ACS degree field.

Evaluating Field Match

The information presented in Table C2 was merged into the ACS data by each participant's census 2010 occupation code. Field match was evaluated by comparing the degree fields related to an occupation to the degree obtained by the participant. An individual was considered to have a field that matched if they obtained a degree in a field that was identified as related to the occupation in Table C2.

Table C1

ACS Degree Fields Linked to CIP Degree Fields

ACS degree field		CIP degree field	
Code	Title	Code	Title
1100	General Agriculture	01.00	Agriculture, General.
1101	Agriculture Production And Management	01.03	Agricultural Production Operations.
1102	Agricultural Economics	01.0103	Agricultural Economics.
1103	Animal Sciences	01.09	Animal Sciences.
1104	Food Science	01.1001	Food Science.
1105	Plant Science And Agronomy	01.11	Plant Sciences.
1106	Soil Science	01.12	Soil Sciences.
1199	Miscellaneous Agriculture	01	AGRICULTURE, AGRICULTURE OPERATIONS, AND RELATED SCIENCES.
1301	Environmental Science	03.0104	Environmental Science.
1302	Forestry	03.05	Forestry.
1303	Natural Resources Management	03.02	Natural Resources Management and Policy.
1401	Architecture	04.02	Architecture.

ACS degree field		CIP degree field	
Code	Title	Code	Title
1501	Area Ethnic And Civilization Studies	05.01, 05.02, 05.0102	Area Studies, Ethnic, Cultural Minority, Gender, and Group Studies, AND American/United States Studies/Civilization.
1901	Communications	09.0100	Communication, General.
1902	Journalism	09.04	Journalism.
1903	Mass Media	09.0102	Mass Communication/Media Studies.
1904	Advertising And Public Relations	09.0900	Public Relations, Advertising, and Applied Communication.
2001	Communication Technologies	09.07	Radio, Television, and Digital Communication.
2100	Computer And Information Systems-General	11.01	Computer and Information Sciences, General.
2102	Computer Science	11.07	Computer Science.
2103	Computer Systems Analysis	11.05	Computer Systems Analysis.
2105	Information Sciences	11.04	Information Science/Studies.
2106	Computer Administration Management And Security	11.10	Computer/Information Technology Administration and Management.
2107	Computer Networking And Telecommunications	11.09	Computer Systems Networking and Telecommunications.
2199	Miscellaneous Computer Sciences	11	COMPUTER AND INFORMATION SCIENCES AND SUPPORT SERVICES.
2101	Computer Programming	11.02	Computer Programming.
2104	Data Processing	11.03	Data Processing.
2201	Cosmetology Services And Culinary Arts	12.04	Cosmetology and Related Personal Grooming Services.
2302	Computer Teacher Education	13.1321	Computer Teacher Education.
2305	Mathematics Teacher Education	13.1311	Mathematics Teacher Education.
2308	Science Teacher Education	13.1316	Science Teacher Education/General Science Teacher Education.
2300	General Education	13.01	Education, General.
2301	Educational Administration And Supervision	13.04	Educational Administration and Supervision.
2303	School Student Counseling	13.11	Student Counseling and Personnel Services.
2304	Elementary Education	13.1202	Elementary Education and Teaching.

ACS degree field		CIP degree field	
Code	Title	Code	Title
2306	Physical And Health Education Teaching	13.1307, 13,1314	Health Teacher Education AND Physical Education Teaching and Coaching.
2307	Early Childhood Education	13.1210	Early Childhood Education and Teaching.
2309	Secondary Teacher Education	13.1205	Secondary Education and Teaching.
2310	Special Needs Education	13.10	Special Education and Teaching.
2311	Social Science Or History Teacher Education	13.1317	Social Science Teacher Education.
2312	Teacher Education: Multiple Levels	13.1206	Teacher Education, Multiple Levels.
2313	Language And Drama Education	13.1306, 13.1324	Foreign Language Teacher Education AND Drama and Dance Teacher Education.
2314	Art And Music Education	13.1302, 13.1324	Art Teacher Education AND Music Teacher Education.
2399	Miscellaneous Education	13	EDUCATION.
2400	General Engineering	14.01	Engineering, General.
2401	Aerospace Engineering	14.02	Aerospace, Aeronautical and Astronautical Engineering.
2402	Biological Engineering	14.45	Biological/Biosystems Engineering.
2403	Architectural Engineering	14.04	Architectural Engineering.
2404	Biomedical Engineering	14.05	Biomedical/Medical Engineering.
2405	Chemical Engineering	14.07	Chemical Engineering.
2406	Civil Engineering	14.08	Civil Engineering.
2407	Computer Engineering	14.09	Computer Engineering.
2408	Electrical Engineering	14.10	Electrical, Electronics and Communications Engineering.
2409	Engineering Mechanics Physics And Science	14.11, 14.12, 14.13	Engineering Mechanics, Engineering Physics, AND Engineering Science.
2410	Environmental Engineering	14.14	Environmental/Environmental Health Engineering.
2411	Geological And Geophysical Engineering	14.39	Geological/Geophysical Engineering.
2412	Industrial And Manufacturing Engineering	14.35, 14.36	Industrial Engineering AND Manufacturing Engineering.
2413	Materials Engineering And Materials Science	14.18	Materials Engineering

ACS degree field		CIP degree field	
Code	Title	Code	Title
2414	Mechanical Engineering	14.19	Mechanical Engineering.
2415	Metallurgical Engineering	14.20	Metallurgical Engineering.
2416	Mining And Mineral Engineering	14.21	Mining and Mineral Engineering.
2417	Naval Architecture And Marine Engineering	14.22	Naval Architecture and Marine Engineering.
2418	Nuclear Engineering	14.23	Nuclear Engineering.
2419	Petroleum Engineering	14.25	Petroleum Engineering.
2420	Operations Research	14.37	Operations Research.
2499	Miscellaneous Engineering	14	ENGINEERING.
2500	Engineering Technologies	15.00	Engineering Technology, General.
2501	Engineering And Industrial Management	15.1501	Engineering/Industrial Management.
2502	Electrical Engineering Technology	15.03	Electrical Engineering Technologies/Technicians.
2503	Industrial Production Technologies	15.06	Industrial Production Technologies/Technicians.
2504	Mechanical Engineering Related Technologies	15.08	Mechanical Engineering Related Technologies/Technicians.
2599	Miscellaneous Engineering Technologies	15	ENGINEERING TECHNOLOGIES AND ENGINEERING-RELATED FIELDS.
2601	Linguistics And Comparative Language And Literature	16.01	Linguistic, Comparative, and Related Language Studies and Services.
2602	French German Latin And Other Common Foreign Language.Studies	16.0101	Foreign Languages and Literatures, General.
2603	Other Foreign Languages	16.0101	Foreign Languages and Literatures, General.
2901	Family And Consumer Sciences	19.01	Family and Consumer Sciences/Human Sciences, General.
3201	Court Reporting	22.0303	Court Reporting/Court Reporter.
3202	Pre-Law And Legal Studies	22.0000, 22.0001	Legal Studies, General AND Pre-Law Studies.
3301	English Language And Literature	23.01	English Language and Literature, General.
3302	Composition And Rhetoric	23.13	Rhetoric and Composition/Writing Studies.

ACS degree field		CIP degree field	
Code	Title	Code	Title
3401	Liberal Arts	24.0101	Liberal Arts and Sciences/Liberal Studies.
3402	Humanities	24.0103	Humanities/Humanistic Studies.
3501	Library Science	25	LIBRARY SCIENCE.
3600	Biology	26.01	Biology, General.
3601	Biochemical Sciences	26.0202	Biochemistry.
3602	Botany	26.03	Botany/Plant Biology.
3603	Molecular Biology	26.0204	Molecular Biology.
3604	Ecology	26.1301	Ecology.
3605	Genetics	26.08	Genetics.
3606	Microbiology	26.0502	Microbiology, General.
3607	Pharmacology	26.1001	Pharmacology.
3608	Physiology	26.0901	Physiology, General.
3609	Zoology	26.07	Zoology/Animal Biology.
3610	Epidemiology	26.1309	Epidemiology.
3611	Neuroscience	26.1501	Neuroscience.
3699	Miscellaneous Biology	26	BIOLOGICAL AND BIOMEDICAL SCIENCES.
5101	Applied Biotechnology	26.12	Biotechnology.
3700	Mathematics	27.01	Mathematics.
3701	Applied Mathematics	27.03	Applied Mathematics.
3702	Statistics	27.05	Statistics.
3705	Decision Science	27	MATHEMATICS AND STATISTICS.
3799	Miscellaneous Mathematics	27	MATHEMATICS AND STATISTICS.
3801	Military Technologies	29	MILITARY TECHNOLOGIES AND APPLIED SCIENCES.
5098	Multi-Disciplinary Or General Science	30.00	Multi-/Interdisciplinary Studies, General.
5099	Miscellaneous Physical Sciences	30.01	Biological and Physical Sciences.
4000	Multi-Disciplinary Studies	30	MULTI/INTERDISCIPLINARY STUDIES.
4001	Intercultural And International Studies	30.20, 30.23	International/Global Studies AND Intercultural/Multicultural and Diversity Studies.

ACS degree field		CIP degree field	
Code	Title	Code	Title
4002	Nutrition Sciences	30.19	Nutrition Sciences.
4004	Accounting And Computer Science	30.16	Accounting and Computer Science.
4005	Mathematics And Computer Science	30.08	Mathematics and Computer Science.
4006	Cognitive Science And Biopsychology	30.25, 30.10	Cognitive Science AND Biopsychology.
4007	Interdisciplinary Social Sciences	30	MULTI/INTERDISCIPLINARY STUDIES.
4101	Physical Fitness Parks Recreation And Leisure	31	PARKS, RECREATION, LEISURE, AND FITNESS STUDIES.
4801	Philosophy And Religious Studies	38.00	Philosophy and Religious Studies, General.
4901	Theology And Religious Vocations	39	THEOLOGY AND RELIGIOUS VOCATIONS.
5000	Physical Sciences	40.01	Physical Sciences.
5001	Astronomy And Astrophysics	40.02	Astronomy and Astrophysics.
5002	Atmospheric Sciences And Meteorology	40.04	Atmospheric Sciences and Meteorology.
5003	Chemistry	40.05	Chemistry.
5004	Geology And Earth Science	40.0601	Geology/Earth Science, General.
5005	Geosciences	40.06	Geological and Earth Sciences/Geosciences.
5006	Oceanography	40.0607	Oceanography, Chemical and Physical.
5007	Physics	40.08	Physics.
5008	Materials Science	40.10	Materials Science.
5102	Nuclear And Industrial Radiology Technologies	41.02	Nuclear and Industrial Radiologic Technologies/Technicians.
5200	Psychology	42.01	Psychology, General.
5201	Educational Psychology	42.2806	Educational Psychology.
5202	Clinical Psychology	42.2801	Clinical Psychology.
5203	Counseling Psychology	42.2803	Counseling Psychology.
5204	Experimental Psychology	42.2704	Experimental Psychology.
5205	Industrial And Organizational Psychology	42.2804	Industrial and Organizational Psychology.
5206	Social Psychology	42.2707	Social Psychology.
5299	Miscellaneous Psychology	42	PSYCHOLOGY.

ACS degree field		CIP degree field	
Code	Title	Code	Title
5301	Criminal Justice And Fire Protection	43.01	Criminal Justice and Corrections.
5401	Public Administration	44.04	Public Administration.
5402	Public Policy	44.05	Public Policy Analysis.
5403	Human Services And Community Organization	44.00, 44.02	Human Services, General AND Community Organization and Advocacy.
5404	Social Work	44.07	Social Work.
5500	General Social Sciences	45.01	Social Sciences, General.
5501	Economics	45.06	Economics.
5502	Anthropology And Archeology	45.02, 45.03	Anthropology AND Archeology.
5503	Criminology	45.04	Criminology.
5504	Geography	45.0701	Geography.
5505	International Relations	45.0901	International Relations and Affairs.
5506	Political Science And Government	45.10	Political Science and Government.
5507	Sociology	45.11	Sociology.
5599	Miscellaneous Social Sciences	45	SOCIAL SCIENCES.
5601	Construction Services	46	CONSTRUCTION TRADES.
5701	Electrical And Mechanic Repairs And Technologies	47	MECHANIC AND REPAIR TECHNOLOGIES/TECHNICIANS.
5801	Precision Production	48	PRECISION PRODUCTION.
5901	Transportation Sciences And Technologies	49	TRANSPORTATION AND MATERIALS MOVING.
6000	Fine Arts	50.0799	Fine Arts and Art Studies, Other.
6001	Drama And Theater Arts	50.05	Drama/Theatre Arts and Stagecraft.
6002	Music	50.09	Music.
6003	Visual And Performing Arts	50.01	Visual and Performing Arts, General.
6004	Commercial Art And Graphic Design	50.0402, 50.0409	Commercial and Advertising Art AND Graphic Design.
6005	Film Video And Photographic Arts	50.06	Film/Video and Photographic Arts.
6006	Art History And Criticism	50.0703	Art History, Criticism and Conservation.
6007	Studio Arts	50.07	Fine and Studio Arts.

ACS degree field		CIP degree field	
Code	Title	Code	Title
6008	Video Game Design And Development	50.0411	Game and Interactive Media Design.
6099	Miscellaneous Fine Arts	50.07	Fine and Studio Arts.
6100	General Medical And Health Services	51.00	Health Services/Allied Health/Health Sciences, General.
6102	Communication Disorders Sciences And Services	51.02	Communication Disorders Sciences and Services.
6103	Health And Medical Administrative Services	51.07	Health and Medical Administrative Services.
6104	Medical Assisting Services	51.08	Allied Health and Medical Assisting Services.
6105	Medical Technologies Technicians	51.1005	Clinical Laboratory Science/Medical Technology/Technologist.
6106	Health And Medical Preparatory Programs	51.11	Health/Medical Preparatory Programs.
6107	Nursing	51.3808	Nursing Science.
6108	Pharmacy Pharmaceutical Sciences And Administration	51.20	Pharmacy, Pharmaceutical Sciences, and Administration.
6109	Treatment Therapy Professions	51	HEALTH PROFESSIONS AND RELATED PROGRAMS.
6110	Community And Public Health	51.22	Public Health.
6111	Energy And Biologically Based Therapies	51.37	Energy and Biologically Based Therapies.
6199	Miscellaneous Health Medical Professions	51	HEALTH PROFESSIONS AND RELATED PROGRAMS.
6101	Medical Office Assistance And Administration	51.0705	Medical Office Management/Administration.
6200	General Business	52.01	Business/Commerce, General.
6201	Accounting	52.0301	Accounting.
6202	Actuarial Science	52.1304	Actuarial Science.
6203	Business Management And Administration	52.0201	Business Administration and Management, General.
6204	Operations Logistics And E-Commerce	52.0205, 52.0208	Operations Management and Supervision AND E-Commerce/Electronic Commerce.
6205	Business Economics	52.06	Business/Managerial Economics.
6206	Marketing	52.14	Marketing.
6207	Finance	52.0801	Finance, General.

ACS degree field		CIP degree field	
Code	Title	Code	Title
6208	Marketing Research	52.1402	Marketing Research.
6209	Human Resources And Personnel Management	52.10	Human Resources Management and Services.
6210	International Business	52.11	International Business.
6211	Hospitality Management	52.09	Hospitality Administration/Management.
6212	Management Information Systems And Statistics	52.12	Management Information Systems and Services.
6299	Miscellaneous Business	52	BUSINESS, MANAGEMENT, MARKETING, AND RELATED SUPPORT SERVICES.
6401	History And Philosophy Of Science And Technology	54.0104	History and Philosophy of Science and Technology.
6402	History	54.0101	History, General.
6403	United States History	54.0102	American History (United States).

Table C2

Census 2010 Codes and Related ACS Degree Fields

Census 2010 occupation		Related ACS degree field
Code	Job title	
0010	Chief executives	5401, 5402, 5403, 5404, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0020	General and operations managers	4101, 5401, 5402, 5403, 5404, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0030	Legislators	5401, 5402, 5403, 5404
0040	Advertising and promotions managers	1901, 1902, 1903, 1904, 2001, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0050	Marketing and sales managers	2901, 6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0060	Public relations and fundraising managers	1901, 1902, 1903, 1904, 2001
0100	Administrative services managers	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199, 6200, 6201, 6202,

Census 2010 occupation		Related ACS degree field
Code	Job title	
		6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0110	Computer and information systems managers	2100, 2101, 2102, 2103, 2104, 2105, 2106, 2107, 2199, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0120	Financial managers	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0135	Compensation and benefits managers	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0136	Human resources managers	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0137	Training and development managers	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0140	Industrial production managers	2400, 2401, 2402, 2403, 2404, 2405, 2406, 2407, 2408, 2409, 2410, 2411, 2412, 2413, 2414, 2415, 2416, 2417, 2418, 2419, 2420, 2499, 2500, 2501, 2502, 2503, 2504, 2599, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0150	Purchasing managers	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0160	Transportation, storage, and distribution managers	5401, 5402, 5403, 5404, 5901, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0205	Farmers, ranchers, and other agricultural managers	1100, 1101, 1102, 1103, 1104, 1105, 1106, 1199
0220	Construction managers	2500, 2501, 2502, 2503, 2504, 2599, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0230	Education administrators	2300, 2301, 2302, 2303, 2304, 2305, 2306, 2307, 2308, 2309, 2310, 2311, 2312, 2313, 2314, 2399
0300	Architectural and engineering managers	1401, 2400, 2401, 2402, 2403, 2404, 2405, 2406, 2407, 2408, 2409, 2410, 2411, 2412, 2413, 2414, 2415, 2416, 2417, 2418, 2419, 2420, 2499, 2500, 2501, 2502, 2503, 2504, 2599, 5000, 5001, 5002, 5003, 5004, 5005, 5006, 5007, 5008
0310	Food service managers	2201, 2901, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0325	Funeral service managers	2201
0330	Gaming managers	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299

Census 2010 occupation		Related ACS degree field
Code	Job title	
0340	Lodging managers	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0350	Medical and health services managers	5401, 5402, 5403, 5404, 6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
0360	Natural sciences managers	2400, 2401, 2402, 2403, 2404, 2405, 2406, 2407, 2408, 2409, 2410, 2411, 2412, 2413, 2414, 2415, 2416, 2417, 2418, 2419, 2420, 2499, 3600, 3601, 3602, 3603, 3604, 3605, 3606, 3607, 3608, 3609, 3610, 3611, 3699, 3700, 3701, 3702, 3705, 3799, 4000, 4001, 4002, 4004, 4005, 4006, 4007, 4801, 5000, 5001, 5002, 5003, 5004, 5005, 5006, 5007, 5008, 5098, 5099, 5101, 6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0400	Postmasters and mail superintendents	5401, 5402, 5403, 5404
0410	Property, real estate, and community association managers	1401, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0420	Social and community service managers	5401, 5402, 5403, 5404, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0425	Emergency management directors	5301
0430	Managers, all other	1301, 1302, 1303, 1901, 1902, 1903, 1904, 2001, 2100, 2101, 2102, 2103, 2104, 2105, 2106, 2107, 2199, 3501, 4101, 5200, 5201, 5202, 5203, 5204, 5205, 5206, 5299, 5301, 5401, 5402, 5403, 5404, 5500, 5501, 5502, 5503, 5504, 5505, 5506, 5507, 5599, 6000, 6001, 6002, 6003, 6004, 6005, 6006, 6007, 6008, 6099, 6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299, 6401, 6402, 6403
0500	Agents and business managers of artists, performers, and athletes	1901, 1902, 1903, 1904, 2001, 6000, 6001, 6002, 6003, 6004, 6005, 6006, 6007, 6008, 6099, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0510	Buyers and purchasing agents, farm products	1100, 1101, 1102, 1103, 1104, 1105, 1106, 1199

Census 2010 occupation		Related ACS degree field
Code	Job title	
0520	Wholesale and retail buyers, except farm products	2201, 2901, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0530	Purchasing agents, except wholesale, retail, and farm products	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0540	Claims adjusters, appraisers, examiners, and investigators	5701, 6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0565	Compliance officers	
0600	Cost estimators	2400, 2401, 2402, 2403, 2404, 2405, 2406, 2407, 2408, 2409, 2410, 2411, 2412, 2413, 2414, 2415, 2416, 2417, 2418, 2419, 2420, 2499, 2500, 2501, 2502, 2503, 2504, 2599, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0630	Human resources workers	4000, 4001, 4002, 4004, 4005, 4006, 4007, 5098, 5099, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0640	Compensation, benefits, and job analysis specialists	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0650	Training and development specialists	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0700	Logisticians	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0710	Management analysts	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0725	Meeting, convention, and event planners	2901, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0726	Fundraisers	
0735	Market research analysts and marketing specialists	2901, 5500, 5501, 5502, 5503, 5504, 5505, 5506, 5507, 5599, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0740	Business operations specialists, all other	
0800	Accountants and auditors	4000, 4001, 4002, 4004, 4005, 4006, 4007, 5098, 5099, 5301, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0810	Appraisers and assessors of real estate	1401, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299

Census 2010 occupation		Related ACS degree field
Code	Job title	
0820	Budget analysts	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0830	Credit analysts	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0840	Financial analysts	3700, 3701, 3702, 3705, 3799, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0850	Personal financial advisors	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0860	Insurance underwriters	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0900	Financial examiners	5301, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0910	Credit counselors and loan officers	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0930	Tax examiners and collectors, and revenue agents	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0940	Tax preparers	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
0950	Financial specialists, all other	3700, 3701, 3702, 3705, 3799, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
1005	Computer and information research scientists	2100, 2101, 2102, 2103, 2104, 2105, 2106, 2107, 2199, 3600, 3601, 3602, 3603, 3604, 3605, 3606, 3607, 3608, 3609, 3610, 3611, 3699, 5101, 6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
1006	Computer systems analysts	2100, 2101, 2102, 2103, 2104, 2105, 2106, 2107, 2199
1007	Information security analysts	2100, 2101, 2102, 2103, 2104, 2105, 2106, 2107, 2199, 5301
1010	Computer programmers	2100, 2101, 2102, 2103, 2104, 2105, 2106, 2107, 2199, 2500, 2501, 2502, 2503, 2504, 2599, 6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
1020	Software developers, applications and systems software	2100, 2101, 2102, 2103, 2104, 2105, 2106, 2107, 2199, 2400, 2401, 2402, 2403, 2404, 2405, 2406, 2407, 2408, 2409, 2410, 2411, 2412, 2413, 2414, 2415, 2416, 2417, 2418, 2419, 2420, 2499, 2500,

Census 2010 occupation		Related ACS degree field
Code	Job title	
		2501, 2502, 2503, 2504, 2599, 3600, 3601, 3602, 3603, 3604, 3605, 3606, 3607, 3608, 3609, 3610, 3611, 3699, 5101, 6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
1030	Web developers	2100, 2101, 2102, 2103, 2104, 2105, 2106, 2107, 2199
1050	Computer support specialists	1100, 1101, 1102, 1103, 1104, 1105, 1106, 1199, 2100, 2101, 2102, 2103, 2104, 2105, 2106, 2107, 2199, 6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
1060	Database administrators	2100, 2101, 2102, 2103, 2104, 2105, 2106, 2107, 2199
1105	Network and computer systems administrators	2100, 2101, 2102, 2103, 2104, 2105, 2106, 2107, 2199
1106	Computer network architects	2100, 2101, 2102, 2103, 2104, 2105, 2106, 2107, 2199, 2400, 2401, 2402, 2403, 2404, 2405, 2406, 2407, 2408, 2409, 2410, 2411, 2412, 2413, 2414, 2415, 2416, 2417, 2418, 2419, 2420, 2499
1107	Computer occupations, all other	2100, 2101, 2102, 2103, 2104, 2105, 2106, 2107, 2199, 3600, 3601, 3602, 3603, 3604, 3605, 3606, 3607, 3608, 3609, 3610, 3611, 3699, 4000, 4001, 4002, 4004, 4005, 4006, 4007, 5098, 5099, 5101, 5301, 6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
1200	Actuaries	3700, 3701, 3702, 3705, 3799, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
1210	Mathematicians	3700, 3701, 3702, 3705, 3799, 4801
1220	Operations research analysts	2400, 2401, 2402, 2403, 2404, 2405, 2406, 2407, 2408, 2409, 2410, 2411, 2412, 2413, 2414, 2415, 2416, 2417, 2418, 2419, 2420, 2499, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
1230	Statisticians	3600, 3601, 3602, 3603, 3604, 3605, 3606, 3607, 3608, 3609, 3610, 3611, 3699, 3700, 3701, 3702, 3705, 3799, 5101, 5500, 5501, 5502, 5503, 5504, 5505, 5506, 5507, 5599, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
1240	Miscellaneous mathematical science occupations	3600, 3601, 3602, 3603, 3604, 3605, 3606, 3607, 3608, 3609, 3610, 3611, 3699, 3700, 3701, 3702,

Census 2010 occupation		Related ACS degree field
Code	Job title	
		3705, 3799, 4000, 4001, 4002, 4004, 4005, 4006, 4007, 5098, 5099, 5101
1300	Architects, except naval	1401
1310	Surveyors, cartographers, and photogrammetrists	2500, 2501, 2502, 2503, 2504, 2599, 5500, 5501, 5502, 5503, 5504, 5505, 5506, 5507, 5599
1320	Aerospace engineers	2400, 2401, 2402, 2403, 2404, 2405, 2406, 2407, 2408, 2409, 2410, 2411, 2412, 2413, 2414, 2415, 2416, 2417, 2418, 2419, 2420, 2499
1330	Agricultural engineers	2400, 2401, 2402, 2403, 2404, 2405, 2406, 2407, 2408, 2409, 2410, 2411, 2412, 2413, 2414, 2415, 2416, 2417, 2418, 2419, 2420, 2499
1340	Biomedical engineers	2400, 2401, 2402, 2403, 2404, 2405, 2406, 2407, 2408, 2409, 2410, 2411, 2412, 2413, 2414, 2415, 2416, 2417, 2418, 2419, 2420, 2499
1350	Chemical engineers	2400, 2401, 2402, 2403, 2404, 2405, 2406, 2407, 2408, 2409, 2410, 2411, 2412, 2413, 2414, 2415, 2416, 2417, 2418, 2419, 2420, 2499
1360	Civil engineers	2400, 2401, 2402, 2403, 2404, 2405, 2406, 2407, 2408, 2409, 2410, 2411, 2412, 2413, 2414, 2415, 2416, 2417, 2418, 2419, 2420, 2499
1400	Computer hardware engineers	2400, 2401, 2402, 2403, 2404, 2405, 2406, 2407, 2408, 2409, 2410, 2411, 2412, 2413, 2414, 2415, 2416, 2417, 2418, 2419, 2420, 2499
1410	Electrical and electronics engineers	2400, 2401, 2402, 2403, 2404, 2405, 2406, 2407, 2408, 2409, 2410, 2411, 2412, 2413, 2414, 2415, 2416, 2417, 2418, 2419, 2420, 2499
1420	Environmental engineers	2400, 2401, 2402, 2403, 2404, 2405, 2406, 2407, 2408, 2409, 2410, 2411, 2412, 2413, 2414, 2415, 2416, 2417, 2418, 2419, 2420, 2499
1430	Industrial engineers, including health and safety	2400, 2401, 2402, 2403, 2404, 2405, 2406, 2407, 2408, 2409, 2410, 2411, 2412, 2413, 2414, 2415, 2416, 2417, 2418, 2419, 2420, 2499, 2500, 2501, 2502, 2503, 2504, 2599
1440	Marine engineers and naval architects	2400, 2401, 2402, 2403, 2404, 2405, 2406, 2407, 2408, 2409, 2410, 2411, 2412, 2413, 2414, 2415, 2416, 2417, 2418, 2419, 2420, 2499
1450	Materials engineers	2400, 2401, 2402, 2403, 2404, 2405, 2406, 2407, 2408, 2409, 2410, 2411, 2412, 2413, 2414, 2415, 2416, 2417, 2418, 2419, 2420, 2499

Census 2010 occupation		Related ACS degree field
Code	Job title	
1460	Mechanical engineers	2400, 2401, 2402, 2403, 2404, 2405, 2406, 2407, 2408, 2409, 2410, 2411, 2412, 2413, 2414, 2415, 2416, 2417, 2418, 2419, 2420, 2499
1500	Mining and geological engineers, including mining safety engineers	2400, 2401, 2402, 2403, 2404, 2405, 2406, 2407, 2408, 2409, 2410, 2411, 2412, 2413, 2414, 2415, 2416, 2417, 2418, 2419, 2420, 2499
1510	Nuclear engineers	2400, 2401, 2402, 2403, 2404, 2405, 2406, 2407, 2408, 2409, 2410, 2411, 2412, 2413, 2414, 2415, 2416, 2417, 2418, 2419, 2420, 2499
1520	Petroleum engineers	2400, 2401, 2402, 2403, 2404, 2405, 2406, 2407, 2408, 2409, 2410, 2411, 2412, 2413, 2414, 2415, 2416, 2417, 2418, 2419, 2420, 2499
1530	Engineers, all other	2400, 2401, 2402, 2403, 2404, 2405, 2406, 2407, 2408, 2409, 2410, 2411, 2412, 2413, 2414, 2415, 2416, 2417, 2418, 2419, 2420, 2499, 2500, 2501, 2502, 2503, 2504, 2599, 6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
1540	Drafters	1401, 2500, 2501, 2502, 2503, 2504, 2599
1550	Engineering technicians, except drafters	2500, 2501, 2502, 2503, 2504, 2599, 5102, 5601
1560	Surveying and mapping technicians	2500, 2501, 2502, 2503, 2504, 2599
1600	Agricultural and food scientists	1100, 1101, 1102, 1103, 1104, 1105, 1106, 1199, 2201
1610	Biological scientists	1100, 1101, 1102, 1103, 1104, 1105, 1106, 1199, 1301, 1302, 1303, 3600, 3601, 3602, 3603, 3604, 3605, 3606, 3607, 3608, 3609, 3610, 3611, 3699, 3700, 3701, 3702, 3705, 3799, 4000, 4001, 4002, 4004, 4005, 4006, 4007, 5098, 5099, 5101
1640	Conservation scientists and foresters	1100, 1101, 1102, 1103, 1104, 1105, 1106, 1199, 1301, 1302, 1303
1650	Medical scientists	3600, 3601, 3602, 3603, 3604, 3605, 3606, 3607, 3608, 3609, 3610, 3611, 3699, 4000, 4001, 4002, 4004, 4005, 4006, 4007, 5098, 5099, 5101, 6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
1660	Life scientists, all other	3600, 3601, 3602, 3603, 3604, 3605, 3606, 3607, 3608, 3609, 3610, 3611, 3699, 4000, 4001, 4002, 4004, 4005, 4006, 4007, 5098, 5099, 5101, 6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199

Census 2010 occupation		Related ACS degree field
Code	Job title	
1700	Astronomers and physicists	2400, 2401, 2402, 2403, 2404, 2405, 2406, 2407, 2408, 2409, 2410, 2411, 2412, 2413, 2414, 2415, 2416, 2417, 2418, 2419, 2420, 2499, 5000, 5001, 5002, 5003, 5004, 5005, 5006, 5007, 5008, 6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
1710	Atmospheric and space scientists	5000, 5001, 5002, 5003, 5004, 5005, 5006, 5007, 5008
1720	Chemists and materials scientists	5000, 5001, 5002, 5003, 5004, 5005, 5006, 5007, 5008
1740	Environmental scientists and geoscientists	1301, 1302, 1303, 4000, 4001, 4002, 4004, 4005, 4006, 4007, 5000, 5001, 5002, 5003, 5004, 5005, 5006, 5007, 5008, 5098, 5099, 6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
1760	Physical scientists, all other	4000, 4001, 4002, 4004, 4005, 4006, 4007, 5000, 5001, 5002, 5003, 5004, 5005, 5006, 5007, 5008, 5098, 5099
1800	Economists	1100, 1101, 1102, 1103, 1104, 1105, 1106, 1199, 3700, 3701, 3702, 3705, 3799, 5500, 5501, 5502, 5503, 5504, 5505, 5506, 5507, 5599, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
1815	Survey researchers	3700, 3701, 3702, 3705, 3799, 5500, 5501, 5502, 5503, 5504, 5505, 5506, 5507, 5599, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
1820	Psychologists	4000, 4001, 4002, 4004, 4005, 4006, 4007, 5098, 5099, 5200, 5201, 5202, 5203, 5204, 5205, 5206, 5299, 6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
1830	Sociologists	5500, 5501, 5502, 5503, 5504, 5505, 5506, 5507, 5599
1840	Urban and regional planners	1401, 5500, 5501, 5502, 5503, 5504, 5505, 5506, 5507, 5599
1860	Miscellaneous social scientists and related workers	1401, 2300, 2301, 2302, 2303, 2304, 2305, 2306, 2307, 2308, 2309, 2310, 2311, 2312, 2313, 2314, 2399, 2601, 2602, 2603, 4000, 4001, 4002, 4004, 4005, 4006, 4007, 5098, 5099, 5401, 5402, 5403, 5404, 5500, 5501, 5502, 5503, 5504, 5505, 5506, 5507, 5599, 6401, 6402, 6403

Census 2010 occupation		Related ACS degree field
Code	Job title	
1900	Agricultural and food science technicians	1100, 1101, 1102, 1103, 1104, 1105, 1106, 1199
1910	Biological technicians	5102
1920	Chemical technicians	5102
1930	Geological and petroleum technicians	2500, 2501, 2502, 2503, 2504, 2599
1940	Nuclear technicians	2500, 2501, 2502, 2503, 2504, 2599, 5102, 6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
1950	Social science research assistants	5500, 5501, 5502, 5503, 5504, 5505, 5506, 5507, 5599
1965	Miscellaneous life, physical, and social science technicians	1301, 1302, 1303, 5000, 5001, 5002, 5003, 5004, 5005, 5006, 5007, 5008, 5102, 5301
2000	Counselors	2300, 2301, 2302, 2303, 2304, 2305, 2306, 2307, 2308, 2309, 2310, 2311, 2312, 2313, 2314, 2399, 5401, 5402, 5403, 5404, 6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
2010	Social workers	5301, 5401, 5402, 5403, 5404, 6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
2015	Probation officers and correctional treatment specialists	5401, 5402, 5403, 5404
2016	Social and human service assistants	2901, 5401, 5402, 5403, 5404
2025	Miscellaneous community and social service specialists, including health educators and community health workers	1901, 1902, 1903, 1904, 2001, 2901, 4000, 4001, 4002, 4004, 4005, 4006, 4007, 5098, 5099, 5401, 5402, 5403, 5404, 6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
2040	Clergy	4901, 6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
2050	Directors, religious activities and education	4901
2060	Religious workers, all other	4901
2100	Lawyers	3201, 3202
2105	Judicial law clerks	3201, 3202
2110	Judges, magistrates, and other judicial workers	3201, 3202, 4000, 4001, 4002, 4004, 4005, 4006, 4007, 5098, 5099
2145	Paralegals and legal assistants	3201, 3202

Census 2010 occupation		Related ACS degree field
Code	Job title	
2160	Miscellaneous legal support workers	3201, 3202
2200	Postsecondary teachers	1100, 1101, 1102, 1103, 1104, 1105, 1106, 1199, 1301, 1302, 1303, 1401, 1501, 1901, 1902, 1903, 1904, 2001, 2100, 2101, 2102, 2103, 2104, 2105, 2106, 2107, 2199, 2201, 2300, 2301, 2302, 2303, 2304, 2305, 2306, 2307, 2308, 2309, 2310, 2311, 2312, 2313, 2314, 2399, 2400, 2401, 2402, 2403, 2404, 2405, 2406, 2407, 2408, 2409, 2410, 2411, 2412, 2413, 2414, 2415, 2416, 2417, 2418, 2419, 2420, 2499, 2500, 2501, 2502, 2503, 2504, 2599, 2601, 2602, 2603, 2901, 3201, 3202, 3301, 3302, 3401, 3402, 3501, 3600, 3601, 3602, 3603, 3604, 3605, 3606, 3607, 3608, 3609, 3610, 3611, 3699, 3700, 3701, 3702, 3705, 3799, 4000, 4001, 4002, 4004, 4005, 4006, 4007, 4101, 4801, 4901, 5000, 5001, 5002, 5003, 5004, 5005, 5006, 5007, 5008, 5098, 5099, 5101, 5200, 5201, 5202, 5203, 5204, 5205, 5206, 5299, 5301, 5401, 5402, 5403, 5404, 5500, 5501, 5502, 5503, 5504, 5505, 5506, 5507, 5599, 5901, 6000, 6001, 6002, 6003, 6004, 6005, 6006, 6007, 6008, 6099, 6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299, 6401, 6402, 6403
2300	Preschool and kindergarten teachers	2300, 2301, 2302, 2303, 2304, 2305, 2306, 2307, 2308, 2309, 2310, 2311, 2312, 2313, 2314, 2399, 2901
2310	Elementary and middle school teachers	2300, 2301, 2302, 2303, 2304, 2305, 2306, 2307, 2308, 2309, 2310, 2311, 2312, 2313, 2314, 2399
2320	Secondary school teachers	2300, 2301, 2302, 2303, 2304, 2305, 2306, 2307, 2308, 2309, 2310, 2311, 2312, 2313, 2314, 2399, 2601, 2602, 2603, 2901, 3301, 3302, 3600, 3601, 3602, 3603, 3604, 3605, 3606, 3607, 3608, 3609, 3610, 3611, 3699, 3700, 3701, 3702, 3705, 3799, 5000, 5001, 5002, 5003, 5004, 5005, 5006, 5007, 5008, 5101, 5500, 5501, 5502, 5503, 5504, 5505, 5506, 5507, 5599, 6000, 6001, 6002, 6003, 6004, 6005, 6006, 6007, 6008, 6099, 6401, 6402, 6403
2330	Special education teachers	2300, 2301, 2302, 2303, 2304, 2305, 2306, 2307, 2308, 2309, 2310, 2311, 2312, 2313, 2314, 2399
2340	Other teachers and instructors	2300, 2301, 2302, 2303, 2304, 2305, 2306, 2307, 2308, 2309, 2310, 2311, 2312, 2313, 2314, 2399

Census 2010 occupation		Related ACS degree field
Code	Job title	
2400	Archivists, curators, and museum technicians	3501, 4000, 4001, 4002, 4004, 4005, 4006, 4007, 5098, 5099, 6000, 6001, 6002, 6003, 6004, 6005, 6006, 6007, 6008, 6099, 6401, 6402, 6403
2430	Librarians	2300, 2301, 2302, 2303, 2304, 2305, 2306, 2307, 2308, 2309, 2310, 2311, 2312, 2313, 2314, 2399, 3501
2440	Library technicians	3501
2540	Teacher assistants	2300, 2301, 2302, 2303, 2304, 2305, 2306, 2307, 2308, 2309, 2310, 2311, 2312, 2313, 2314, 2399
2550	Other education, training, and library workers	1100, 1101, 1102, 1103, 1104, 1105, 1106, 1199, 2300, 2301, 2302, 2303, 2304, 2305, 2306, 2307, 2308, 2309, 2310, 2311, 2312, 2313, 2314, 2399, 2901
2600	Artists and related workers	2100, 2101, 2102, 2103, 2104, 2105, 2106, 2107, 2199, 6000, 6001, 6002, 6003, 6004, 6005, 6006, 6007, 6008, 6099, 6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
2630	Designers	1100, 1101, 1102, 1103, 1104, 1105, 1106, 1199, 1401, 2100, 2101, 2102, 2103, 2104, 2105, 2106, 2107, 2199, 2500, 2501, 2502, 2503, 2504, 2599, 2901, 6000, 6001, 6002, 6003, 6004, 6005, 6006, 6007, 6008, 6099
2700	Actors	6000, 6001, 6002, 6003, 6004, 6005, 6006, 6007, 6008, 6099
2710	Producers and directors	1901, 1902, 1903, 1904, 2001, 6000, 6001, 6002, 6003, 6004, 6005, 6006, 6007, 6008, 6099
2720	Athletes, coaches, umpires, and related workers	2300, 2301, 2302, 2303, 2304, 2305, 2306, 2307, 2308, 2309, 2310, 2311, 2312, 2313, 2314, 2399, 4101
2740	Dancers and choreographers	6000, 6001, 6002, 6003, 6004, 6005, 6006, 6007, 6008, 6099
2750	Musicians, singers, and related workers	4901, 6000, 6001, 6002, 6003, 6004, 6005, 6006, 6007, 6008, 6099
2760	Entertainers and performers, sports and related workers, all other	1901, 1902, 1903, 1904, 2001, 6000, 6001, 6002, 6003, 6004, 6005, 6006, 6007, 6008, 6099
2800	Announcers	1901, 1902, 1903, 1904, 2001
2810	News analysts, reporters and correspondents	1100, 1101, 1102, 1103, 1104, 1105, 1106, 1199, 1901, 1902, 1903, 1904, 2001
2825	Public relations specialists	1901, 1902, 1903, 1904, 2001, 2901

Census 2010 occupation		Related ACS degree field
Code	Job title	
2830	Editors	1901, 1902, 1903, 1904, 2001, 3301, 3302, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
2840	Technical writers	1901, 1902, 1903, 1904, 2001, 2901, 3301, 3302, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
2850	Writers and authors	1901, 1902, 1903, 1904, 2001, 2901, 3301, 3302, 6000, 6001, 6002, 6003, 6004, 6005, 6006, 6007, 6008, 6099, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
2860	Miscellaneous media and communication workers	1501, 1901, 1902, 1903, 1904, 2001, 2300, 2301, 2302, 2303, 2304, 2305, 2306, 2307, 2308, 2309, 2310, 2311, 2312, 2313, 2314, 2399, 2601, 2602, 2603
2900	Broadcast and sound engineering technicians and radio operators	1100, 1101, 1102, 1103, 1104, 1105, 1106, 1199, 5701, 6000, 6001, 6002, 6003, 6004, 6005, 6006, 6007, 6008, 6099
2910	Photographers	1901, 1902, 1903, 1904, 2001, 6000, 6001, 6002, 6003, 6004, 6005, 6006, 6007, 6008, 6099
2920	Television, video, and motion picture camera operators and editors	1901, 1902, 1903, 1904, 2001, 6000, 6001, 6002, 6003, 6004, 6005, 6006, 6007, 6008, 6099
2960	Media and communication equipment workers, all other	
3000	Chiropractors	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
3010	Dentists	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
3030	Dietitians and nutritionists	2901, 4000, 4001, 4002, 4004, 4005, 4006, 4007, 5098, 5099, 6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
3040	Optometrists	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
3050	Pharmacists	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
3060	Physicians and surgeons	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
3110	Physician assistants	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
3120	Podiatrists	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199

Census 2010 occupation		Related ACS degree field
Code	Job title	
3140	Audiologists	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
3150	Occupational therapists	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
3160	Physical therapists	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
3200	Radiation therapists	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
3210	Recreational therapists	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
3220	Respiratory therapists	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
3230	Speech-language pathologists	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
3235	Exercise physiologists	3600, 3601, 3602, 3603, 3604, 3605, 3606, 3607, 3608, 3609, 3610, 3611, 3699, 4101, 5101, 6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
3245	Therapists, all other	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
3250	Veterinarians	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
3255	Registered nurses	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
3256	Nurse anesthetists	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
3257	Nurse midwives	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
3258	Nurse practitioners	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
3260	Health diagnosing and treating practitioners, all other	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
3300	Clinical laboratory technologists and technicians	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
3310	Dental hygienists	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
3320	Diagnostic related technologists and technicians	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
3400	Emergency medical technicians and paramedics	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199

Census 2010 occupation		Related ACS degree field
Code	Job title	
3420	Health practitioner support technologists and technicians	2901, 4000, 4001, 4002, 4004, 4005, 4006, 4007, 5098, 5099, 6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
3500	Licensed practical and licensed vocational nurses	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
3510	Medical records and health information technicians	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
3520	Opticians, dispensing	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
3535	Miscellaneous health technologists and technicians	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
3540	Other healthcare practitioners and technical occupations	2500, 2501, 2502, 2503, 2504, 2599, 4101, 6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
3600	Nursing, psychiatric, and home health aides	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
3610	Occupational therapy assistants and aides	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
3620	Physical therapist assistants and aides	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
3630	Massage therapists	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
3640	Dental assistants	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
3645	Medical assistants	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
3646	Medical transcriptionists	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
3647	Pharmacy aides	
3648	Veterinary assistants and laboratory animal caretakers	
3649	Phlebotomists	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
3655	Healthcare support workers, all other, including medical equipment preparers	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
3700	First-line supervisors of correctional officers	5301
3710	First-line supervisors of police and detectives	1301, 1302, 1303, 5301

Census 2010 occupation		Related ACS degree field
Code	Job title	
3720	First-line supervisors of fire fighting and prevention workers	1301, 1302, 1303, 5301
3730	First-line supervisors of protective service workers, all other	5301
3740	Firefighters	1301, 1302, 1303, 5301
3750	Fire inspectors	1301, 1302, 1303, 5301
3800	Bailiffs, correctional officers, and jailers	5301
3820	Detectives and criminal investigators	1301, 1302, 1303, 5301
3830	Fish and game wardens	1301, 1302, 1303
3840	Parking enforcement workers	
3850	Police and sheriff's patrol officers	1301, 1302, 1303, 5301
3860	Transit and railroad police	5301
3900	Animal control workers	
3910	Private detectives and investigators	5301
3930	Security guards and gaming surveillance officers	
3940	Crossing guards	
3945	Transportation security screeners	
3955	Lifeguards and other recreational, and all other protective service workers	1301, 1302, 1303
4000	Chefs and head cooks	2201
4010	First-line supervisors of food preparation and serving workers	2201, 2901
4020	Cooks	2201, 2901
4030	Food preparation workers	
4040	Bartenders	2201
4050	Combined food preparation and serving workers, including fast food	
4060	Counter attendants, cafeteria, food concession, and coffee shop	

Census 2010 occupation		Related ACS degree field
Code	Job title	
4110	Waiters and waitresses	
4120	Food servers, nonrestaurant	
4130	Dining room and cafeteria attendants and bartender helpers	
4140	Dishwashers	
4150	Hosts and hostesses, restaurant, lounge, and coffee shop	
4160	Food preparation and serving related workers, all other	
4200	First-line supervisors of housekeeping and janitorial workers	5601
4210	First-line supervisors of landscaping, lawn service, and groundskeeping workers	1100, 1101, 1102, 1103, 1104, 1105, 1106, 1199, 4101
4220	Janitors and building cleaners	
4230	Maids and housekeeping cleaners	
4240	Pest control workers	
4250	Grounds maintenance workers	1100, 1101, 1102, 1103, 1104, 1105, 1106, 1199
4300	First-line supervisors of gaming workers	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
4320	First-line supervisors of personal service workers	2201
4340	Animal trainers	1100, 1101, 1102, 1103, 1104, 1105, 1106, 1199
4350	Nonfarm animal caretakers	1100, 1101, 1102, 1103, 1104, 1105, 1106, 1199
4400	Gaming services workers	
4410	Motion picture projectionists	
4420	Ushers, lobby attendants, and ticket takers	
4430	Miscellaneous entertainment attendants and related workers	
4460	Embalmers and funeral attendants	2201
4465	Morticians, undertakers, and funeral directors	2201
4500	Barbers	2201
4510	Hairdressers, hairstylists, and cosmetologists	2201

Census 2010 occupation		Related ACS degree field
Code	Job title	
4520	Miscellaneous personal appearance workers	2201
4530	Baggage porters, bellhops, and concierges	
4540	Tour and travel guides	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
4600	Childcare workers	2901
4610	Personal care aides	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
4620	Recreation and fitness workers	2300, 2301, 2302, 2303, 2304, 2305, 2306, 2307, 2308, 2309, 2310, 2311, 2312, 2313, 2314, 2399, 4101, 6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
4640	Residential advisors	
4650	Personal care and service workers, all other	
4700	First-line supervisors of retail sales workers	1100, 1101, 1102, 1103, 1104, 1105, 1106, 1199, 2901, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
4710	First-line supervisors of non-retail sales workers	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
4720	Cashiers	
4740	Counter and rental clerks	
4750	Parts salespersons	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
4760	Retail salespersons	
4800	Advertising sales agents	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
4810	Insurance sales agents	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
4820	Securities, commodities, and financial services sales agents	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
4830	Travel agents	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
4840	Sales representatives, services, all other	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
4850	Sales representatives, wholesale and manufacturing	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299

Census 2010 occupation		Related ACS degree field
Code	Job title	
4900	Models, demonstrators, and product promoters	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
4920	Real estate brokers and sales agents	1401, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
4930	Sales engineers	
4940	Telemarketers	
4950	Door-to-door sales workers, news and street vendors, and related workers	
4965	Sales and related workers, all other	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
5000	First-line supervisors of office and administrative support workers	1100, 1101, 1102, 1103, 1104, 1105, 1106, 1199, 6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
5010	Switchboard operators, including answering service	
5020	Telephone operators	
5030	Communications equipment operators, all other	
5100	Bill and account collectors	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
5110	Billing and posting clerks	
5120	Bookkeeping, accounting, and auditing clerks	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
5130	Gaming cage workers	
5140	Payroll and timekeeping clerks	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
5150	Procurement clerks	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
5160	Tellers	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
5165	Financial clerks, all other	
5200	Brokerage clerks	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
5210	Correspondence clerks	
5220	Court, municipal, and license clerks	

Census 2010 occupation		Related ACS degree field
Code	Job title	
5230	Credit authorizers, checkers, and clerks	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
5240	Customer service representatives	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
5250	Eligibility interviewers, government programs	5401, 5402, 5403, 5404
5260	File clerks	
5300	Hotel, motel, and resort desk clerks	
5310	Interviewers, except eligibility and loan	
5320	Library assistants, clerical	
5330	Loan interviewers and clerks	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
5340	New accounts clerks	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
5350	Order clerks	
5360	Human resources assistants, except payroll and timekeeping	
5400	Receptionists and information clerks	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
5410	Reservation and transportation ticket agents and travel clerks	
5420	Information and record clerks, all other	
5500	Cargo and freight agents	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
5510	Couriers and messengers	
5520	Dispatchers	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
5530	Meter readers, utilities	
5540	Postal service clerks	
5550	Postal service mail carriers	
5560	Postal service mail sorters, processors, and processing machine operators	
5600	Production, planning, and expediting clerks	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299

Census 2010 occupation		Related ACS degree field
Code	Job title	
5610	Shipping, receiving, and traffic clerks	
5620	Stock clerks and order fillers	
5630	Weighers, measurers, checkers, and samplers, recordkeeping	
5700	Secretaries and administrative assistants	3201, 3202, 6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
5800	Computer operators	2100, 2101, 2102, 2103, 2104, 2105, 2106, 2107, 2199
5810	Data entry keyers	2100, 2101, 2102, 2103, 2104, 2105, 2106, 2107, 2199, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
5820	Word processors and typists	2100, 2101, 2102, 2103, 2104, 2105, 2106, 2107, 2199, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
5830	Desktop publishers	
5840	Insurance claims and policy processing clerks	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
5850	Mail clerks and mail machine operators, except postal service	
5860	Office clerks, general	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
5900	Office machine operators, except computer	
5910	Proofreaders and copy markers	
5920	Statistical assistants	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
5940	Office and administrative support workers, all other	
6005	First-line supervisors of farming, fishing, and forestry workers	1100, 1101, 1102, 1103, 1104, 1105, 1106, 1199, 1301, 1302, 1303
6010	Agricultural inspectors	1100, 1101, 1102, 1103, 1104, 1105, 1106, 1199
6020	Animal breeders	1100, 1101, 1102, 1103, 1104, 1105, 1106, 1199
6040	Graders and sorters, agricultural products	1100, 1101, 1102, 1103, 1104, 1105, 1106, 1199
6050	Miscellaneous agricultural workers	1100, 1101, 1102, 1103, 1104, 1105, 1106, 1199

Census 2010 occupation		Related ACS degree field
Code	Job title	
6100	Fishers and related fishing workers	1301, 1302, 1303
6110	Hunters and trappers	
6120	Forest and conservation workers	
6130	Logging workers	5901
6200	First-line supervisors of construction trades and extraction workers	5601
6210	Boilermakers	5801
6220	Brickmasons, blockmasons, and stonemasons	5601
6230	Carpenters	5601
6240	Carpet, floor, and tile installers and finishers	5601
6250	Cement masons, concrete finishers, and terrazzo workers	5601
6260	Construction laborers	
6300	Paving, surfacing, and tamping equipment operators	5901
6310	Pile-driver operators	5901
6320	Operating engineers and other construction equipment operators	5901
6330	Drywall installers, ceiling tile installers, and tapers	5601
6355	Electricians	5601
6360	Glaziers	5601
6400	Insulation workers	5601
6420	Painters, construction and maintenance	5601
6430	Paperhangers	5601
6440	Pipelayers, plumbers, pipefitters, and steamfitters	5601
6460	Plasterers and stucco masons	
6500	Reinforcing iron and rebar workers	
6515	Roofers	5601
6520	Sheet metal workers	5801

Census 2010 occupation		Related ACS degree field
Code	Job title	
6530	Structural iron and steel workers	5601
6540	Solar photovoltaic installers	2500, 2501, 2502, 2503, 2504, 2599, 5601
6600	Helpers, construction trades	
6660	Construction and building inspectors	5601
6700	Elevator installers and repairers	5701
6710	Fence erectors	
6720	Hazardous materials removal workers	2500, 2501, 2502, 2503, 2504, 2599
6730	Highway maintenance workers	5901
6740	Rail-track laying and maintenance equipment operators	5901
6750	Septic tank servicers and sewer pipe cleaners	5601
6765	Miscellaneous construction and related workers	
6800	Derrick, rotary drill, and service unit operators, oil, gas, and mining	2500, 2501, 2502, 2503, 2504, 2599, 5601
6820	Earth drillers, except oil and gas	5601, 5901
6830	Explosives workers, ordnance handling experts, and blasters	5601
6840	Mining machine operators	5901
6910	Roof bolters, mining	
6920	Roustabouts, oil and gas	
6930	Helpers--extraction workers	
6940	Other extraction workers	5901
7000	First-line supervisors of mechanics, installers, and repairers	5601, 5701, 6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
7010	Computer, automated teller, and office machine repairers	5701
7020	Radio and telecommunications equipment installers and repairers	5701
7030	Avionics technicians	5701
7040	Electric motor, power tool, and related repairers	5701

Census 2010 occupation		Related ACS degree field
Code	Job title	
7050	Electrical and electronics installers and repairers, transportation equipment	5701
7100	Electrical and electronics repairers, industrial and utility	5701
7110	Electronic equipment installers and repairers, motor vehicles	5701
7120	Electronic home entertainment equipment installers and repairers	5701
7130	Security and fire alarm systems installers	5601, 5701
7140	Aircraft mechanics and service technicians	1100, 1101, 1102, 1103, 1104, 1105, 1106, 1199, 5701
7150	Automotive body and related repairers	5701
7160	Automotive glass installers and repairers	5701
7200	Automotive service technicians and mechanics	2500, 2501, 2502, 2503, 2504, 2599, 5701
7210	Bus and truck mechanics and diesel engine specialists	5701
7220	Heavy vehicle and mobile equipment service technicians and mechanics	1100, 1101, 1102, 1103, 1104, 1105, 1106, 1199, 5701
7240	Small engine mechanics	5701
7260	Miscellaneous vehicle and mobile equipment mechanics, installers, and repairers	5701
7300	Control and valve installers and repairers	
7315	Heating, air conditioning, and refrigeration mechanics and installers	2500, 2501, 2502, 2503, 2504, 2599, 5701
7320	Home appliance repairers	5701
7330	Industrial and refractory machinery mechanics	5701
7340	Maintenance and repair workers, general	5601

Census 2010 occupation		Related ACS degree field
Code	Job title	
7350	Maintenance workers, machinery	5701
7360	Millwrights	5701
7410	Electrical power-line installers and repairers	5601
7420	Telecommunications line installers and repairers	5701
7430	Precision instrument and equipment repairers	2500, 2501, 2502, 2503, 2504, 2599, 5701
7440	Wind turbine service technicians	5701
7510	Coin, vending, and amusement machine servicers and repairers	
7520	Commercial divers	5901
7540	Locksmiths and safe repairers	5701
7550	Manufactured building and mobile home installers	5601
7560	Riggers	
7600	Signal and track switch repairers	5601
7610	Helpers--installation, maintenance, and repair workers	
7630	Other installation, maintenance, and repair workers	5701
7700	First-line supervisors of production and operating workers	6200, 6201, 6202, 6203, 6204, 6205, 6206, 6207, 6208, 6209, 6210, 6211, 6212, 6299
7710	Aircraft structure, surfaces, rigging, and systems assemblers	5701
7720	Electrical, electronics, and electromechanical assemblers	
7730	Engine and other machine assemblers	5701
7740	Structural metal fabricators and fitters	5801
7750	Miscellaneous assemblers and fabricators	5701
7800	Bakers	2201
7810	Butchers and other meat, poultry, and fish processing workers	2201

Census 2010 occupation		Related ACS degree field
Code	Job title	
7830	Food and tobacco roasting, baking, and drying machine operators and tenders	
7840	Food batchmakers	
7850	Food cooking machine operators and tenders	
7855	Food processing workers, all other	
7900	Computer control programmers and operators	5801
7920	Extruding and drawing machine setters, operators, and tenders, metal and plastic	5801
7930	Forging machine setters, operators, and tenders, metal and plastic	5801
7940	Rolling machine setters, operators, and tenders, metal and plastic	5801
7950	Cutting, punching, and press machine setters, operators, and tenders, metal and plastic	5801
7960	Drilling and boring machine tool setters, operators, and tenders, metal and plastic	5801
8000	Grinding, lapping, polishing, and buffing machine tool setters, operators, and tenders, metal and plastic	5801
8010	Lathe and turning machine tool setters, operators, and tenders, metal and plastic	5801
8020	Milling and planing machine setters, operators, and tenders, metal and plastic	5801
8030	Machinists	5801
8040	Metal furnace operators, tenders, pourers, and casters	
8060	Model makers and patternmakers, metal and plastic	5801

Census 2010 occupation		Related ACS degree field
Code	Job title	
8100	Molders and molding machine setters, operators, and tenders, metal and plastic	5801
8120	Multiple machine tool setters, operators, and tenders, metal and plastic	5801
8130	Tool and die makers	5801
8140	Welding, soldering, and brazing workers	2500, 2501, 2502, 2503, 2504, 2599, 5801
8150	Heat treating equipment setters, operators, and tenders, metal and plastic	5801
8160	Layout workers, metal and plastic	5801
8200	Plating and coating machine setters, operators, and tenders, metal and plastic	
8210	Tool grinders, filers, and sharpeners	5801
8220	Metal workers and plastic workers, all other	5801
8250	Prepress technicians and workers	
8255	Printing press operators	
8256	Print binding and finishing workers	
8300	Laundry and dry-cleaning workers	
8310	Pressers, textile, garment, and related materials	
8320	Sewing machine operators	
8330	Shoe and leather workers and repairers	5801
8340	Shoe machine operators and tenders	5801
8350	Tailors, dressmakers, and sewers	
8360	Textile bleaching and dyeing machine operators and tenders	
8400	Textile cutting machine setters, operators, and tenders	

Census 2010 occupation		Related ACS degree field
Code	Job title	
8410	Textile knitting and weaving machine setters, operators, and tenders	
8420	Textile winding, twisting, and drawing out machine setters, operators, and tenders	
8430	Extruding and forming machine setters, operators, and tenders, synthetic and glass fibers	
8440	Fabric and apparel patternmakers	2901
8450	Upholsterers	5801
8460	Textile, apparel, and furnishings workers, all other	
8500	Cabinetmakers and bench carpenters	5801
8510	Furniture finishers	5801
8520	Model makers and patternmakers, wood	5801
8530	Sawing machine setters, operators, and tenders, wood	5801
8540	Woodworking machine setters, operators, and tenders, except sawing	5801
8550	Woodworkers, all other	5801
8600	Power plant operators, distributors, and dispatchers	5102
8610	Stationary engineers and boiler operators	
8620	Water and wastewater treatment plant and system operators	2500, 2501, 2502, 2503, 2504, 2599
8630	Miscellaneous plant and system operators	5102
8640	Chemical processing machine setters, operators, and tenders	5102
8650	Crushing, grinding, polishing, mixing, and blending workers	
8710	Cutting workers	

Census 2010 occupation		Related ACS degree field
Code	Job title	
8720	Extruding, forming, pressing, and compacting machine setters, operators, and tenders	
8730	Furnace, kiln, oven, drier, and kettle operators and tenders	
8740	Inspectors, testers, sorters, samplers, and weighers	2500, 2501, 2502, 2503, 2504, 2599
8750	Jewelers and precious stone and metal workers	5701, 6000, 6001, 6002, 6003, 6004, 6005, 6006, 6007, 6008, 6099
8760	Medical, dental, and ophthalmic laboratory technicians	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
8800	Packaging and filling machine operators and tenders	
8810	Painting workers	5701
8830	Photographic process workers and processing machine operators	
8840	Semiconductor processors	2500, 2501, 2502, 2503, 2504, 2599, 5701
8850	Adhesive bonding machine operators and tenders	
8860	Cleaning, washing, and metal pickling equipment operators and tenders	
8900	Cooling and freezing equipment operators and tenders	
8910	Etchers and engravers	
8920	Molders, shapers, and casters, except metal and plastic	
8930	Paper goods machine setters, operators, and tenders	
8940	Tire builders	
8950	Helpers--production workers	
8965	Production workers, all other	
9000	Supervisors of transportation and material moving workers	5901
9030	Aircraft pilots and flight engineers	5901
9040	Air traffic controllers and airfield operations specialists	5901

Census 2010 occupation		Related ACS degree field
Code	Job title	
9050	Flight attendants	5901
9110	Ambulance drivers and attendants, except emergency medical technicians	6100, 6101, 6102, 6103, 6104, 6105, 6106, 6107, 6108, 6109, 6110, 6111, 6199
9120	Bus drivers	5901
9130	Driver/sales workers and truck drivers	5901
9140	Taxi drivers and chauffeurs	
9150	Motor vehicle operators, all other	
9200	Locomotive engineers and operators	5901
9230	Railroad brake, signal, and switch operators	5901
9240	Railroad conductors and yardmasters	5901
9260	Subway, streetcar, and other rail transportation workers	5901
9300	Sailors and marine oilers	
9310	Ship and boat captains and operators	5901
9330	Ship engineers	5901
9340	Bridge and lock tenders	
9350	Parking lot attendants	
9360	Automotive and watercraft service attendants	
9410	Transportation inspectors	
9415	Transportation attendants, except flight attendants	
9420	Other transportation workers	
9500	Conveyor operators and tenders	
9510	Crane and tower operators	5901
9520	Dredge, excavating, and loading machine operators	5901
9560	Hoist and winch operators	5901
9600	Industrial truck and tractor operators	

Census 2010 occupation		Related ACS degree field
Code	Job title	
9610	Cleaners of vehicles and equipment	
9620	Laborers and freight, stock, and material movers, hand	
9630	Machine feeders and offbearers	
9640	Packers and packagers, hand	
9650	Pumping station operators	
9720	Refuse and recyclable material collectors	
9730	Mine shuttle car operators	
9740	Tank car, truck, and ship loaders	
9750	Material moving workers, all other	
9800	Military officer special and tactical operations leaders	3801, 5301
9810	First-line enlisted military supervisors	
9820	Military enlisted tactical operations and air/weapons specialists and crew members	3801
9830	Military, rank not specified	3801, 5301

Appendix D: Supplementary Results

The current appendix provides four tables relevant to the study results. The first table provides a summary of the final dummy coding scheme using in analyses to address research question three. The second displays the correlations between the skill and ability measures. The third is actually a set of tables that provide the log odds and standard errors for each model run to address research question 3. The fourth is another set of tables that provide the distributions of the predictor variables across the latent classes.

Summary of Final Dummy Coding Scheme

Table D1

Final Dummy Coding Scheme by Model

Categorical variable	Categories	Dummy coding by LCA model ([R] = reference category; V1-V6 = dummy coded variables created)				
		M1	M2	M3	M4	M5
Gender	Male	[R]	[R]	[R]	[R]	[R]
	Female	V1	V1	V1	V1	V1
Race/ethnicity	White	[R]	[R]	[R]	[R]	[R]
	Black	V1	V1	V1	V1	V1
	Asian & Pacific Islander	V2	V2	V2	V2	V2
	Hispanic	V3	V3	V3	V3	V3
	Native American	V4	V4	V3	V3	V4
	Multiracial	V4	V4	V3	V3	V4
	Other	V4	V4	V3	V3	V4
Attained education	Less than HS	V1	V1	--	--	V1
	HS diploma or equiv.	[R]	V2	--	--	V2

Categorical variable	Categories	Dummy coding by LCA model ([R] = reference category; V1-V6 = dummy coded variables created)				
		M1	M2	M3	M4	M5
	Some college, no degree	V2	[R]	--	--	V3
	Associate's degree	V3	V3	--	--	V4
	Bachelor's degree	V4	--	[R]	[R]	[R]
	Graduate degree	V4	--	V1	V1	V5
Bachelor field of study	No Bachelor's Degree	--	--	--	--	V1
	Arts, Humanities, and Other	--	--	V1	V1	V2
	Business	--	--	V2	[R]	V3
	Education	--	--	V3	V2	V4
	Science and Engineering	--	--	[R]	V3	[R]
	Science and Engineering Related Fields	--	--	V4	V4	V5
Major occupational group	Computer, Engineering, & Science	--	V1	V1	V1	V1
	Education, Legal, Community Service, Arts, & Media	V1	[R]	V2	[R]	V1
	Healthcare Practitioners & Technical	V1	V2	V3	V2	V1
	Management, Business, & Financial	V1	V3	[R]	V3	V1
	Military Specific	V1	V4	V4	V4	V1
	Natural Resources, Construction, and Maintenance	V2	V5	V4	V4	V2
	Production, Transportation, and Material Moving	V3	V4	V4	V4	V3
	Sales and Office	[R]	V4	V5	V4	[R]
	Service	V4	V6	V4	V4	V4
Required level of education	Less than high school	V1	--	--	--	V1

Categorical variable	Categories	Dummy coding by LCA model ([R] = reference category; V1-V6 = dummy coded variables created)				
		M1	M2	M3	M4	M5
	High school or equivalent	[R]	--	--	--	[R]
	Post-secondary certificate	--	V1	V1	V1	V2
	Some college, no degree	--	V1	V1	V1	V2
	Associate's degree	--	V2	V1	V1	V3
	Bachelor's degree	--	[R]	[R]	[R]	V4
	Graduate degree	--	V3	V2	V2	V5
Required work experience	None	V1	V1	V1	V1	V1
	Up to 2 years	[R]	[R]	V1	V1	[R]
	Over 2 years, up to 6 years	[R]	V2	[R]	[R]	V2
	Over 6 years, up to 10 years	--	V2	[R]	[R]	V2
	Over 10 years	[R]	V2	[R]	[R]	V2
On-the-job training	None or short demonstration	V1	V1	V1	V1	V1
	Beyond short demonstration, up to 1 month	V1	V1	V1	V1	V2
	Over 1 month, up to 1 year	[R]	[R]	[R]	[R]	[R]
	Over 1 year, up to 2 years	[R]	[R]	[R]	[R]	[R]
	Over 2 years, up to 4 years	[R]	[R]	[R]	[R]	[R]
	Over 4 years	[R]	[R]	[R]	[R]	[R]
Education level match	Undereducation	V1	[R]	V1	V1	V1
	Adequate education	V2	V1	[R]	[R]	[R]
	Overeducation	[R]	V2	V2	V2	V2
Field match	No Bachelor's degree	V1	--	--	--	V1
	Mismatch	[R]	--	--	--	[R]
	Match	V2	--	--	--	V2

Note. If more than one category is presented with the same code within the model, it indicates the categories were collapsed.

Correlations Between the Skill and Ability Measures

Table D2

Correlations Between the Skill and Ability Measures

Skill and Ability Measures	1	2	3	4	5	6	7	8	9
1. Cognitive abilities	--	-0.27	-0.08	0.32	0.92	0.63	0.84	0.68	0.84
2. Physical abilities	-0.27	--	0.77	0.54	-0.44	-0.06	-0.10	-0.27	-0.19
3. Psychomotor abilities	-0.08	0.77	--	0.80	-0.35	0.11	-0.01	-0.43	-0.04
4. Sensory abilities	0.32	0.54	0.80	--	0.06	0.22	0.33	-0.11	0.25
5. Basic skills	0.92	-0.44	-0.35	0.06	--	0.62	0.82	0.81	0.83
6. Complex problem solving skills	0.63	-0.06	0.11	0.22	0.62	--	0.57	0.53	0.76
7. Resource management skills	0.84	-0.10	-0.01	0.33	0.82	0.57	--	0.66	0.77
8. Social skills	0.68	-0.27	-0.43	-0.11	0.81	0.53	0.66	--	0.64
9. Systems skills	0.84	-0.19	-0.04	0.25	0.83	0.76	0.77	0.64	--
10. Technical skills	0.13	0.51	0.82	0.77	-0.11	0.26	0.22	-0.33	0.17

Note. The above correlations were computed based on the imputed datasets.

Log-Odds and Standard Errors for Predictive LCA Models

Table D3

Log-Odds and Standard Errors for Model 1

Model and variable(s)	Log-odds and standard errors			
	AAA vs. LLL	ALH vs. LLL	ALA vs. LLL	HHH vs. LLL
1. Demographics:				
Age	0.05 (0.00)	-0.02 (0.01)	0.04 (0.00)	0.10 (0.01)
Male [R: 55.5%]	-----	-----	-----	-----
Female	-1.06 (0.02)	0.4 (0.05)	1.14 (0.02)	-1.76 (0.05)
White [R: 68.5%]	-----	-----	-----	-----

Model and variable(s)	Log-odds and standard errors			
	AAA vs. LLL	ALH vs. LLL	ALA vs. LLL	HHH vs. LLL
Black	-0.44 (0.03)	-0.22 (0.08)	0.11 (0.03)	-0.71 (0.06)
Asian	-0.22 (0.05)	0.42 (0.09)	0.01 (0.05)	-0.57 (0.09)
Hispanic	-0.59 (0.04)	-1.03 (0.15)	-0.41 (0.04)	-1.08 (0.08)
Other [a]	-0.27 (0.05)	-0.11 (0.12)	0.02 (0.05)	-0.31 (0.08)
2. Attained education:				
Less than HS	-0.57 (0.03)	-2.47 (0.43)	-0.38 (0.04)	-0.86 (0.07)
HS diploma or equiv. [R: 32.5%]	-----	-----	-----	-----
Some college, no degree	0.16 (0.02)	1.05 (0.08)	0.30 (0.03)	0.75 (0.04)
Associate's degree	0.26 (0.03)	1.69 (0.09)	0.47 (0.03)	1.05 (0.05)
Bachelor's degree or more	0.39 (0.03)	1.49 (0.09)	0.41 (0.03)	1.43 (0.04)
3. Occupational group:				
Sales and Office [R: 33.7%]	-----	-----	-----	-----
Natural Resources, Construction, and Maintenance	0.72 (0.03)	----[c]	1.04 (0.04)	2.05 (0.08)
Production, Transportation, and Material Moving	0.93 (0.02)	----[c]	-0.6 (0.05)	2.12 (0.08)
Service	-3.04 (0.10)	----[c]	0.22 (0.02)	2.25 (0.07)
Other [b]	----[c]	----[c]	----[c]	----[c]
4. Required level of education:				
Less than HS	-0.61 (0.03)	-1.55 (0.11)	-22.01 (0.08)	-1.82 (0.08)
HS or equivalent [R: 88.5%]	-----	-----	-----	-----
5. Required work experience:				
None	-2.01 (0.03)	-0.42 (0.06)	-1.29 (0.03)	0.57 (0.03)

Model and variable(s)	Log-odds and standard errors			
	AAA vs. LLL	ALH vs. LLL	ALA vs. LLL	HHH vs. LLL
More than none [R: 69.6%]	-----	-----	-----	-----
6. On-the-job training:				
None, up to 1 month	-1.08 (0.02)	-18.6 (0.07)	-0.77 (0.02)	-2.92 (0.07)
Over 1 month [R: 56.5%]	-----	-----	-----	-----
7. Education level match:				
Undereducation	-0.54 (0.03)	-4.33 (0.93)	-0.34 (0.04)	-1.53 (0.07)
Adequate education	-0.19 (0.02)	-1.18 (0.07)	-0.22 (0.02)	-0.92 (0.04)
Overeducation [R: 57.2%]	-----	-----	-----	-----
8. Field match:				
No Bachelor's degree[d]	-0.18 (0.03)	-0.71 (0.06)	-0.10 (0.03)	-0.81 (0.04)
Mismatch [R: 13.0%]	-----	-----	-----	-----
Match	1.39 (0.06)	0.88 (0.13)	1.20 (0.06)	1.72 (0.07)
9-12. Occupational abilities:				
Cognitive	1.63 (0.19)	0.91 (0.30)	1.13 (0.29)	1.14 (1.09)
Physical	1.53 (0.55)	0.72 (0.32)	1.06 (0.48)	0.74 (0.25)
Psychomotor	1.58 (0.37)	0.74 (0.25)	1.04 (0.52)	0.79 (0.09)
Sensory	1.58 (0.36)	0.75 (0.21)	1.07 (0.44)	0.85 (0.10)
13-18. Occupational skills:				
Basic	1.63 (0.22)	0.98 (0.55)	1.16 (0.22)	1.07 (0.83)
Complex problem solving	1.68 (0.06)	0.93 (0.38)	1.13 (0.29)	1.28 (1.55)
Resource management	1.63 (0.22)	0.81 (0.02)	1.11 (0.34)	0.86 (0.13)
Social	1.55 (0.49)	0.77 (0.15)	1.08 (0.40)	0.83 (0.06)

Model and variable(s)	Log-odds and standard errors			
	AAA vs. LLL	ALH vs. LLL	ALA vs. LLL	HHH vs. LLL
Systems	1.69 (0.01)	0.94 (0.39)	1.13 (0.27)	1.07 (0.85)
Technical	1.60 (0.31)	0.80 (0.05)	1.06 (0.46)	0.80 (0.07)

[a] Other includes: Native American; Asian & Pacific Islander; and Other.
[b] Other includes: Education, Legal, Community Service, Arts, and Media; Healthcare Practitioners and Technical; Management, Business, and Financial; and Military Specific occupations.
[c] Cell counts for one or more categories were relatively small or zero and a reliable estimate could not be produced.
[d] Included as a control variable to estimate the relationship of interest.
Note. *p<.05. Statistically significant odds ratios ≥ 3.0 or ≤ .33 are presented in bold. Reference groups are identified with an [R] next to the variable name, along with the percentage in the sample. Demographic variables presented at the top of the table were included in all subsequent models as control variables.

Table D4

Log-Odds and Standard Errors for Model 2

Model and variable(s)	Log-odds and standard errors	
	ALA vs. AHH	AAA vs. AHH
1. Demographics:		
Age	-0.06 (0.01)	-0.04 (0.00)
Male [R: 51.2%]	-----	-----
Female	1.66 (0.04)	-0.15 (0.03)
White [R: 73.6%]	-----	-----
Black	0.44 (0.05)	0.15 (0.05)
Asian	0.75 (0.07)	-0.22 (0.07)
Hispanic	0.55 (0.07)	0.25 (0.07)
Other [a]	0.08 (0.08)	-0.02 (0.07)
2. Attained education:		
Less than HS	0.9 (0.08)	0.66 (0.07)
HS diploma or equiv.	0.64 (0.04)	0.40 (0.04)
Some college, no degree [R: 42.8%]	-----	-----

Model and variable(s)	Log-odds and standard errors	
	ALA vs. AHH	AAA vs. AHH
Associate's degree	-0.61 (0.04)	-0.46 (0.04)
3. Occupational group:		
Education, Legal, Community Service, Arts, and Media [R: 14.3%] [b]	-----	-----
Computer, Engineering, and Science	----[c]	-4.99 (0.21)
Healthcare Practitioners and Technical	----[c]	-1.96 (0.08)
Management, Business, and Financial	----[c]	-3.71 (0.08)
Natural Resources, Construction, and Maintenance	----[c]	1.21 (0.14)
Service	5.35 (0.47)	1.44 (0.48)
Other [d]	----[c]	-1.67 (0.07)
4. Required level of education:		
Post-secondary certificate or some college	6.15 (0.15)	4.13 (0.15)
Associate's degree	0.95 (0.09)	-0.08 (0.05)
Bachelor's degree [R: 54.1%]	-----	-----
Graduate degree	0.40 (0.12)	0.58 (0.07)
5. Required work experience:		
None	-22.42 (0.00)	0.15 (0.08)
Up to 2 years [R: 48.2%]	-----	-----
Over 2 years	-3.34 (0.08)	-1.13 (0.03)
6. On-the-job training:		
None, up to 1 month	1.55 (0.06)	1.74 (0.06)
Over 1 month [R: 89.6%]	-----	-----
7. Education level match:		
Undereducation [R: 66.5%]	-----	-----
Adequate education	1.74 (0.05)	0.66 (0.04)
Overeducation	4.86 (0.17)	3.69 (0.18)
8-11. Occupational abilities:		
Cognitive	-2.37 (0.04)	-1.11 (0.03)
Physical	0.89 (0.01)	0.79 (0.02)

Model and variable(s)	Log-odds and standard errors	
	ALA vs. AHH	AAA vs. AHH
Psychomotor	0.59 (0.01)	0.66 (0.01)
Sensory	-0.18 (0.01)	0.80 (0.02)
12-17. Occupational skills:		
Basic	-1.73 (0.02)	-0.98 (0.02)
Complex problem solving	-3.01 (0.04)	-1.42 (0.02)
Resource management	-1.25 (0.03)	-0.22 (0.01)
Social	-0.49 (0.01)	-0.26 (0.01)
Systems	-2.26 (0.03)	-1.15 (0.03)
Technical	-0.13 (0.01)	0.35 (0.01)

[a] Other includes: Native American; Asian & Pacific Islander; and Other.
[b] The Management, Business, and Financial group contained the largest portion (23.8%) of the sample but was not observed in the ALA class thus the reference category was changed.
[c] Cell counts for one or more categories were relatively small or zero and a reliable estimate could not be produced.
[d] Other includes: Military Specific; Production, Transportation, and Material Moving; and Sales and Office occupations
Note. *p<.05. Statistically significant odds ratios ≥ 3.0 or ≤ .33 are presented in bold. Reference groups are identified with an [R] next to the variable name, along with the percentage in the sample. Demographic variables presented at the top of the table were included in all subsequent models as control variables.

Table D5

Log-Odds and Standard Errors for Model 3

Model and variable(s)	Log-odds and standard errors				
	AAL vs. HHH	AHH vs. HHH	HHA vs. HHH	ALA vs. HHH	AAH vs. HHH
1. Demographics:					
Age	-0.11 (0.01)	-0.05 (0.01)	-0.02 (0.01)	-0.08 (0.01)	-0.08 (0.01)
Male [R: 45.1%]	-----	-----	-----	-----	-----
Female	0.42 (0.06)	0.7 (0.04)	-0.12 (0.04)	1.08 (0.06)	0.51 (0.04)
White [R: 74.5%]	-----	-----	-----	-----	-----

Model and variable(s)	Log-odds and standard errors AAL vs. HHH	AHH vs. HHH	HHA vs. HHH	ALA vs. HHH	AAH vs. HHH
Black	0.29 (0.11)	0.33 (0.08)	0.23 (0.08)	0.78 (0.1)	0.58 (0.08)
Asian	-0.48 (0.08)	-1.09 (0.07)	-0.46 (0.05)	-0.69 (0.09)	-1.16 (0.07)
Other [a]	0.35 (0.13)	0.12 (0.09)	0.07 (0.1)	0.74 (0.11)	0.42 (0.08)
2. Attained education:					
Bachelor's degree [R: 50.5%]	-----	-----	-----	-----	-----
Graduate degree	-1.31 (0.06)	-0.76 (0.04)	-1.28 (0.04)	-1.90 (0.07)	-1.06 (0.04)
3. Field of Study:					
Science and Engineering Group [R: 61.3%]	-----	-----	-----	-----	-----
Science and Engineering Related Fields	0.90 (0.14)	0.88 (0.10)	0.79 (0.09)	0.44 (0.16)	-0.37 (0.15)
Business	0.43 (0.09)	0.19 (0.07)	-0.71 (0.08)	0.91 (0.08)	0.21 (0.06)
Education	0.43 (0.18)	-0.11 (0.16)	0.65 (0.11)	-0.05 (0.18)	0.75 (0.11)
Arts, Humanities, and Other	0.71 (0.06)	0.84 (0.04)	0.33 (0.04)	0.60 (0.07)	0.37 (0.04)
4. Occupational group:					
Management, Business, and Financial [R: 28.6%][e]	-----	-----	-----	-----	-----
Computer, Engineering, and Science	-0.88 (0.08)	-2.23 (0.1)	-1.21 (0.05)	----[c]	----[c]
Education, Legal, Community Service, Arts, and Media	1.14 (0.07)	1.13 (0.05)	----[c]	----[c]	3.91 (0.16)
Healthcare Practitioners and Technical	----[c]	-2.29 (0.09)	----[c]	----[c]	1.21 (0.16)
Sales and Office	3.22 (0.26)	----[c]	3.32 (0.24)	----[c]	6.24 (0.28)
Other [b]	1.66 (0.17)	0.98	-0.91 (0.22)	----[c]	4.33 (0.19)

Model and variable(s)	Log-odds and standard errors				
	AAL vs. HHH	AHH vs. HHH	HHA vs. HHH	ALA vs. HHH	AAH vs. HHH
5. Required level of education:					
Associate's degree or less	-1.25 (0.10)	-2.40 (0.12)	-3.48 (0.21)	1.53 (0.07)	-0.59 (0.07)
Bachelor's degree [R: 65.5%]	-----	-----	-----	-----	-----
Graduate degree	----[c]	-2.07 (0.05)	-3.23 (0.08)	-1.59 (0.1)	-0.61 (0.04)
6. Required work experience:					
None to 2 years	0.49 (0.06)	1.79 (0.05)	-0.08 (0.05)	4.17 (0.13)	1.63 (0.04)
Over 2 years [R: 60.5%]	-----	-----	-----	-----	-----
7. On-the-job training:					
None, up to 1 month	-1.95 (0.13)	-2.79 (0.15)	----[c]	0.37 (0.06)	-0.95 (0.06)
Over 1 month [R: 90.1%]	-----	-----	-----	-----	-----
8. Education level match:					
Undereducation	----[c]	0.15 (0.08)	-1.66 (0.17)	0.91 (0.12)	1.18 (0.06)
Adequate education [R: 63.6%]	-----	-----	-----	-----	-----
Overeducation	0.38 (0.06)	0.46 (0.04)	-0.14 (0.04)	1.77 (0.06)	0.04 (0.05)
9-12. Occupational abilities:					
Cognitive	-3.33 (0.28)	-1.14 (0.12)	-3.26 (0.33)	-0.37 (0.51)	-2.27 (0.29)
Physical	0.73 (0.03)	0.20 (0.03)	0.62 (0.03)	-0.24 (0.03)	0.12 (0.02)
Psychomotor	0.04 (0.03)	-0.42 (0.03)	0.01 (0.02)	-0.65 (0.03)	-0.30 (0.02)
Sensory	-0.10 (0.04)	0.07 (0.02)	-0.51 (0.05)	0.09 (0.02)	-0.09 (0.02)
13-18. Occupational skills:					
Basic	-4.68 (0.11)	-2.93 (0.1)	-4.55 (0.11)	-3.16 (0.13)	-3.69 (0.11)
Complex problem solving	-3.03 (0.06)	-1.17 (0.03)	-2.72 (0.06)	-0.85 (0.03)	-1.58 (0.05)

Model and variable(s)	Log-odds and standard errors				
	AAL vs. HHH	AHH vs. HHH	HHA vs. HHH	ALA vs. HHH	AAH vs. HHH
Resource management	-1.20 (0.05)	0.02 (0.01)	-1.02 (0.04)	0.18 (0.01)	-0.07 (0.01)
Social	-0.13 (0.04)	8.76 (28.31)	-0.14 (0.04)	0.00 (0.04)	0.04 (0.03)
Systems	-2.72 (0.07)	-0.68 (0.04)	-2.50 (0.06)	-0.29 (0.02)	-1.41 (0.05)
Technical	-0.33 (0.04)	-0.38 (0.02)	-1.15 (0.18)	-0.18 (0.02)	-0.39 (0.02)

[a] Other includes: Native American; Asian & Pacific Islander; Hispanic; and Other.
[b] Other includes: Natural Resources, Construction, and Maintenance; Production, Transportation, and Material Moving; and Military Specific; and Service occupations.
[c] Cell counts for one or more categories were relatively small or zero and a reliable estimate could not be produced.
[d] Estimate suffered from quasi-separation of data and was thus repressed.
[e] The education group contained the largest proportion of the sample (31%) but it contained a small number of observations for the third largest class, the HHA class, which did not permit reliable estimates for the class. Thus, the next largest group was used instead.
Note. *p<.05. Statistically significant odds ratios ≥ 3.0 or ≤ .33 are presented in bold. Reference groups are identified with an [R] next to the variable name, along with the percentage in the sample. Demographic variables presented at the top of the table were included in all subsequent models as control variables.

Table D6

Log-Odds and Standard Errors for Model 4

Model and variable(s)	Class comparisons		
	HAH vs. HHH	HHA vs. HHH	ALA vs. HHH
1. Demographics:			
Age	0.00 (0.01)	0.04 (0.01)	-0.08 (0.02)
Male [R: 44.8%]	-----	-----	-----
Female	-0.10 (0.03)	-0.45 (0.05)	0.91 (0.13)
White [R: 75.6%]	-----	-----	-----
Black	0.28 (0.06)	0.16 (0.10)	0.16 (0.19)
Asian	-0.67 (0.05)	-0.40 (0.07)	-1.00 (0.22)

Model and variable(s)	Class comparisons		
	HAH vs. HHH	HHA vs. HHH	ALA vs. HHH
Other [a]	0.23 (0.07)	0.22 (0.11)	0.46 (0.24)
2. Attained education:			
Bachelor's degree [R: 65.3%]	-----	-----	-----
Graduate degree	-0.87 (0.04)	-0.59 (0.05)	-0.96 (0.12)
3. Field of Study:			
Business [R: 28.6%]	-----	-----	-----
Science and Engineering Group	-2.00 (0.05)	-0.92 (0.05)	----[c]
Science and Engineering Related Fields	-2.13 (0.07)	-2.74 (0.14)	----[c]
Education	-2.33 (0.07)	-3.04 (0.15)	----[c]
Arts, Humanities, and Other	0.41 (0.04)	0.03 (0.07)	----[c]
4. Occupational group:			
Education, Legal, Community Service, Arts, and Media [R: 32.6%]	-----	-----	-----
Computer, Engineering, and Science	-1.17 (0.06)	40.11 (0.17)	-4.51 (1.29)
Healthcare Practitioners and Technical	-2.38 (0.11)	----[c]	-2.16 (0.26)
Management, Business, and Financial	0.22 (0.04)	43.26 (0.15)	----[c]
Other [b]	3.19 (0.08)	----[c]	4.10 (0.13)
5. Required level of education:			
Associate's degree or less	-2.58 (0.14)	-5.21 (1.70)	1.74 (0.15)
Bachelor's degree [R: 65.3%]	-----	-----	-----
Graduate degree	-1.05 (0.04)	-0.76 (0.05)	-0.35 (0.15)
6. Required work experience:			

Model and variable(s)	Class comparisons		
	HAH vs. HHH	HHA vs. HHH	ALA vs. HHH
None, up to 2 years	-0.64 (0.04)	-1.89 (0.08)	2.91 (0.34)
Over 2 years [R: 60.6%]	-----	-----	-----
7. On-the-job training:			
None, up to 1 month	-1.82 (0.09)	-21.06 (0.00)	1.29 (0.11)
Over 1 month [R: 88.4%]	-----	-----	-----
8. Education level match:			
Undereducation	-0.37 (0.07)	-2.78 (0.39)	-0.17 (0.23)
Adequate education [R: 62.8%]	-----	-----	-----
Overeducation	-1.05 (0.04)	-0.56 (0.05)	0.88 (0.12)
9-12. Occupational abilities:			
Cognitive	-0.63 (0.06)	0.99 (0.08)	0.07 (0.23)
Physical	0.58 (0.03)	0.08 (0.03)	0.03 (0.08)
Psychomotor	0.17 (0.04)	0.19 (0.01)	0.00 (0.01)
Sensory	0.01 (0.05)	0.05 (0.04)	0.04 (0.12)
13-18. Occupational skills:			
Basic	-0.59 (0.06)	1.07 (0.05)	0.04 (0.14)
Complex problem solving	-1.29 (0.08)	0.57 (0.08)	0.06 (0.21)
Resource management	-1.51 (0.05)	-0.32 (0.03)	0.02 (0.08)
Social	0.06 (0.04)	-0.15 (0.02)	0.02 (0.05)
Systems	-1.86 (0.15)	-0.63 (0.23)	0.06 (0.19)
Technical	-1.74 (0.16)	-0.44 (0.03)	-0.03 (0.11)

[a] Other includes: Native American; Asian & Pacific Islander; Hispanic; and Other.
[b] Other includes: Natural Resources, Construction, and Maintenance; Production, Transportation, and Material Moving; and Military Specific occupations.
[c] Cell counts for one or more categories were relatively small or zero and a reliable estimate could not be produced.
Note. **p*<.05. Statistically significant odds ratios ≥ 3.0 or ≤ .33 are presented in bold. Reference groups are identified with an [R] next to the variable name, along with the percentage in the sample. Demographic variables presented at the top of the table were included in all subsequent models as control variables.

Table D7

Log-Odds and Standard Errors for Model 5

Model and variable(s)	Class comparisons			
	ALA vs. LLL	AAA vs. LLL	AHA vs. LLL	HHH vs. LLL
1. Demographics:				
Age	0.02 (0.00)	0.05 (0.00)	0.07 (0.00)	0.07 (0.00)
Male [R: 51.9%]	-----	-----	-----	-----
Female	0.93 (0.02)	-1.03 (0.02)	-0.22 (0.01)	0.20 (0.01)
White [R: 68.5%]	-----	-----	-----	-----
Black	0.00 (0.02)	-0.48 (0.03)	-0.66 (0.02)	-0.85 (0.02)
Asian	0.03 (0.04)	-0.29 (0.05)	0.21 (0.03)	0.80 (0.02)
Hispanic	-0.34 (0.03)	-0.67 (0.04)	-0.98 (0.03)	-1.63 (0.04)
Other [a]	-0.02 (0.04)	-0.28 (0.05)	-0.28 (0.03)	-0.42 (0.03)
2. Attained education:				
Less than HS	-0.84 (0.04)	-1.34 (0.04)	-3.18 (0.04)	-4.86 (0.07)
HS diploma or equiv.	-0.43 (0.03)	-0.73 (0.03)	-2.23 (0.02)	-3.60 (0.03)
Some college, no degree	-0.07 (0.03)	-0.56 (0.03)	-1.53 (0.02)	-2.34 (0.02)

Model and variable(s)	Class comparisons ALA vs. LLL	AAA vs. LLL	AHA vs. LLL	HHH vs. LLL
Associate's degree	0.23 (0.03)	-0.35 (0.04)	-1.12 (0.03)	-1.28 (0.02)
Bachelor's degree [R: 24.4%]	-----	-----	-----	-----
Graduate degree	0.10 (0.05)	0.29 (0.05)	0.68 (0.03)	1.47 (0.03)
3. Field of Study:				
No Bachelor's degree[b]	-0.38 (0.04)	-0.68 (0.04)	-2.12 (0.02)	-3.26 (0.02)
Science and Engineering Group [R: 13.2%]	-----	-----	-----	-----
Science and Engineering Related Fields	0.39 (0.08)	0.13 (0.10)	-0.17 (0.06)	0.71 (0.05)
Business	-0.38 (0.06)	0.05 (0.05)	0.02 (0.03)	-0.57 (0.03)
Education	0.44 (0.07)	0.18 (0.09)	-0.99 (0.07)	0.52 (0.05)
Arts, Humanities, and Other	-0.27 (0.05)	0.03 (0.05)	-0.23 (0.03)	-0.74 (0.03)
4. Occupational group:				
Sales and Office [R: 22.8%]	-----	-----	-----	-----
Computer, Engineering, and Science; Education, Legal, Community Service, Arts, and Media; Healthcare Practitioners and Technical; Management, Business, and Financial; and Military Specific[e]	24.93 (0.13)	24.6 (0.13)	26.39 (0.13)	30.87 (0.00)
Natural Resources, Construction, and Maintenance	1.56 (0.03)	0.67 (0.03)	-0.04 (0.03)	1.07 (0.16)
Production, Transportation, and Material Moving	-0.49 (0.05)	0.88 (0.02)	-1.27 (0.04)	1.44 (0.14)
Service	0.64 (0.02)	-3.02 (0.11)	-3.97 (0.12)	2.58 (0.13)
5. Required level of education:				
Less than HS	-3.72 (0.18)	-0.63 (0.04)	-1.79 (0.16)	-31.40 (0.16)
HS or equivalent [R: 50.0%]	-----	-----	-----	-----

Model and variable(s)	Class comparisons ALA vs. LLL	 AAA vs. LLL	 AHA vs. LLL	 HHH vs. LLL
Post-secondary certificate or some college	1.94 (0.03)	0.13 (0.05)	3.31 (0.04)	3.01 (0.04)
Associate's degree or less	32.24 (0.06)	32.22 (0.06)	35.04 (0.05)	36.66 (0.00)
Bachelor's degree	2.54 (0.09)	3.89 (0.09)	8.45 (0.09)	8.13 (0.09)
Graduate degree	30.01 (0.11)	28.89 (0.47)	36.05 (0.04)	36.84 (0.00)
6. Required work experience:				
None	-1.31 (0.02)	-2.00 (0.05)	-0.84 (0.03)	-1.23 (0.02)
Up to 2 years [R: 51.4%]	-----	-----	-----	-----
Over 2 years	65.74 (0.03)	66.73 (0.02)	68.41 (0.02)	67.52 (0.00)
7. On-the-job training:				
None or short demonstration	1.14 (0.04)	-0.27 (0.07)	-21.74 (0.03)	1.18 (0.03)
Up to 1 month	-1.63 (0.02)	-1.26 (0.02)	-4.45 (0.06)	-3.01 (0.02)
Over 1 month [R: 70.8%]	-----	-----	-----	-----
8. Education level match:				
Undereducation	0.42 (0.03)	-0.05 (0.03)	1.02 (0.02)	-0.07 (0.02)
Adequate education [R: 37.5%]	-----	-----	-----	-----
Overeducation	0.27 (0.02)	0.01 (0.02)	-1.42 (0.02)	-0.98 (0.01)
9. Field match:				
No Bachelor's degree [b]	-0.04 (0.02)	-0.58 (0.02)	-1.54 (0.02)	-2.33 (0.02)
Mismatch [R: 20.9%]	-----	-----	-----	-----
Match	1.46 (0.05)	1.03 (0.06)	2.10 (0.04)	2.60 (0.04)

Model and variable(s)	Class comparisons			
	ALA vs. LLL	AAA vs. LLL	AHA vs. LLL	HHH vs. LLL
10-13. Occupational abilities: [d]				
Cognitive	0.96 (0.01)	1.09 (0.01)	2.68 (0.02)	3.96 (0.02)
Physical	-0.07 (0.01)	-0.07 (0.14)	-0.68 (0.01)	-0.59 (0.01)
Psychomotor	-0.08 (0.01)	0.32 (0.01)	-0.74 (0.01)	-0.60 (0.01)
Sensory	0.19 (0.02)	0.53 (0.01)	0.16 (0.02)	0.21 (0.04)
14-19. Occupational skills: [d]				
Basic	1.30 (0.01)	1.16 (0.01)	2.84 (0.01)	3.84 (0.02)
Complex problem solving	0.86 (0.05)	1.69 (0.67)	3.65 (0.07)	4.27 (0.05)
Resource management	0.66 (0.01)	1.68 (0.02)	1.91 (0.01)	1.77 (0.01)
Social	0.31 (0.01)	0.34 (0.01)	0.95 (0.01)	1.00 (0.01)
Systems	1.16 (0.01)	1.63 (0.02)	2.77 (0.02)	3.38 (0.02)
Technical	0.28 (0.01)	0.60 (0.01)	0.27 (0.01)	0.35 (0.00)

[a] Other includes: Native American; Asian & Pacific Islander; and Other.
[b] Included as a control variable to estimate the relationship of interest.
[c] Cell counts for one or more categories were relatively small or zero and a reliable estimate could not be produced.
[d] The Hispanic, Asian, and Other categories were collapsed in the estimation of this model due to near zero variance for some of the class and race/ethnic combinations.
[e] These categories were collapsed due to low counts in the reference class.
Note. **p*<.05. Statistically significant odds ratios ≥ 3.0 or ≤ .33 are presented in bold. Reference groups are identified with an [R] next to the variable name, along with the percentage in the sample. Demographic variables presented at the top of the table were included in all subsequent models as control variables.

Distributions of Predictor Variables Across Latent Classes

Table D8

Categorical Variable Distribution Across Latent Classes in Model 1

Variable	Category	Categorical % across class				
		LLL	AAA	ALH	ALA	HHH
Race/ethnicity	White	41.1	14.5	1.1	8.5	3.2
	Black	10.2	2.4	0.2	2.3	0.4
	Native American	0.6	0.2	0.0	0.1	0.0
	Asian & Pacific Islander	2.7	0.8	0.1	0.6	0.1
	Other	0.1	0.0	0.0	0.0	0.0
	Multiracial	1.9	0.5	0.1	0.4	0.1
	Hispanic	5.4	1.2	0.1	0.7	0.2
Gender	Male	33.2	14.3	0.7	3.9	3.4
	Female	28.8	5.3	0.9	8.8	0.6
Attained education	Lt High School	10.8	2.1	0.0	1.2	0.2
	High School or equivalent	21.1	6.7	0.3	3.5	0.9
	Some college no degree	16.8	5.7	0.6	4.1	1.3
	Associates	4.9	1.8	0.3	1.5	0.5
	Bachelors	7.1	2.8	0.4	2.0	0.9
	Graduate	1.2	0.5	0.1	0.4	0.2
Bachelor field of study	No Degree	53.7	16.3	1.2	10.3	2.9
	Science and Engineering Group	2.6	1.1	0.2	0.8	0.4
	Science and Engineering Related Fields	0.4	0.1	0.1	0.2	0.0
	Business	1.8	1.0	0.1	0.5	0.2
	Education	0.5	0.1	0.0	0.1	0.0
	Arts, Humanities, and Other	2.9	1.0	0.1	0.8	0.5
Education level match	Undereducated	8.1	1.9	0.0	1.2	0.2
	Adequately Educated	20.4	6.3	0.3	3.5	0.9

Variable	Category	Categorical % across class				
		LLL	AAA	ALH	ALA	HHH
	Overeducated	33.5	11.5	1.3	7.9	3.0
Field match	No Degree	53.7	16.3	1.2	10.3	2.9
	Not Matched	7.6	2.5	0.4	1.8	0.8
	Matched	0.8	0.8	0.1	0.6	0.3
Required level of education	Lt High School	9.4	1.9	0.1	0.1	0.1
	High School or equivalent	52.6	17.8	1.5	12.6	3.9
Required work experience	None	23.9	1.9	0.5	2.2	1.9
	Up to 2 years	37.6	12.1	1.1	8.0	0.5
	Over 2 years, up to 6 years	0.4	5.7	0.0	2.6	0.9
	Over 10 years	0.0	0.0	0.0	0.0	0.7
On-the-job training	None or short demonstration	0.7	0.5	0.0	1.5	0.0
	Anything beyond short demonstration, up to 1 month	32.3	4.9	0.0	3.4	0.2
	Over 1 month, up to 1 year	28.3	14.0	1.5	7.8	3.2
	Over 1 year, up to 2 years	0.3	0.0	0.0	0.0	0.0
	Over 2 years, up to 4 years	0.0	0.3	0.0	0.0	0.0
	Over 4 years	0.4	0.1	0.0	0.0	0.6
Major occupational group	Education, Legal, Community Service, Arts, and Media	0.1	0.4	0.0	0.3	0.0
	Healthcare Practitioners and Technical	0.0	0.0	1.1	0.2	0.0
	Management, Business, and Financial	0.0	1.3	0.0	0.0	0.1
	Military Specific	0.0	0.0	0.4	0.2	0.2
	Natural Resources, Construction, and Maintenance	6.7	4.3	0.0	1.6	0.7
	Production, Transportation, and Material Moving	10.4	7.0	0.0	1.1	1.0
	Sales and Office	23.1	5.8	0.0	4.6	0.2
	Service	21.8	0.8	0.0	4.7	1.8

Table D9

Continuous Variable Distribution Across Latent Classes in Model 1

Variable	Mean by class				
	LLL	AAA	ALH	ALA	HHH
Cognitive abilities	-2.02	-0.73	0.26	-1.05	1.45
Physical abilities	0.75	1.02	0.18	0.15	1.29
Psychomotor abilities	0.09	1.11	0.10	-0.48	1.34
Sensory abilities	-0.96	0.71	-0.64	-1.14	2.36
Basic skills	-1.87	-0.93	0.50	-0.78	0.81
Social skills	-0.67	-0.31	0.43	-0.12	1.72
Complex problem solving skills	-2.14	-0.91	-0.45	-1.40	0.47
Technical skills	-1.30	0.36	-0.34	-1.47	0.36
Systems skills	-2.09	-0.71	0.11	-1.49	0.94
Resource management skills	-1.51	0.45	0.09	-0.98	1.08

Note. The above means were computed based on the imputed datasets.

Table D10

Categorical Variable Distribution Across Latent Classes in Model 2

Variable	Category	Categorical % across class		
		ALA	AAA	AHH
Race/ethnicity	White	12.9	27.8	32.9
	Black	3.1	4.5	4.7
	Native American	0.2	0.3	0.4
	Asian & Pacific Islander	1.5	1.4	1.9
	Other	0.0	0.1	0.1
	Multiracial	0.6	1.1	1.3
	Hispanic	1.2	2.1	2.0
Gender	Male	4.3	22.2	24.6
	Female	15.2	14.9	18.7
Attained education	Lt High School	1.3	2.5	1.7
	High School or equivalent	6.3	11.0	9.2
	Some college no degree	8.2	15.9	18.7

Variable	Category	Categorical % across class		
		ALA	AAA	AHH
	Associates	3.8	7.7	13.6
Education level match	Undereducated	6.7	23.0	36.7
	Adequately Educated	5.3	6.0	5.6
	Overeducated	7.5	8.2	1.0
Required level of education	Post-secondary certificate	11.6	14.5	1.6
	Some college no degree	2.4	0.2	0.0
	Associates	2.0	3.0	6.6
	Bachelors	3.2	17.8	33.1
	Graduate	0.4	1.7	2.0
Required work experience	None	0.0	2.0	1.3
	Up to 2 years	17.4	18.3	12.5
	Over 2 years, up to 6 years	2.1	16.8	25.8
	Over 6 years, up to 10 years	0.0	0.0	3.6
	Over 10 years	0.0	0.0	0.2
On-the-job training	None or short demonstration	1.2	0.4	1.3
	Anything beyond short demonstration, up to 1 month	2.3	4.8	0.4
	Over 1 month, up to 1 year	16.0	28.9	40.8
	Over 1 year, up to 2 years	0.0	0.0	0.1
	Over 2 years, up to 4 years	0.0	3.0	0.5
	Over 4 years	0.0	0.1	0.2
Major occupational group	Computer, Engineering, and Science	0.0	1.0	7.8
	Education, Legal, Community Service, Arts, and Media	4.7	7.7	1.9
	Healthcare Practitioners and Technical	0.0	5.8	6.2
	Management, Business, and Financial	0.0	4.5	19.3
	Military Specific	0.0	0.0	0.1
	Natural Resources, Construction, and Maintenance	0.3	9.9	1.3
	Production, Transportation, and Material Moving	0.0	1.4	0.6
	Sales and Office	0.1	5.8	5.9
	Service	14.5	1.0	0.1

Table D11

Continuous Variable Distribution Across Latent Classes in Model 2

Variable	Mean by class		
	ALA	AAA	AHH
Cognitive abilities	-0.44	0.95	1.63
Physical abilities	0.37	0.14	-1.46
Psychomotor abilities	-0.45	-0.07	-1.56
Sensory abilities	-1.15	0.43	-0.81
Basic skills	0.24	0.87	1.78
Social skills	1.18	1.28	1.86
Complex problem solving skills	-0.83	0.52	1.68
Technical skills	-1.21	0.52	-0.62
Systems skills	-0.56	0.89	2.00
Resource management skills	-0.20	0.92	1.93

Note. The above means were computed based on the imputed datasets.

Table D12

Categorical Variable Distribution Across Latent Classes in Model 3

Variable	Category	Categorical % across class					
		AAL	AHH	HHA	ALA	AAH	HHH
Race/ ethnicity	White	4.5	17.1	14.2	3.5	13.2	22.0
	Black	0.5	2.0	1.5	0.6	1.9	1.9
	Native American	0.0	0.1	0.0	0.0	0.1	0.0
	Asian & Pacific Islander	0.7	1.7	2.3	0.5	1.2	5.5
	Other	0.0	0.0	0.0	0.0	0.1	0.1
	Multiracial	0.2	0.6	0.5	0.2	0.6	0.8
	Hispanic	0.1	0.4	0.3	0.2	0.5	0.4
Gender	Male	2.6	8.3	10.1	1.4	7.0	15.8
	Female	3.5	13.6	8.8	3.6	10.4	14.9
Attained education	Bachelors	4.5	13.4	13.7	4.2	12.0	13.6
	Graduate	1.6	8.5	5.2	0.9	5.4	17.1

Variable	Category	Categorical % across class					
		AAL	AHH	HHA	ALA	AAH	HHH
Education level match	Undereducated	0.0	1.5	0.4	0.4	3.0	1.8
	Adequately Educated	4.0	13.3	13.8	1.5	10.4	20.5
	Overeducated	2.1	7.1	4.7	3.1	4.0	8.4
Bachelor field of study	Science and Engineering Group	2.6	9.4	10.0	2.1	8.6	17.8
	Science and Engineering Related Fields	0.3	1.0	1.0	0.2	0.3	0.9
	Business	0.7	1.9	1.0	0.9	1.8	3.3
	Education	0.2	0.4	0.7	0.1	0.7	0.7
	Arts, Humanities, and Other	2.3	9.2	6.2	1.8	5.9	8.1
Required level of education	Post-secondary certificate	0.2	0.1	0.2	1.5	0.9	0.0
	Some college no degree	0.0	0.0	0.0	1.0	0.1	0.0
	Associates	0.3	0.7	0.2	0.3	0.7	3.9
	Bachelors	5.5	17.5	17.3	1.8	9.9	13.5
	Graduate	0.0	3.6	1.2	0.5	5.8	13.3
Required work experience	None	0.1	0.5	0.1	0.0	2.1	0.8
	Up to 2 years	1.8	11.6	4.0	4.7	7.6	6.2
	Over 2 years, up to 6 years	4.1	9.6	13.4	0.4	7.8	19.7
	Over 6 years, up to 10 years	0.0	0.1	1.4	0.0	0.0	3.6
	Over 10 years	0.0	0.0	0.0	0.0	0.0	0.4
On-the-job training	None or short demonstration	0.1	0.1	0.0	0.2	0.9	4.8
	Anything beyond short demonstration, up to 1 month	0.1	0.6	0.0	1.1	0.7	1.2
	Over 1 month, up to 1 year	5.8	21.2	18.8	3.7	15.6	19.5
	Over 1 year, up to 2 years	0.0	0.0	0.0	0.0	0.0	4.8
	Over 2 years, up to 4 years	0.0	0.0	0.1	0.0	0.3	0.0
	Over 4 years	0.0	0.0	0.0	0.0	0.0	0.4
	Computer, Engineering, and Science	0.8	1.4	3.7	0.0	0.1	9.0

Variable	Category	Categorical % across class					
		AAL	AHH	HHA	ALA	AAH	HHH
Major occupational group	Education, Legal, Community Service, Arts, and Media	2.6	10.8	0.6	2.3	10.3	4.5
	Healthcare Practitioners and Technical	0.0	1.5	0.1	0.0	1.8	8.7
	Management, Business, and Financial	1.7	7.4	10.3	0.0	1.1	8.1
	Military Specific	0.0	0.2	0.0	0.0	0.0	0.0
	Natural Resources, Construction, and Maintenance	0.2	0.1	0.2	0.1	0.7	0.0
	Production, Transportation, and Material Moving	0.1	0.1	0.1	0.0	0.1	0.3
	Sales and Office	0.6	0.4	4.0	0.1	2.8	0.2
	Service	0.1	0.0	0.0	2.6	0.4	0.0

Table D13

Continuous Variable Distribution Across Latent Classes in Model 3

Variable	Mean by class					
	AAL	AHH	HHA	ALA	AAH	HHH
Cognitive abilities	0.83	2.02	1.27	-0.48	1.24	2.38
Physical abilities	-1.50	-1.56	-2.01	0.58	-0.78	-1.81
Psychomotor abilities	-1.67	-1.96	-2.08	-0.98	-1.53	-1.73
Sensory abilities	-1.04	-0.85	-1.16	-1.14	-0.68	-1.02
Basic skills	1.13	2.21	1.55	0.22	1.55	2.62
Social skills	1.54	2.11	1.75	1.55	2.38	2.01
Complex problem solving skills	0.66	1.48	1.45	-0.61	1.07	2.91
Technical skills	-1.14	-1.26	-1.24	-1.38	-1.24	-0.59
Systems skills	0.52	1.88	1.70	-0.36	1.23	3.05
Resource management skills	0.31	1.31	1.87	-0.30	0.71	1.70

Note. The above means were computed based on the imputed datasets.

Table D14

Categorical Variable Distribution Across Latent Classes in Model 4

Variable	Category	Categorical % across class			
		HAH	HHA	ALA	HHH
Race/ethnicity	White	16.5	6.8	1.1	51.1
	Black	1.8	0.7	0.1	4.3
	Native American	0.1	0.0	0.0	0.1
	Asian & Pacific Islander	1.8	0.9	0.1	10.3
	Other	0.1	0.0	0.0	0.2
	Multiracial	0.6	0.3	0.0	1.5
	Hispanic	0.4	0.2	0.0	1.0
Gender	Male	9.7	4.7	0.4	30.0
	Female	11.6	4.1	1.0	38.5
Attained education	Bachelors	16.5	6.5	1.1	41.2
	Graduate	4.8	2.4	0.3	27.3
Education level match	Undereducated	1.3	0.1	0.1	4.4
	Adequately Educated	16.2	6.5	0.6	39.5
	Overeducated	3.8	2.2	0.8	24.6
Bachelor field of study	Science and Engineering Group	2.3	2.3	0.1	21.5
	Science and Engineering Related Fields	1.4	0.3	0.3	13.6
	Business	10.2	4.2	0.1	14.2
	Education	1.2	0.3	0.5	13.5
	Arts, Humanities, and Other	6.3	1.8	0.4	5.8
Required level of education	Post-secondary certificate	0.1	0.0	0.2	0.1
	Some college no degree	0.0	0.0	0.4	0.0
	Associates	0.4	0.0	0.1	8.4
	Bachelors	18.2	8.5	0.7	45.1
	Graduate	2.6	0.3	0.1	14.8
Required work experience	None	1.1	0.0	0.0	1.1
	Up to 2 years	5.6	1.2	1.2	29.2
	Over 2 years, up to 6 years	12.7	7.6	0.2	33.8
	Over 6 years, up to 10 years	1.9	0.0	0.0	3.1

Variable	Category	Categorical % across class			
		HAH	HHA	ALA	HHH
	Over 10 years	0.0	0.0	0.0	1.4
On-the-job training	None or short demonstration	0.1	0.0	0.0	9.0
	Anything beyond short demonstration, up to 1 month	0.6	0.0	0.5	1.4
	Over 1 month, up to 1 year	20.3	8.8	0.9	56.2
	Over 1 year, up to 2 years	0.0	0.0	0.0	0.8
	Over 2 years, up to 4 years	0.0	0.0	0.0	0.0
	Over 4 years	0.2	0.0	0.0	1.2
Major occupational group	Computer, Engineering, and Science	1.7	0.4	0.0	16.6
	Education, Legal, Community Service, Arts, and Media	7.9	0.3	0.6	23.8
	Healthcare Practitioners and Technical	0.5	0.0	0.0	11.9
	Management, Business, and Financial	6.5	7.5	0.0	15.4
	Military Specific	0.0	0.0	0.0	0.0
	Natural Resources, Construction, and Maintenance	0.0	0.0	0.0	0.0
	Production, Transportation, and Material Moving	0.0	0.0	0.0	0.2
	Sales and Office	4.4	0.6	0.0	0.5
	Service	0.2	0.0	0.7	0.0

Table D15

Continuous Variable Distribution Across Latent Classes in Model 4

Variable	Mean by class			
	HAH	HHA	ALA	HHH
Cognitive abilities	1.21	1.79	-0.60	2.07
Physical abilities	-1.65	-1.79	0.70	-1.54
Psychomotor abilities	-2.02	-2.19	-1.19	-1.83
Sensory abilities	-1.11	-0.86	-1.33	-1.02
Basic skills	1.44	1.87	0.34	2.41

Variable	Mean by class			
	HAH	HHA	ALA	HHH
Social skills	2.06	2.19	1.79	1.80
Complex problem solving skills	1.25	1.76	-0.51	1.90
Technical skills	-1.43	-1.33	-1.40	-0.87
Systems skills	1.32	2.38	-0.40	2.19
Resource management skills	1.57	2.79	-0.30	1.02

Note. The above means were computed based on the imputed datasets.

Table D16

Categorical Variable Distribution Across Latent Classes in Model 5

Variable	Category	Categorical % across class				
		ALA	LLL	AAA	AHA	HHH
Race/ethnicity	White	7.4	24.5	9.5	13.1	16.7
	Black	1.8	6.0	1.5	1.7	1.8
	Native American	0.1	0.4	0.1	0.1	0.1
	Asian & Pacific Islander	0.5	1.7	0.5	1.1	2.6
	Other	0.0	0.1	0.0	0.0	0.1
	Multiracial	0.3	1.1	0.3	0.5	0.6
	Hispanic	0.6	3.1	0.7	0.7	0.4
Gender	Male	3.5	19.2	8.9	9.8	10.5
	Female	7.4	17.6	3.9	7.4	11.8
Attained education	Lt High School	0.9	6.2	1.2	0.5	0.1
	High School or equivalent	2.9	12.6	4.0	2.5	0.9
	Some college no degree	3.5	10.2	3.5	3.7	2.3
	Associates	1.5	3.0	1.2	1.7	2.0
	Bachelors	1.7	4.2	2.3	6.5	9.6
	Graduate	0.4	0.7	0.5	2.3	7.3
Bachelor field of study	No Degree	8.8	32.0	9.9	8.4	5.3
	Science and Engineering Group	0.7	1.5	0.9	3.2	6.8
	Science and Engineering Related Fields	0.2	0.3	0.1	0.4	2.1
	Business	0.4	1.1	0.7	2.3	2.7

Variable	Category	Categorical % across class				
		ALA	LLL	AAA	AHA	HHH
	Education	0.2	0.3	0.2	0.2	2.0
	Arts, Humanities, and Other	0.6	1.7	0.9	2.7	3.4
Education level match	Undereducated	1.7	4.9	1.8	7.0	3.9
	Adequately Educated	2.9	12.1	4.3	7.0	11.1
	Overeducated	6.2	19.9	6.7	3.2	7.2
Field match	No Degree	8.8	32.0	9.9	8.4	5.3
	Not Matched	1.5	4.5	2.2	5.1	7.7
	Matched	0.6	0.4	0.6	3.7	9.3
Required level of education	Lt High School	0.1	5.3	1.0	0.1	0.0
	High School or equivalent	7.5	30.1	9.6	1.5	1.3
	Post-secondary certificate	1.6	1.2	0.4	1.0	0.9
	Some college no degree	0.6	0.0	0.0	0.0	0.0
	Associates	0.4	0.0	0.2	0.4	2.8
	Bachelors	0.6	0.2	1.4	12.7	12.6
	Graduate	0.1	0.0	0.1	1.6	4.7
Required work experience	None	1.3	13.5	1.0	1.0	1.6
	Up to 2 years	7.7	23.1	7.4	4.3	8.9
	Over 2 years, up to 6 years	1.9	0.3	4.3	10.8	10.2
	Over 6 years, up to 10 years	0.0	0.0	0.0	0.7	1.2
	Over 10 years	0.0	0.0	0.0	0.4	0.3
On-the-job training	None or short demonstration	0.9	0.6	0.3	0.0	2.2
	Anything beyond short demonstration, up to 1 month	2.0	18.8	2.9	0.4	1.1
	Over 1 month, up to 1 year	8.0	17.0	9.3	15.8	17.9
	Over 1 year, up to 2 years	0.0	0.2	0.0	0.0	0.8
	Over 2 years, up to 4 years	0.0	0.0	0.1	0.6	0.0
	Over 4 years	0.0	0.2	0.0	0.4	0.3
Major occupational group	Education, Legal, Community Service, Arts, and Media	0.0	0.0	0.1	1.7	4.3
	Healthcare Practitioners and Technical	1.4	0.1	0.9	3.2	5.8

Variable	Category	Categorical % across class				
		ALA	LLL	AAA	AHA	HHH
	Management, Business, and Financial	0.7	0.0	0.0	0.3	5.0
	Military Specific	0.0	0.0	1.1	6.0	5.4
	Natural Resources, Construction, and Maintenance	0.2	0.0	0.0	0.1	0.3
	Production, Transportation, and Material Moving	1.6	3.8	2.5	1.6	0.1
	Sales and Office	0.6	6.0	4.0	0.7	0.2
	Service	2.4	13.3	3.5	3.5	0.2

Table D17

Continuous Variable Distribution Across Latent Classes in Model 5

Variable	Mean by class				
	ALA	LLL	AAA	AHA	HHH
Cognitive abilities	-0.56	-1.99	-0.58	1.19	2.08
Physical abilities	0.32	0.73	0.75	-1.27	-1.14
Psychomotor abilities	-0.32	0.08	0.76	-1.47	-1.38
Sensory abilities	-0.77	-0.97	0.42	-0.60	-0.60
Basic skills	-0.30	-1.82	-0.70	1.31	2.28
Social skills	0.35	-0.64	-0.08	1.77	1.98
Complex problem solving skills	-1.05	-2.09	-0.73	1.11	1.91
Technical skills	-0.96	-1.30	0.18	-0.73	-0.72
Systems skills	-0.92	-2.04	-0.55	1.40	2.20
Resource management skills	-0.55	-1.49	0.37	1.68	1.26

Note. The above means were computed based on the imputed datasets.

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